Wharton

The Rodney L. White Center for Financial Research

*Skill, Luck and the Multiproduct Firm: Evidence from Hedge Funds*

**Rui J. P. de Figueiredo, Jr.**
**Evan Rawley**

**15-10**

The Wharton School
**University of Pennsylvania**

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

Rui J.P. de Figueiredo, Jr.
*University of California Berkeley, Haas School of Business, Berkeley CA 97405, rui@haas.berkeley.edu*

Evan Rawley
*The Wharton School, University of Pennsylvania, Philadelphia, Pennsylvania 19104, rawley@wharton.upenn.edu*

We propose that when managers require external investment to expand, higher skilled firms will diversify on average, even though managers can exploit asymmetric information about their ability to raise money from investors. We formalize this intuition in an equilibrium model and test our predictions using a large panel dataset on the hedge fund industry 1977-2006. We show that excess returns fall following diversification—defined as the launch of new fund—but are 11 basis points per month higher in diversified firms compared to a matched sample of focused firms. 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. The results provide large sample empirical evidence that agency effects and firm capabilities both influence diversification decisions.

*Key words:* Diversification, skill, capabilities, agency costs.

---

## 1. Introduction

Why do firms diversify? Since Penrose (1959), scholars have advanced the idea that diversification creates value by enabling firms to apply their unique capabilities across multiple products (Teece 1980; Panzar and Willig 1981). By contrast, the "diversification discount" literature proposes that managers diversify for private gain, even when doing so destroys firm value (Lang and Stulz 1994, Berger and Ofek 1995), a perspective that draws heavily on agency theory (Jensen and Meckling 1976). While capabilities and agency theories ostensibly make different predictions about the effect of diversification on firm performance, they are not mutually exclusive with respect to the causes of diversification. In this paper, we integrate the joint predictions of capabilities and agency theories into a simple equilibrium model, and

* We thank Vineet Budhraja, Jacques Chappuis, Paul Gertler, Margaret Kyle, Ryan Meredith, Philipp Meyer, John Morgan, Gabriel Natividad, Santiago Oliveros, Chris Rider, Robert Stambaugh, Pablo Spiller, Steve Tadelis, Oliver Williamson and participants at the 2009 CRES conference on the foundations of business strategy at Washington University, the ISNIE conference in Berkeley, the Econometric Society meeting in Boston, the Academy of Management meeting in Chicago, 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.

use the model to predict a broad pattern of returns before and after diversification events. We then test the predictions of the model, using a series of increasingly stringent econometric tests that identify capability and agency effects in the decision to diversify.

The model integrates the predictions of agency and capabilities theories in a straightforward way. Firms are more likely to diversify when they possess unique skills and knowledge in one domain that would enable them to generate higher future returns in a related activity (Kogut and Zander 1992; Farjoun 1998). However, lucky firms are also likely to try to diversify if they can use idiosyncratic performance shocks to extract value form investors (Jensen 1983). We explore the rich interactions between skill, luck, performance and diversification and show conditions under which firms will be more likely to diversify when their returns are higher independent of their ability—when they are lucky—and when their ability is higher independent of their returns—when they are skilled. The key insight from the model is that less skillful firms always have weaker incentives to diversify given a particular track record. The intuition behind this result is that while managers are able to increase their own compensation in the short-run 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.

We test the predictions of the model, using a large and rich panel dataset on 1,576 hedge funds over the period 1977-2006. The hedge fund industry 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.

The pattern evident, in the data on diversifiers' returns, is striking. Excess returns are well above the sample mean prior to diversifying and fall rapidly following the launch of a second fund. However, after matching diversifiers to non-diversifiers, based on all the observable differences *ex ante*, diversifiers outperform non-diversifiers even when controlling for all time-invariant firm-specific effects. The results suggest that, consistent with the agency cost literature, managers time diversification decisions to exploit private information about their own ability to their private advantage; yet, market forces constrain lower ability firms' expansion options. Thus, firms launching new funds tend to posses 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 capabilities literature.

In the remainder of the paper, we develop this argument in more detail. In the following section, we introduce our model of diversification and derive the above described predictions. In Section 3, we discuss the hedge fund industry and describe the data. In Section 4 we develop our empirical specification and discuss the results. In Section 5, we offer conclusions.

**2. Skill, Luck and the Multiproduct Firm**

In this section, we develop a formal model of diversification in the presence of skill and luck. For tractability, we tailor the analysis toward the hedge fund industry, though we discuss how the model generalizes in more detail below. In our model, managers are classic agents as in Jensen and Meckling's (1976)—they are purely self-interested and actively seek the opportunity to use asymmetric information to exploit investors. However, a firm's unique investment ability represents a knowledge asset that can be exploited across multiple products (Kogut and Zander 1992; Farjoun 1998).

Investors are perfectly rational in our model. They 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 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 and their previous decisions whether to diversify. 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.

Managers know that investors are rational and will use all observable information about the firm to form beliefs about the firm's underlying ability, expecting that investors update their beliefs in each period, but managers also know investors can be fooled 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. The solution to the joint optimization problem delivers several testable predictions about the pattern of returns around diversification events,

*A. Model Setup*

There are $N$ investment managers, indexed $j = 1,...N$, 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 asset* for investment manager $j$, $\theta_j$ is a firm's capability level or, specifically, the investment skill of the manager, and $\varepsilon_{jt}$ 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.† If a manager decides to launch a second fund, they pay a cost $c_j$ in the period when the second fund is launched, a decision tracked by an indicator variable

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

* 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 $r_{jt} = R_{jt} - R_{ft}$.

† We make this assumption for analytic convenience—assuming that an existing firm has already sunk the costs necessary to operate an initial fund.

If a second fund is launched, we denote each of the funds with a superscript *l* and assume that returns are generated according to $r_{jt}^{l} = \theta_j + \varepsilon_{jt}^{l}$, where $E(\varepsilon_{jt}^{l}, \varepsilon_{jt}^{m})$ for *l≠m*. Thus, firm *j*'s capabilities are defined by a draw from the underlying distribution of *θ*, and they are manifest in a within-firm correlation in performance *r* between funds.

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:

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

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

$$\theta_j = \begin{cases} 1 \; with\ probability \quad p \\ 0 \qquad otherwise \end{cases}$$

and where $c_j \sim h(c)$. Further, we assume that that the two types are drawn independently so $Corr(c_j, \theta_j) = 0$.§

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

‡ 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).

§ 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 thoughts 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.

$$u_{It} = w_t^T \mu_t - \frac{\lambda}{2} w_t^T \Omega_t w \qquad (1)$$

where $w$ is a vector of allocation weights, $\mu$ is a vector of expectations of excess returns, $\Omega$ is the variance-covariance of returns the investor faces, and $\lambda$ 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). Because investors choose where to allocate their investments each period based on past performance managers have an incentive not to dilute their track record.[**]

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. Therefore, in the 3-period model, the sequence is as follows. In the first period, Nature draws a type for each investment manager *j;* investor *I* chooses a vector of weights $w_1$ to each fund; and returns are realized and period payoffs are obtained. In the second period, each investment manager chooses whether to launch a second fund *($d_j$)*; investor *I* chooses a vector of weights $w_2$ to each fund; and returns are realized and period payoffs are obtained. Finally, in the third period, investor *I* chooses a vector of weights $w_3$ to each fund and returns are realized and period payoffs are obtained.[††]

*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'

[**] 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 (see also Campbell and Viceira 2002).

[††] 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.

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 *ex post*, firms that diversify perform worse than they did *ex ante*. Finally, we show that given a particular pre-diversification level performance, those with greater investment skill will diversify at a higher rate than those with lesser investment skill. Taken together, the results imply that diversifiers will revert to the mean, but not 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 $\boldsymbol{\mu}_t$ denote a vector with K elements indexed by *jl*–for each fund in the opportunity set—of expected returns in period *t* to each fund. Let $\boldsymbol{\Omega}_t$ be the associated *ex ante* variance-covariance matrix of the return of the funds in the investors' opportunity set

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

$$\int \mathbf{w}_t^* = \frac{\boldsymbol{\Omega}_t^{-1}\boldsymbol{\mu}_t}{\lambda}. \tag{2}$$

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 $\theta_j$ 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 $\boldsymbol{\Omega}_t$ are zero.

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 since manager returns are drawn independently; and there is no full-investment constraint (see Lemma A1, all proofs appear in the appendix). Further, although weights to managers are independent, weights 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.

Next, we turn to our results concerning diversification. As with many 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, 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 in equilibrium.

What about equilibria in which some separation occurs? As a first step in answering this question, we now turn to 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 $r_1$.[‡‡] A manager will diversify iff:

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

The left hand side of (3) is the payoff in the second period and expected payoff in the third period for a manager who 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 who chooses to diversify.[§§]

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 $c_j^*(r_1)$:

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

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, because returns are *ex ante* correlated, the allocation weight investors give 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 all the foregoing discussion, we assume that diversification is an equilibrium action, which we will prove later.
[§§] Note that incorporated in (3) are any beliefs the investor may have after first and second period returns, conditional on diversification.

There is also 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 mean reversion implies that, 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. With the launch of the second fund, the manager should expect to be closer to the mean return (their type $\theta_j$) than in the case where they do not launch a second fund. Since investors update their beliefs of a manager's type based on the additional information embedded in the second fund's returns, diversification creates a *track record dilution effect.* Finally, these (potential) costs will 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. Thus, a second fund produces incremental revenue for the firm's managers and, therefore, managers will always be better off when they diversify, conditional on the cannibalization and track record dilution effects and the costs of diversification. We refer to the unambiguous benefits of diversification as the *scope extension effect.*

Even though managers with identical histories will be treated symmetrically by the investor in period two, managers with lower investment skill will have less strong incentives, for every level of realized returns in period 1, to launch a second fund, because their expectation of future performance depends on their type. The fact that second period performance, in expectation, is lower for low skilled means they can expect lower allocations in the third period and, therefore, will be less willing to launch an additional fund. In other words, $c_H^*(r_1) \geq c_L^*(r_1)$. 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.*

To pin down our analysis further, we return to the issue of pooling equilibria. One feature of this model is that after the first period, there is no dependence between the equilibria that are played for a given path $r$. This means that if separation occurs in equilibrium for some $r$, it could be the case that for an arbitrary small value $\eta$ there could be pooling for $r+\eta$. In fact, this leads to the possibility that measures of $r$ alternate 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. To rule these cases out, we make an additional assumption. Namely, that $\frac{\partial c_k^*(r)}{\partial r} \geq 0$ . This assumption allows us to establish that there is an equilibrium in which semi-separation occurs at every level or track record $r$. Namely, an equilibrium exists in which firms will diversify if costs are sufficiently low.

**Lemma 2**. *Assume* $\frac{\partial c_k^*(r)}{\partial r} \geq 0$. *There exists an equilibrium in which for sufficiently low costs as determined by (3), managers will diversify, and otherwise will stay focused.*

We now turn to our primary result, Result 1, which summarizes three results from our model.

**Result 1**. *Consider a separating equilibrium, 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 outperform 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 1 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 the more skillful managers are more likely to diversify conditional on any $r$. Given that the distribution of returns exhibit first order stochastic dominance in the types (see proof in the Appendix) 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 turns 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: 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.

Our theory predicts a pattern of returns that is broadly consistent with a set of stylized facts, reported in the empirical diversification literature. 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). Our model explains these stylized facts in a simple testable equilibrium framework.[***] Neither agency effects nor capabilities alone can explain the full set of results demonstrated.

The hedge fund industry is somewhat unique, and so caution should be applied in generalizing the model 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 funds require new investment to diversify. Furthermore, 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 reputation (Wernerfelt 1988; Cabral 2000), industrial customers are not typically investors, and industrial investors cannot usually choose which of the firm's products to invest in. To the extent that product performance is not be as volatile in industrial markets, agency costs

[***] The model is, of course, not completely unique. 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. MacDonald and Slavinski (1987) provide a general equilibrium model 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, however in equilibrium, investment managers' investment and pricing decisions result in little persistence in outperformance.

associated with market timing around peak performance may be less important. On the other hand, agency costs will tend to be more severe when managers have access to free cash flow and do not have to tap external capital markets to fund their diversification strategies (Jensen 1983). Nevertheless, the model proposed is quite general, and the hedge fund industry is interesting to study in its own right as we discuss briefly below.

## 3. Data and institutional context

### *A. The hedge fund industry*

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.

Consistent with the standard definition of diversified firms as multiproduct firms (Teece 1982), and with the literature on mutual fund product diversification (Siggelkow 2003), we consider hedge fund firms to be diversified when they operate multiple funds. With the exception of onshore/offshore twin funds, which we consider a single fund in our sample, hedge funds generally launch new funds with distinct investment objectives from their existing funds. Thus, diversification is usually distinct from expansion in the context of hedge funds.[†††]

[†††] Admittedly the distinction between expansion and diversification can be somewhat arbitrary when a new fund's investments are different but very closely related to an existing fund's investments. We verify that our results are not being driven by closely related new fund launches, which might be more intellectually consistent with firm expansion as opposed to diversification, as we discuss in the robustness checks section below.

The hedge fund industry offers a unique laboratory for studying capabilities and agency effects. Hedge funds are owned by the managers who run them, which minimizes the potential that traditional agency costs between investors and managers in operating the firm *ex post*. However, as residual claimants of funds, investors are exposed to managers' incentives to misrepresent their skill *ex ante* ($\theta$ in the notation above), which managers accomplish by raising money to launch additional funds. Thus, the hedge fund context facilitates a precise test of *ex ante* agency costs associated with diversification. Furthermore, firm performance is readily measureable over relatively long periods of time, which allows us to separate persistent skill effects from idiosyncratic luck.

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 financial crisis temporarily clouded the outlook for the industry, it appears likely that hedge funds will remain as important financial market intermediaries going forward.

*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, from Lipper-TASS (TASS) and Hedge Fund Research (HFR), was 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 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,

[‡‡‡] 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.

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.[§§§]

To make the analysis tractable, we examine the performance of a firm's first fund before and after the firm's first horizontal expansion (i.e. the launch of a second fund). 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,[****] excluding 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 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 in detail 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.

*C. Dependent Variables*

We test our predictions using risk-adjusted excess returns as our key measure of firm performance. In our theoretical model, short-run relative performance enables managers to extract value from investors due to asymmetric information, while long-run relative performance reveals the underlying skill of a firm. Empirically the appropriate measure of performance depends crucially on the risks against which performance is evaluated. The recent financial crisis has raised questions about how well hedge fund risks are understood. We, therefore, use a range of measures intended to control for systematic and non-systematic risk exposure to 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 risk exposure, we assume hedge fund investors benchmark performance against broad market indices as a first approximation of fund performance. Thus, we use standard asset pricing models to estimate excess returns in our baseline specification. However, hedge funds may also be

[§§§] 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.
[****] 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 funds as a single fund.

exposed to non-systematic risks that are not priced by standard passive market benchmarks. If funds take on significant non-systematic risks, due perhaps through investing in illiquid assets or through aggressive use of leverage, they may appear to generate large average excess returns that are really an artifact of model mispricing. We account for the non-systematic riskiness of a fund's underlying investments using a dynamic version of the information ratio and by including additional controls in the standard asset pricing model. We also control for biases that may arise due to self-reporting, including serial correlation in the time series of returns using an autoregressive lag one (AR1) correction and for backfill bias by dropping the first reported monthly return.

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:

$$R_{it} = a_i + R_{ft} + \boldsymbol{X_t B_i} + e_{it}, \tag{5}$$

where i and t index funds and time (in months) respectively; $R_i$ is a fund's raw return and the vector **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,[††††] $R_i$ from TASS and HFR, and compute *a,* the coefficients on ***X*** and *e* by running 2,045 fund-level longitudinal regressions. 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. We call the resulting measure "4-factor excess returns." We then compute the (dynamic) information ratio as excess returns ($Y_{it}$) divided by the standard deviation of excess returns. Both the information ratio and excess returns are winsorized at the 1% and 99% level to control for extreme values, though doing so has no meaningful impact on our results.

[††††] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Because hedge funds often hold illiquid investments, 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. We create our second return benchmark by including the Pastor-Stambaugh (2003) "traded liquidity factor", which we call "5-factor excess returns".[‡‡‡‡] We also replicated all of our results using Fung and Hsieh's (2001) 7-factor asset pricing model, which controls for exposures to equity, bond, commodity and option-based factors.

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 $CAR = \Sigma\, Y_{in}/n$, 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 a 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.[§§§§]

Table 1 shows descriptive statistics for the main sample, including our excess return and information ratio measures. On average, the funds in our baseline sample generated a 34-35 basis points of risk-adjusted (excess) returns per month with a standard deviation of about 4% per month. Adjusting for non-systematic risk exposure, using the information ratio, the average fund generated 13 basis points of excess return per unit of risk with a standard deviation of about 1% per month.

*D. Controls*

Table 1 also shows descriptive statistics for the control variables drawn from TASS and HFR including size, measured by assets under management, investment strategy, time and regional location. The average fund had $93 million of assets under management (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

[‡‡‡‡] These data are available at http://finance.wharton.upenn.edu/~stambaug/ liq_data_1962_2008.txt.
[§§§§] The results are not sensitive to the number of months used in the average *CAR* calculation.

billion.[*****] 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. Our results are unchanged 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.

18% of funds reported that they were fund-of-funds that invest in other hedge funds.[†††††] 22% were long/short funds – a general type of hedge fund that often has no meaningful restrictions on investment strategy. The other 60% 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.

The growth of the hedge fund industry is also reflected in the time weighting of returns. The mean observation year for the test sample was 1999, as 49% of reported fund-months came in the last five years of the sample period. We report calendar year average in Table 1, but we use periodicity in three ways in our analysis: (1) twenty-one year fixed effects control for hedge-fund specific calendar time effects; (2) market returns for 360 calendar months control for time series variation in market returns in our computation of excess returns; and (3) sixty to 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.

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 where appropriate.

## 4. Empirical specification and results

### *A. Within-firm changes*

---

[*****] AUMs are reported winsorized at the 1st and 99th percentile, though winsorizing has no effect on the results.
[†††††] 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 (results available from the authors upon request).

One of our key results is evident in a simple time-series plots of excess returns. Figure 1 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. As Figure 1 shows, firms tend to diversify when excess returns are very high, and excess returns fall precipitously almost immediately following diversification. We estimate within-firm[‡‡‡‡‡] changes in performance more precisely, using:

$$Y_{it} = \alpha + \lambda_i + DIVERSIFIED_{it} + T_t + \boldsymbol{X_{it}\beta_c} + \varepsilon_{it}, \qquad (6)$$

where *i* and *t* index funds and time (in months), respectively, for all first funds in firms that eventually diversify; *Y* represents firm performance measured by excess returns and the information ratio; 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 $\mathbf{X_c}$ is a vector of fund size dummies measured by assets under management; and ε is the residual. Standard errors are clustered by fund.

Table 2 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 4factor 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.

Clearly, excess returns are falling in hedge funds following diversification. However, the results also raise questions about the selection process firms undergo when choosing to launch a new fund, as excess returns are quite high prior to the launch of a new fund. Figure 1 suggests that higher excess returns may cause firms to launch a new fund. To understand if hedge fund returns fall following diversification

[‡‡‡‡‡] Because our tests are performed at the level of the fund for a firm's first fund only, we use "fund" and "firm" interchangeably in the empirical tests.

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 diversify*

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 all the information embedded in returns and other observable characteristics of firms and funds to identify a valid control group of focused firms against which to measure performance after diversification. First, 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 1 (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:

$$LAUNCH_{it}^{*} = \boldsymbol{x_{it}\beta} + \xi_{it}, \qquad (7)$$

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; $\boldsymbol{x}$ 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 $\boldsymbol{x}$ 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 $\xi$ is 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 3 columns 1-2. Column 1 shows the raw coefficients and standard errors from selected variables from the probit estimation.[§§§§§] 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 0.05% in a given month (or an increase of 6% from the baseline diversification rate of 0.85% per month) and is strongly statistically significant.

Columns 3-4 in Table 3 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: 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 gives rise to fundamental questions about what the appropriate control group is in this setting.

We find and exploit a valid control group, using standard propensity score matching techniques. First, following 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 $1^{st}$ and $99^{th}$ 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

[§§§§§] For presentation purposes, we suppress coefficients for 21 year fixed effects.

of the control group is that for each fund that did diversify, in a particular month, we have identified the fund that was most similar in terms of all observable characteristics that did not ever diversify. Columns 6-8 in Table 3 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 2 shows this effect graphically. Figure 2a 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 2b) 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 periods around the event in terms of event time. 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). The event takes place at event time zero. Altering the window around the event had no qualitative effect on our results, although the results are generally more precise the wider the window.

*C. Matched sample ex post performance*

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 pooled OLS model (8):

$$Y_{it} = \alpha + DIVERSIFIED_{it} + T_t + \boldsymbol{X_{it}\beta}_c + \varepsilon_{it}, \tag{8}$$

where i indexes 1,576 firms and t indexes calendar time; performance (*Y*), *DIVERSIFIED* and *T* are as above in (6); and $\boldsymbol{X}$ includes fund size dummies. We also include in $\boldsymbol{X}$ 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 $\varepsilon$ is the residual. Standard errors are clustered by fund. 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 4 shows the matched sample 4-factor *ex post* returns in columns 1 and 2. Excess returns are 11 basis points per month higher, and the information ratio is 4 basis points per month higher per unit of risk, and the coefficients are reliably different from zero. 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*.

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, our capabilities-based hypotheses are supported, but if the differences are due to other firm-specific factors, like prestige or unique access capital, that are unrelated to skill these effects could contaminate the results. 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 results*

To address identification issues associated with unobserved heterogeneity across firms, we specify a matched sample differences-in-differences model with firm and time fixed effects using:

$$Y_{it} = \alpha + \lambda_i + DIVERSIFIED_{it} + T_t + \boldsymbol{X_c \beta_c} + \varepsilon_{it}, \qquad (9)$$

which is identical to model (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 (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 4 columns 3 and 4 show the relationship between diversification and within-firm changes in fund performance, measured by 4-factor excess returns and the information ratio. The results are consistent with the matched *ex post* results. Changes in excess returns are 12 basis points per month higher in diversifying firms relative to changes in firms that remain focused, and the results are statistically significant at the 5% level. The information ratio results indicate that changes in returns are 3 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. 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.

*E. Robustness checks*

We are concerned about six 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) the results may be influenced by survivor bias; (3) the results may be sensitive to the matching process; (4) self-reported returns may be manipulated in ways that bias our results; (5) our measure of diversification may be confounded with expansion; and (6) firms might launch new funds and use them to subsidize their legacy funds. In this section, we discuss each of these issues in turn.

The results are robust to alternative measures of performance. As shown in Table 5 Panels A and B, we find very similar results using 5-factor and 7-factor models, respectively, to measure performance.[******] We also found similar results using simple raw returns (not shown).

Survivorship bias in the data could be problematic for our interpretation. For example, 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 (TASS 1994-2006). We find that the results are broadly consistent with the full sample results though the smaller sample leads to noisier estimates (Table 5 Panel B). While the precision is worse—only the

[******] The 7-factor data series is shorter, therefore, the test sample size is approximately 8,000 observations smaller.

information ratio results are significant at the 5% level—the point estimates are consistent with the full sample results.

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. 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 3. The expanded matching model generated "second stage" coefficient estimates on *DIVERSIFIED* that are quite similar in terms of magnitude and statistical significance, compared to the baseline model (Table 5 Panel B).

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, 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-reporting bias is not a problem for our 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 agency effects. 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.[††††††] While we cannot rule systematic earnings manipulation for any given fund, given the empirical design, it seems unlikely that this effect is driving our results.

Another concern is that our key explanatory variable, *DIVERSIFIED*, may confound expansion with diversification. If hedge funds launch new funds with nearly identical investment objectives as their existing funds, perhaps for administrative reasons, one might reasonably consider the new fund launch to represent a form of expansion rather than a diversification event. To evaluate whether our results are sensitive to very closely related new fund launches, we create a binary measure of relatedness of diversification, *CLOSELY RELATED*, based on the correlation of raw returns between first and second funds. In the fixed effects specification *CLOSELY RELATED* enters as an interaction term *CLOSELY RELATED* x *DIVERSIFIED*, where *CLOSELY RELATED* is equal to one when the correlation between first and second funds is greater than 0.9, and zero otherwise.[‡‡‡‡‡‡] Controlling for very closely related diversification has little effect on point estimate or the precision of the main effect of *DIVERSIFIED* (see Table 5 Panel A). We also experimented with alternative samples where closely related funds were dropped from the sample before matching and found very similar results. Thus, we conclude that diversification, not expansion, is driving our results.

Finally, 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 4. 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

[††††††] We replicated all of the tests in this paper after dropping firms in the top 1%, 5% and 10% of the information ratio distribution, and found that the results were qualitatively unchanged.
[‡‡‡‡‡‡] Our measure of "very closely related" at correlation 0.9 is admittedly somewhat arbitrary. However, our results were not substantively changed using other cutoff values for relatedness.

relationship between diversification and aggregate performance relative to the matched control group. Interestingly, we find that the results are even larger and more precise than in the fund-level tests for both equal weighted and value weighted firm-level performance (Table 5 Panel A).

*F. Discussion of results*

The overall pattern of evidence is consistent with a joint theory of diversification that takes both agency costs and capabilities seriously. Managers time their diversification events around idiosyncratic performance shocks, but on average better firms diversify. Neither agency costs nor capabilities alone can explain the full set of results observed, but together these theories explain the rich pattern of evidence observed in this study and in the literature more broadly. The results herein exploit revealed skill *ex post* to show how agency effects and capabilities influence strategy decisions *ex ante*. Thus, the key causal inference is that skill and luck cause a firm to diversify in a predictable manner.

While the results are consistent with the prior theoretical and empirical literature on diversification and with our model, there are some limitations to the interpretation of skill and luck as drivers of a selection effects. Most importantly, we cannot completely rule the alternative hypothesis that diversification itself is a causal mechanism driving improved performance. However, there are several reasons to suspect that the observed correlation between diversification and performance is a selection effect based on skill and luck and not a causal effect of diversification *per se*.

First, if diversification causes firm performance to improve, every firm should diversify. The fact that some firms remain focused would appear to undercut the face validity of the argument that diversification causes performance to improve. Second, 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 is consistent with our interpretation. Another 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 potential economies of scope based on firm capabilities. 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.

Consistent with the capabilities literature, we interpret persistent product-level performance as a measure of a firm's underlying ability (Barney 1986). The idea that product-level skill is indicative of a firm-level capability seems quite natural in the hedge fund industry, where product-level (i.e., fund) skill is tantamount to investment ability. However, it is important to note that the mapping between product-level skill and firm capabilities may not always generalize well to other settings. Thus, some caution is in order in applying the methodology used in this paper to other settings. Indeed, the precise manner in which capabilities may be extended within the firm is a subtle and important issue in the diversification literature that we abstract from in this paper (for a further discussion see Montgomery 1994, pp. 167-168). Interestingly, the observed skill effects, in this study, are robust to the inclusion of fund fixed effects, which suggests that the capabilities that support hedge fund diversification efforts are not only time-invariant firm-specific effects, but are also dynamic firm-level effects or dynamic capabilities (Eisenhardt and Martin 2000).

## 5. Conclusion

This paper integrates agency and capabilities theories into a simple equilibrium framework that yields rich predictions about the pattern of returns before and after diversification, and then tests these propositions in the context of the global hedge fund industry 1977-2006. The evidence supports agency theory's prediction that diversification decisions are influenced by manager's private information and the predictions of the capabilities literature that horizontal firm growth is enabled by unique firm capabilities that can be leveraged across products within the firm. Our key finding is that better firms diversify in equilibrium, even though agency effects appear to be an important driver of diversification decisions. Thus, at least in the context of hedge funds, market discipline constrains lucky but lower skilled firms' horizontal expansion choices.

This paper sheds light on two of the most important explanations for why firms diversify: agency costs and capabilities. We provide an equilibrium explanation for how agency costs influence the firm's decision to diversify even when diversification creates value on average, and present evidence that confirms this effect. Moreover, we address one of the major criticisms of the capabilities literature—that it is tautological and inherently untestable (Williamson 1999)—by providing large sample, well identified evidence that capabilities influence diversification choices in a predictable manner. Furthermore, we show how agency and capabilities theories are complementary perspectives in the context of diversification, and offer a road map for identifying the impact of both on diversification decisions.

**Acknowledgements**

We thank Vineet Budhraja, Jacques Chappuis, Paul Gertler, Margaret Kyle, Ryan Meredith, Philipp Meyer, John Morgan, Gabriel Natividad, Santiago Oliveros, Chris Rider, Robert Stambaugh, Pablo Spiller, Steve Tadelis, Oliver Williamson and participants at the 2009 CRES conference on the foundations of business strategy at Washington University, the ISNIE conference in Berkeley, the Econometric Society meeting in Boston, the Academy of Management meeting in Chicago, 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.

**References**

Barney, J.B. 1986. Strategic Factor Markets: Expectations, Luck and Business Strategy. *Management Science* **32**(10) 1231-1241.

Berger, P.G., E. Ofek, 1995. Diversification's Effect on Firm Value. *Journal of Financial Economics* **37**(1) 39-65.

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

Cabral, L.M.B. 2000. Stretching Firm and Brand Reputation. *RAND Journal of Economics* **31**(4) 658-673.

Campbell, J.Y., L. Vicera. 2002. Strategic Asset Allocation for Long-term Investors. Oxford University Press.

Carhart, M. 1997. On Persistence in Mutual Fund Performance. *Journal of Finance* **52**(1) 57-82.

Chevalier, J., G. Ellison. 1997. Risk Taking by Mutual Funds as a Response to Incentives. *Journal of Political Economy* **105**(6) 1167-1200.

Eisenhardt, K.M., J.A. Martin. 2000. Dynamic Capabilities What Are They? *Strategic Management Journal* **21**(10/11) 1105-1121.

Fama, E.F., K. French. 1996. Multifactor Explanations of Asset Pricing Anomalies. *Journal of Finance* **51**(1) 55-84.

Farjoun, M. 1998. The Independent and Joint Effects of the Skill and Physical Bases of Relatedness in Diversification. *Strategic Management Journal* **19**(7) 611-630.

Fung, W., D.A. Hsieh. 2001. The Risk in Hedge Fund Strategies, Theory and Evidence from Trend Followers. *Review of Financial Studies* **14**(2) 313-341.

Jensen, M.C., W.H. Meckling. 1976. Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure. *Journal of Financial Economics* **3**(4) 305-360.

Jensen, M.C. 1983. Agency Costs of Free Cash Flow, Corporate Finance and Takeovers. *American Economic Review* **76**(2) 323-329.

Kaplan, S.N., A. Schoar. 2005. Private Equity Performance: Returns, Persistence, and Capital Flows. *Journal of Finance* **60**(4) 1791-1823.

Kogut, B., U. Zander. 1992. Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. *Organization Science* **3**(3) 383-397.

Lang, L.H.P., R.M. Stulz. 1994. Tobin's q, Corporate Diversification and Firm Performance. *Journal of Political Economy* **102**(6) 1248-1280.

MacDonald, G.M., A. Slivinski. 1987. The Simple Analytics of Competitive Equilibrium with Multi-Product Firms. *American Economic Review* **77**(5) 941-953.

Merton, R.C. 1969. Lifetime Portfolio Selection Under Uncertainty: The Continuous Time Case, *Review of Economics and Statistics* **51**(3) 247-257.

Merton, R.C., 1971, Optimum Consumption and Portfolio Rules in a Continuous-time Model. *Journal of Economic Theory* **3**(4) 373-413.

Montgomery, C.A. 1994. Corporate Diversification. *Journal of Economic Perspectives* **8**(3) 163-178.

Panzar, John C., and Robert D. Willig, 1981, Economies of Scope, *The American Economic Review* 71, 268-272.

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

Penrose, E. 1959. The Theory of the Growth of the Firm. New York: John Wiley.

Rosenbaum, P.R., D.B. Rubin. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* 70(1) 41-55.

Samuelson, P. 1969. Lifetime Portfolio Selection by Dynamic Stochastic Programming. *Review of Economics and Statistics* **51**(3) 239-246.

Schoar, A. 2002. Effects of Corporate Diversification on Productivity. *Journal of Finance* **57**(6) 2379-2403.

Sharpe, W. 1964. Capital Asset Prices: A theory of Market Equilibrium Under Conditions of Risk. *Journal of Finance* **19**(3) 425-442.

Siggelkow, Nicolaj. 2003. Why Focus? A Study of Intra-Industry Focus Effects. *The Journal of Industrial Economics* **51**(2) 121-150.

Stulz, R. 2007. Hedge Funds: Past Present and Future. *Journal of Economic Perspectives* **21**(2) 175-194.

Teece, D.J. 1980. Economies of Scope and the Scope of the Enterprise. *Journal of Economic Behavior and Organization* **1**(3) 223-247

Teece, D.J. 1982. Towards and Economic Theory of the Multiproduct Firm. *Journal of Economic Behavior and Organization* **3**(1) 39-63.

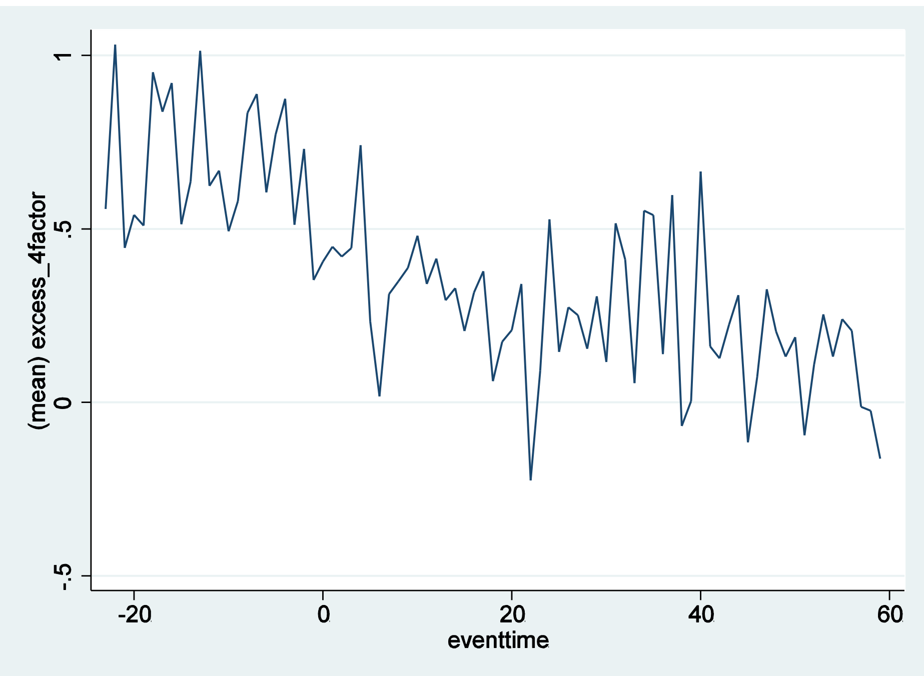
Teoh, S.H., I. Welch, T.J. Wong. 1998. Earnings Management and the Long-run Market Performance of Initial Public Offerings. *Journal of Finance* **53**(6) 1935-1974.

Villalonga, B. 2004. Diversification Discount or Premium? New Evidence from the Business Information Tracking Series. *Journal of Finance* **59**(2) 479-506.

Wernerfelt, B. 1998. Umbrella Branding as a Signal of New Product Quality: An Example of Signaling by Posting a Bond. *RAND Journal of Economics* **19**(3) 458-466.

Williamson, O. 1999. Strategy Research: Governance and Competence Perspectives. *Strategic Management Journal* **20**(12) 1087-1108.

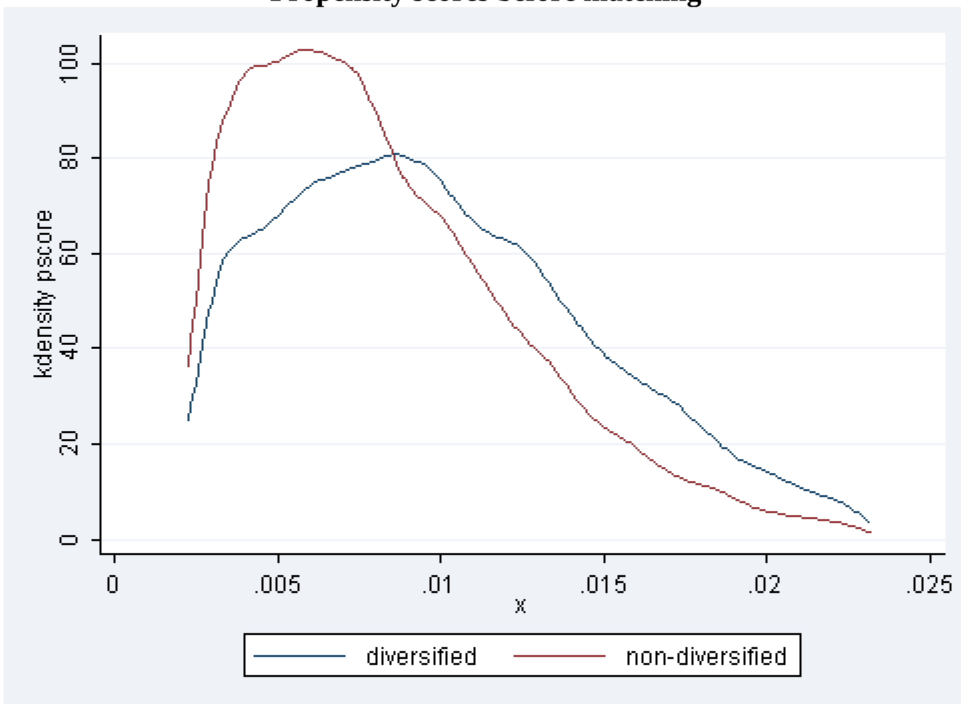
**Figure 1: Time path of excess returns for diversifiers**




This figure shows average 4-factor excess returns (vertical axis) for the first fund from all diversified hedge funds in our sample versus event-time on the horizontal axis. Event time is measured in months around the event (e.g., diversification) at time 0. The chart shows the time path of returns from twenty-four months before diversification to five years after diversification for 48,410 fund-months from 788 diversifying firms.

**Figure 2: Propensity score predicting diversification before and after matching**

**Propensity scores before matching**




**Propensity scores after matching**

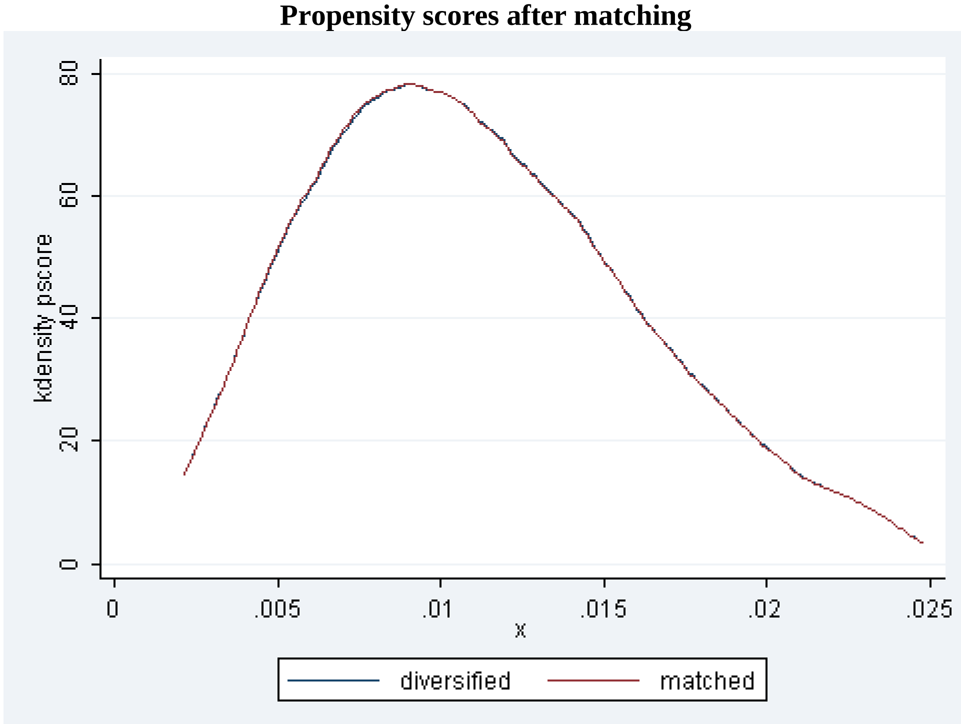


**Table 1: Descriptive statistics for the main (matched) sample**

| 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 2: Within-fund changes in performance for diversifiers**

| | 4-factor excess returns | | | | 5-factor excess returns | | | |
|---|---|---|---|---|---|---|---|---|
| | Returns | | Inf. ratio | | Returns | | Inf. ratio | |
| | (1) | | (2) | | (3) | | (4) | |
| ***DIVERSIFIED*** | ***-0.12*** | ** | ***-0.03*** | ** | ***-0.11*** | ** | ***-0.02*** | * |
| | ***(0.05)*** | | ***(0.01)*** | | ***(0.05)*** | | ***(0.01)*** | |
| Constant | Y | | Y | | Y | | Y | |
| Size fixed effects | 11 | | 11 | | 11 | | 11 | |
| 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 3: Matching**

Dependent variable = firm launches a second fund at time e

| | | | Full sample means | | | Matched sample means | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Coef. | ∂y/∂u at ū | Focused | Divers. | t on Δ | Focused | Divers. | t on Δ |
| Avg. CAR | 0.03 | 0.0005* | 0.49 | 0.71 | -4.5 | 0.57 | 0.68 | -1.5 |
| | (0.01) | (0.0002) | (0.00) | (0.05) | | (0.06) | (0.05) | |
| Missing AUM | 0.06 | -0.0011 | 0.16 | 0.19 | -2.1 | 0.17 | 0.19 | -1.2 |
| | (0.07) | (0.0012) | (0.00) | (0.01) | | (0.01) | (0.01) | |
| Log age | -0.13 | -0.0027* | 3.42 | 3.10 | 9.4 | 2.95 | 3.14 | -4.2 |
| | (0.01) | (0.0003) | (0.00) | (0.03) | | (0.03) | (0.03) | |
| Avg. CAR Strategy | 0.04 | 0.0008 | 0.40 | 0.45 | -2.2 | 0.39 | 0.43 | -1.4 |
| | (0.03) | (0.0005) | (0.00) | (0.02) | | (0.02) | (0.02) | |
| Fund of funds (1) | 0.04 | 0.0009 | 0.18 | 0.19 | -0.9 | 0.16 | 0.19 | -1.3 |
| | (0.04) | (0.0011) | (0.00) | (0.01) | | (0.01) | (0.01) | |
| Long/short (2) | -0.13 | -0.0025* | 0.26 | 0.19 | 4.6 | 0.23 | 0.19 | 1.8 |
| | (0.05) | (0.0008) | (0.00) | (0.01) | | (0.01) | (0.01) | |
| Equity hedge (3) | 0.01 | 0.0002 | 0.08 | 0.08 | -0.5 | 0.08 | 0.09 | -0.3 |
| | (0.06) | (0.0011) | (0.00) | (0.01) | | (0.01) | (0.01) | |
| Managed futures (4) | 0.13 | 0.0030* | 0.10 | 0.12 | -2.0 | 0.11 | 0.12 | -0.8 |
| | (0.05) | (0.0014) | (0.00) | (0.01) | | (0.01) | (0.01) | |
| Equity driven neutral (5) | 0.01 | 0.0002 | 0.04 | 0.05 | -0.4 | 0.04 | 0.05 | -0.5 |
| | (0.07) | (0.0015) | (0.00) | (0.01) | | (0.01) | (0.01) | |
| Event driven (6) | 0.01 | 0.0001 | 0.07 | 0.08 | -0.5 | 0.06 | 0.08 | -1.1 |
| | (0.06) | (0.0012) | (0.00) | (0.00) | | (0.01) | (0.01) | |
| Emerging markets (7) | 0.06 | 0.0014 | 0.04 | 0.05 | -1.3 | 0.05 | 0.05 | -0.5 |
| | (0.07) | (0.0016) | (0.00) | (0.01) | | (0.01) | (0.01) | |
| Global macro macro (8) | 0.06 | 0.0012 | 0.03 | 0.04 | -0.7 | 0.04 | 0.04 | 0.6 |
| | (0.08) | (0.0018) | (0.00) | (0.01) | | (0.01) | (0.01) | |
| Convertible arbitrage (9) | 0.10 | 0.0023 | 0.02 | 0.03 | -1.9 | 0.02 | 0.03 | -1.2 |
| | (0.09) | (0.0023) | (0.00) | (0.01) | | (0.00) | (0.01) | |
| Fixed income arbitrage (10) | 0.05 | 0.0011 | 0.02 | 0.03 | -1.6 | 0.04 | 0.02 | 1.9 |
| | (0.09) | (0.002) | (0.00) | (0.01) | | (0.01) | (0.01) | |
| Size fixed effects | Y | Y | Y | Y | | Y | Y | |
| Yr. fixed effects | Y | Y | Y | Y | | Y | Y | |
| Region f.e. | Y | Y | Y | Y | | Y | Y | |
| 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

Note: all explanatory variables are lagged one month to t-1

**Table 4: Matched sample performance**

| | *Ex post* returns | | | | Differences in differences | | | |
|---|---|---|---|---|---|---|---|---|
| | Excess returns | | Inf. ratio | | Excess returns | | Inf. ratio | |
| | (1) | | (2) | | (3) | | (4) | |
| ***DIVERSIFIED*** | ***0.11*** | ** | ***0.04*** | *** | ***0.12*** | ** | ***0.03*** | ** |
| | ***(0.04)*** | | ***(0.01)*** | | ***(0.06)*** | | ***(0.01)*** | |
| Size decile 2 | 0.10 | | 0.01 | | -0.02 | | -0.03 | |
| | (0.12) | | (0.03) | | (0.11) | | (0.02) | |
| Size decile 3 | 0.17 | | 0.03 | | -0.05 | | -0.04 | * |
| | (0.11) | | (0.02) | | (0.10) | | (0.02) | |
| Size decile 4 | 0.24 | ** | 0.06 | ** | -0.12 | | -0.06 | ** |
| | (0.11) | | (0.03) | | (0.11) | | (0.02) | |
| Size decile 5 | 0.22 | ** | 0.06 | ** | -0.22 | * | -0.10 | *** |
| | (0.11) | | (0.03) | | (0.11) | | (0.03) | |
| Size decile 6 | 0.17 | | 0.07 | *** | -0.37 | *** | -0.14 | *** |
| | (0.11) | | (0.03) | | (0.11) | | (0.03) | |
| Size decile 7 | 0.20 | * | 0.08 | *** | -0.36 | *** | -0.14 | *** |
| | (0.11) | | (0.03) | | (0.12) | | (0.03) | |
| Size decile 8 | 0.25 | ** | 0.08 | *** | -0.49 | ** | -0.17 | *** |
| | (0.11) | | (0.03) | | (0.12) | | (0.03) | |
| Size decile 9 | 0.30 | *** | 0.12 | *** | -0.42 | *** | -0.20 | *** |
| | (0.11) | | (0.03) | | (0.13) | | (0.03) | |
| Size decile 10 | 0.33 | *** | 0.13 | *** | -0.46 | *** | -0.22 | *** |
| | (0.11) | | (0.03) | | (0.14) | | (0.03) | |
| Missing size | 0.29 | *** | 0.09 | *** | -0.20 | * | -0.10 | *** |
| | (0.11) | | (0.03) | | (0.12) | | (0.03) | |
| Constant | Y | | Y | | Y | | Y | |
| Year fixed effects | 21 | | 21 | | 21 | | 21 | |
| Event time fixed effects | 60 | | 60 | | 84 | | 84 | |
| Fund fixed effects | N | | N | | 1,576 | | 1,576 | |
| N | 61,072 | | 61,072 | | 86,976 | | 86,976 | |
| $R^2$ | 0.01 | | 0.01 | | 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. Excess returns and the information ratio are from the 4-factor model.

**Table 5: Robustness checks**

| Panel A: Alternative regressions on the baseline sample (n=86,976) | | | | |
|---|---|---|---|---|
| | Dependent variables | | | |
| Regression description | Excess returns | | Inf. ratio | |
| 5-factor performance | 0.13 | ** | 0.04 | ** |
| | (0.06) | | (0.01) | |
| Control for very closely related diversification | 0.14 | ** | 0.05 | ** |
| | (0.07) | | (0.02) | |
| Equal weighted firm returns | 0.22 | *** | 0.09 | ** |
| | (0.06) | | (0.02) | |
| Value weighted firm returns | 0.22 | *** | 0.07 | *** |
| | (0.07) | | (0.02) | |

| Panel B: Alternative samples | | | | | |
|---|---|---|---|---|---|
| | | Dependent variables | | | |
| Regression description | n | Excess returns | | Inf. ratio | |
| 7-factor performance | 78,939 | 0.15 | ** | 0.04 | *** |
| | | (0.06) | | (0.02) | |
| Survivor-bias free sample | 44,330 | 0.13 | | 0.04 | ** |
| | | (0.08) | | (0.02) | |
| Alternative matching regime sample | 88,782 | 0.14 | ** | 0.03 | ** |
| | | (0.06) | | (0.02) | |

*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level
Standard errors are clustered by fund or firm. Coefficient values for *DIVERSIFIED* are reported. All dependent variables are from the 4-factor model, except in the "5-factor performance" and "7-factor performance" regressions. All regressions contain the same controls as in the differences in differences specifications in Table 4, except in the "Control for very closely related diversification" regression, which has an additional control: a discrete dummy "*CLOSELY RELATED*" that is equal to one if the correlation between the second fund and the first fund is higher than 0.9, interacted with *DIVERSIFIED*. The "Survivor-bias free sample" regression uses only the subset of the sample that is free of survivor bias (TASS 1994-2006). The "Alternative matching regime" regression relies on an expanded matching model to generate the matched sample.

## Appendix 1: Proofs of results

**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* $\mu_{i*}$*, and therefore is decreasing in* $q_{i*}$

(iii) *is decreasing in the variance (diagonal element of* $\mathbf{\Omega}_t$ *)*

(iv) *is decreasing in* $R^2_{i*}$ *where* $R^2_{i*}$ *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 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 $c^*_H(r_1) \geq c^*_L(r_1)$. Since $c_j \sim h(c)$ is the same for low and high types, and $Corr(c_j,\theta_j)=0$, 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**. Let $\frac{\partial c^*_k(r)}{\partial r} \geq 0$. Consider a set of cutoff functions $\{c^*_k(r_1)\}$. For all $r_1$, we must check whether deviations are profitable for type $\theta_k$. Consider $\theta_L$ 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 $\Pr(d_j=1 \mid \theta_H, r_1)=\Pr(c_j < c^*_H(r_1))$. 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 $\Pr(\theta_k \mid d_j=1, r_1)$ and $\Pr(\theta_k \mid d_j=0, r_1)$. By Bayes Rule and the above results, we have

$$\Pr(\theta_k \mid d_j=1, r_1)=\frac{\Pr(r_1 \mid \theta_k)\Pr(\theta_k)\Pr(c_j < c^*_k(r_1))}{\Pr(r_1 \mid \theta_k)\Pr(\theta_k)+\Pr(r_1 \mid \theta_{\sim k})\Pr(\theta_{\sim k})} \quad \text{(A1)}$$

and

$$\Pr(\theta_k \mid d_j=0, r_1)=\frac{\Pr(r_1 \mid \theta_k)\Pr(\theta_k)\Pr(c_j > c^*_k(r_1))}{\Pr(r_1 \mid \theta_k)\Pr(\theta_k)+\Pr(r_1 \mid \theta_{\sim k})\Pr(\theta_{\sim k})}. \quad \text{(A2)}$$

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

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

and $EU(\theta_k \mid d_j=0, r_1)=w^*(\Pr(\theta_H \mid d_j=0, r_1))+\delta w^*(\Pr(\theta_H \mid d_j=0,(r_1, E(r_2 \mid \theta_k))))$. So a type $\theta_L$ to stay on the equilibrium path is such that she will diversify iff

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

Similarly, a type $\theta_H$ will diversify iff

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

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

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

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 ( $\sum_i w_i^*(\Pr(\theta_H \mid d_j = 1, r_1)) - w^*(\Pr(\theta_H \mid d_j = 0, r_1))$) and the second-period terms $\sum_i \delta w_i^*(\Pr(\theta_H \mid d_j = 1, (r_1, E(r_2 \mid \theta_L))) - \delta w^*(\Pr(\theta_H \mid d_j = 0, (r_1, E(r_2 \mid \theta_L))))$ 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 $c_k \ge 0$ 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 1**. Part (i). By assumption, $\frac{\partial c_k^*(r^*)}{\partial r} \ge 0$. Since *c* is independent of *r*, this implies that his implies that $\frac{\partial \Pr(d = 1 \mid r, \theta_k)}{\partial r} \ge 0$. Further, by Lemma 1, we have that $\Pr(d = 1 \mid r, \theta_H) \ge \Pr(d = 1 \mid r, \theta_L)$. Using the fact that $\Pr(r_{1i} > r \mid \theta_H) > \Pr(r_{1i} > r \mid \theta_L)$ we have the result. Part (ii) This follows directly from the fact that $\frac{\partial c_k^*(r^*)}{\partial r} \ge 0$. Part (iii) follows directly from Lemma 1.

## The Rodney L. White Center for Financial Research

The Wharton School
University of Pennsylvania
3254 Steinberg Hall-Dietrich Hall
3620 Locust Walk
Philadelphia, PA 19104-6367

(215) 898-7616
(215) 573-8084 Fax
http://finance.wharton.upenn.edu/~rlwctr


The Rodney L. White Center for Financial Research is one of the oldest financial research centers in the country. It was founded in 1969 through a grant from Oppenheimer & Company in honor of its late partner, Rodney L. White. The Center receives support from its endowment and from annual contributions from its Members.

The Center sponsors a wide range of financial research. It publishes a working paper series and a reprint series. It holds an annual seminar, which for the last several years has focused on household financial decision making.

The Members of the Center gain the opportunity to participate in innovative research to break new ground in the field of finance. Through their membership, they also gain access to the Wharton School's faculty and enjoy other special benefits.

## Members of the Center
**2009 – 2010**

*Directing Members*

**Aronson + Johnson + Ortiz, LP**
**Ballyshannon Partners**
**Goldman Sachs**
**The Nasdaq OMX Educational Foundation**
**Ther Terker Family**
**The Vanguard Group**

*Founding Members*

**Ford Motor Company Fund**
**Merrill Lynch, Pierce, Fenner & Smith, Inc.**
**Oppenheimer & Company**
**Philadelphia National Bank**
**Salomon Brothers**
**Weiss, Peck and Greer**