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

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We formalize the idea that when managers require external investment to expand, higher-skilled firms will be more likely to diversify in equilibrium, even though managers can exploit asymmetric information about their ability to raise capital from investors. We exploit the timing of new fund launches in the hedge fund industry to distinguish between agency and capability effects in firm product diversification decisions, using a large survivor-bias-free panel data set on the hedge fund industry from 1994 to 2006. Empirically we show that diversifying firms' excess returns are high relative to those of other firms prior to diversification and fall within firm following diversification, but are six basis points higher per month per unit of risk ex post compared to a matched sample of focused firms. The evidence suggests that managers exploit asymmetric information about their own ability to time diversification decisions; yet, the discipline of markets ensures that better firms diversify, on average. The results provide large-sample empirical evidence that agency effects and firm capabilities jointly influence diversification decisions.

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1. Introduction

Scholars have long 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). Although capabilities and agency theories 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 predictions of capabilities and agency theories into a simple equilibrium model and use the model to predict a broad pattern of performance before and after diversification events. We then test the predictions of the model, using a series of 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, enabling them to generate higher future returns in a related activity (Peteraf 1993, Bernard et al. 2010). However, agency theory implies that lucky firms are also likely to try to diversify if they can use idiosyncratic performance shocks to extract value from investors (Jensen 1983). We explore the rich interplay among skill, luck, performance, and diversification to show conditions under which firms will be more likely to diversify. The key insight from the model is that when managers require external capital to expand, less skillful firms always have weaker incentives to diversify given a particular track record. The intuition behind this result is that although 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. Because firms reveal their true type through performance over time, and do so even faster when they diversify, as in Cabral (2000), less skillful firms always have weaker incentives to diversify given a particular track record.

We test the predictions of the model in the context of the $1.7 trillion hedge fund industry (Hedge Fund Research 2010) using a large and rich panel data set on 1,353 hedge funds from 1994 to 2006. The hedge fund industry offers a unique laboratory for studying capabilities and agency effects. As residual claimants of funds, investors are exposed to managers' incentives to misrepresent their skill ex ante, which managers may take advantage of by raising money to launch additional funds when the firm experiences a lucky streak. Thus, the hedge fund context facilitates a test of ex ante agency costs, or timing effects, associated with diversification. Another advantage of the hedge fund context is that firm performance is readily measureable at the product (fund) level over relatively long periods of time, which allows us to separate persistent skill effects from idiosyncratic shocks.

The pattern evident in the data 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 nondiversifiers, based on all the observable differences ex ante, diversifiers outperform nondiversifiers. Consistent with the agency cost literature, the results suggest managers time diversification decisions to exploit asymmetric information about their own ability to private advantage; yet, market forces constrain lower-ability firms' expansion options. Thus, firms launching new funds tend to possess greater investment skill than firms that remain focused and are able to leverage their investment skill across new funds in a manner consistent with the capabilities literature.

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

2. Skill, Luck, and the Multiproduct Firm

A number of papers, using agency cost logic, have shown that there are costs associated with diversification: in internal capital markets (Lamont 1997), in hierarchical management structures (Rajan et al. 2000, Scharfstein and Stein 2000), and in managements' span of control (Schoar 2002). However, studies using Coasin logic (Coase 1937), fine-grained microdata (Villalonga 2004), and controls for endogeneity (Campa and Kedia 2002) have raised questions about whether the costs of diversification systematically exceed the benefits of diversification, or if the early results are artifacts of the data or methods. This paper takes a step toward reconciling the ostensive conflict between agency theory and the Coasian tradition (Coase 1937) reflected in recent empirical work and in the capabilities literature on diversification. By shifting the emphasis away from the ex post costs of diversification toward the ex ante costs, the costs investors bear when managers time their investments to take advantage of asymmetric information, which more closely map to the original basis for agency theory, this paper shows how the agency cost literature and the capabilities literature complement one another.

In the remainder of this section, we develop a formal model of diversification in the presence of skill and luck that builds on and extends the capabilities and agency cost literatures in the context of diversification. We define skill as an inimitable rent-generating capability (Barney 1986). We also follow the capabilities literature by focusing on the role of skill transference across products in the context of related diversification. For tractability, we tailor the analysis toward the hedge fund industry, though we also discuss how the model generalizes to other contexts. In our context, skill can be characterized as investment ability, a conception of skill that is closely related to forecasting skill in the sense that firms possess heterogeneous ability with respect to anticipating future payoffs from current investments (Makadok and Walker 2000, Pierce 2009). Skills are transferable across products to the extent that investment ability in one strategy class is correlated with investment ability in another strategy class.

Though we do not explicitly measure relatedness in our empirical work, hedge fund diversification would appear to satisfy any of the standard measures of related diversification.[1] The relatedness assumption is important because the capabilities literature has long argued that firm resources, tangible or intangible, are more readily transferable across related products (Wernerfelt and Montgomery 1988, Silverman 1999). By extending their capabilities into related activities, high-ability firms can create value by expanding the scope of the firm. We extend the capabilities literature by formalizing the idea that higher-skilled firms are more likely to diversify in the context of an equilibrium model that also takes agency costs into account.

In our model, managers are classic agents, as in Jensen and Meckling (1976), who are purely self-interested and actively seek the opportunity to use asymmetric information to exploit investors. While the model builds on the seminal notion of agency costs by examining how managers use asymmetric information for private gain, our approach differs from agency theoretic models that assume managers can exploit internally generated free cash flow to fund the firm's expansion (Jensen 1983). Instead, we focus on

[1] Relatedness is typically defined using SIC (Standard Industrial Classification) codes or by evaluating whether the two business units have similar activities, resources, skills, customer groups, and physical bases. Our study of new fund launches by hedge funds meets both definitions of related diversification.

agency costs that operate through asymmetric information managers hold about their own ability when tapping external capital markets.

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, while harboring no illusions about managers' private incentives and information. Given asymmetric information between managers and investors about the managers' true ability level, investors make inferences about managerial 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 capital to managers, where the capital allocations are correlated with firm performance. However, only managers know their true investment ability. Investors only receive a noisy signal of the managers' ability based on the firm's track record, which opens the door for managers to exploit their asymmetric information for private gain.

Managers know that investors are rational and will use all observable information about the firm to form beliefs about the firm's managers' underlying ability, expecting that investors update their beliefs in each period. Managers also know investors can be fooled temporarily by idiosyncratic performance shocks, but that diversification reveals more information about the firm by sending multiple signals to investors about the firm's true ability in any given time period (Cabral 2000). Thus, the manager's problem is whether and when to diversify, based on the firm's performance track record and their true ability, whereas 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.

2.1. Model Setup

There are N investment managers, indexed $j = 1, \ldots, N$, and a (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; θ_j is a firm's capability level or, specifically, the investment skill of the manager; and ε_{jt} is a random shock. Furthermore, we assume for simplicity that ε_{jt} is independent and identically distributed with $E(\varepsilon_{jt}) = 0$ and $V(\varepsilon_{jt}) = \sigma_\varepsilon^2$, which means $E(\varepsilon_{jt}\varepsilon_{kt}) = 0$ 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.[2] 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}, which is 1 if a second fund is launched in t or 0 otherwise.

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 $E(\varepsilon_{jt}^l, \varepsilon_{jt}^m) > 0$ for $l \neq m$.[3] 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, which we denote ρ_j, 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 $w_{jt}^2 = 0$. In other words, the payoff is increasing linearly in the allocation weight the investor gives to the investment manager's funds, less the cost of the fund. The equation 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).

Furthermore, the investment manager's multiperiod utility function is simply

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

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 $c_j \sim h(c)$, where $h(c)$ is a continuous distribution with nonnegative support and associated cumulative distribution function $H(c)$. Furthermore, we assume that that the two types are drawn independently so that $\text{Corr}(c_j, \theta_j) = 0$.[4]

[2] We make the assumption that an existing firm has already sunk the costs necessary to operate an initial fund for analytic convenience. It has no bearing on the substantive analysis.

[3] To make the model tractable, we assume investment skill is constant across funds within a firm. A more general model might allow investment skill to vary within a firm, based on how closely related the new fund is to the firm's existing fund. Although introducing variation in investment skill would be an interesting extension of our model, our results will continue to hold as long as investment skill is positively correlated between funds within a firm.

[4] In this setup, θ can be thought of as *investment skill*, because it measures how effectively a manager generates excess returns for

The investor has a standard mean–variance utility function. In each period, the investor obtains the ex ante utility of

$$u_{It} = w_t^T \mu_t - \frac{\lambda}{2} w_t^T \Omega_t w_t, \tag{1}$$

where w is a vector of allocation weights, μ is a vector of expectations of excess returns, $\mathbf{\Omega}_t$ is the ex ante 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 multiperiod 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 the foregoing, we assume that the investor, in each period, acts myopically with respect to (1).[5]

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 three-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, returns are realized, and period payoffs are obtained. In the second period, each investment manager chooses whether to launch a second fund (d_{j2}), investor I chooses a vector of weights w_2 to each fund, 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, returns are realized, and period payoffs are obtained.[6]

2.2. 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. We derive three primary results, which we then evaluate empirically. First, firms that have enjoyed above average performance are more likely to diversify. Second, ex post, on average, firms that diversify perform worse than they did ex ante. Finally, we show that given a particular prediversification track record, those with greater investment skill will diversify at a higher rate than those with less investment skill. Collectively, the results imply that diversifiers will revert to the mean, but not as strongly as nondiversifiers with the same prediversification performance.

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.

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

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

This setup has a number of features that substantially simplify characterization of the equilibrium of the game. Perhaps most notable is a result from the standard capital asset pricing model (Sharpe 1964): The weights to managers are independent because manager returns are drawn independently, and there is no full-investment constraint. Furthermore, although weights to managers are independent, weights to different funds, provided by the same manager, are not independent both because the εs within a period are correlated and the error in estimating a manager's skill also creates correlated risk across a manager's funds for the investor. Said differently, the ex ante uncertainty in a manager's returns is common across all of their funds, because 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.

We now turn to our results concerning diversification. As with many signaling models, in this model

investors, and c_j can be thought of as *managerial skill*, because 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.

[5] 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. It is important to note that in this case, the conditions for myopia are potentially complicated by the strategic aspects of the game for both investors and investment managers. In particular, because there is potential information revealed after each round about the investment manager's type, it may be possible that fully rational investors would shade down their allocations to account for the reduced risk introduced by type uncertainty in every round. Indeed, this intuition that investors shade their allocations in early periods because of greater uncertainty and allocate more in later periods is correct, but in the game is driven by the fact that posteriors—including uncertainty about types—after each round are weakly more precise. That said, there is no additional effect (i.e., holding back capital for the known higher risk-adjusted returns later) because the extant results are invariant to changing opportunity sets (see Campbell and Viceira 2002). If one knows that future risk-adjusted returns will be higher than present ones, one would still like to have more capital to deploy in those later periods, because it will maximize final consumption or wealth. That causes one to optimally take risk given the current period's opportunity set.

[6] 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.

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 diversification occurs? As a first step to answering this question, we establish a result that must hold in any equilibrium in which diversification occurs. We will then turn to the task of establishing the existence of a particular form of equilibrium.

Consider first how such an equilibrium may behave. 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 history (r_t, d), where r_t indicates the manager's returns up to period t, and d indicates whether a manager has diversified. A manager will diversify if and only if the expected payoff from diversification is greater than the expected payoff from nondiversification:

$$w_2^1(r_1,0)+\delta E(w_3^1(r_2,0)) \le w_2^1(r_1,1)+w_2^2(r_1,1) + \delta E(w_3^1(r_2,1)+w_3^2(r_2,1)) - c_j. \qquad (3)$$

The left-hand side of (3) is the expected payoff for staying focused: the sum of the size of the allocation to the manager's only fund in the second period and what the manager can expect to be allocated in the third period. Importantly, this latter value will be a function of investors' beliefs about the manager's type at the end of the first period and the expected return of the manager in the second period. The right-hand side is a similar expression for the expected payoff for a manager who chooses to diversify.[7]

Rearranging terms, we have the result that if diversification is an equilibrium, a firm will diversify if and only if their costs to launch a new fund are below a critical level, $c_j^{\text{crit}}(r_1)$:

$$c_j \le c_j^{\text{crit}}(r_1) = [w_2^1(r_1, 1) - w_2^1(r_1, 0)] + \delta[E(w_3^1(r_2, 1)) - E(w_3^1(r_2, 0))] + [w_2^2(r_1, 1) + \delta E(w_3^2(r_2, 1))]. \qquad (4)$$

The inequality in (4) illustrates the trade-off for the manager. First, to diversify, the manager must pay c_j, which is captured on the left side of Equation (4). Second, 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. This is captured by the term $w_2^1(r_1, 1) - w_2^1(r_1, 0)$ in (4), which one might call a *cannibalization effect*: diversification is costly to the firm, on the margin, in terms of lowering investor allocations to fund 1. 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. Simply put, mean reversion implies that if r_1 is below the manager's type, in expectation, the manager's returns in future periods will be higher, and if it is above the manager's type, in expectation, it will be lower. Moreover, with the launch of the second fund, the manager should expect to be closer to the mean return (their type θ_j) than in the case where they do not launch a second fund at every point in time in the future. Because 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*, which is captured by the term $\delta[E(w_3^1(r_2, 1)) - E(w_3^1(r_2, 0))]$ in (4), as in Cabral (2000). Finally, these (potential) costs will be compared with an unambiguous benefit. Because investors are assumed to be unconstrained in borrowing, investors face no trade-off 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 cannibalization, track record dilution, and diversification costs. We refer to the unambiguous benefits of diversification as the *scope extension effect*, which is captured by the term $w_2^2(r_1, 1) + \delta E(w_3^2(r_2, 1))$.

Even though managers with identical histories will be treated symmetrically by the investor in period 2, managers with lower investment skill will have weaker 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 managers means they can expect lower allocations in the third period and, therefore, will be less willing to launch an additional fund. In other words, in any diversification equilibrium, $c_H^*(r_1) \ge c_L^*(r_1)$, where $c_j^*(r_1)$ denotes the equilibrium $c_j^{\text{crit}}(r_1)$ for a type j. This conclusion is summarized as follows:

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.*

[7] Note that incorporated in (3) are any beliefs the investor may have after first and second period returns, conditional on diversification.

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_1. This means that if separation occurs in equilibrium for some r, it could be the case that for an arbitrary small value η there could be pooling for $r_1 + \eta$. In fact, this leads to the possibility that measures of r_1 alternate between pooling and separation. Because each unique "slice" of r_1 may pool, there are equilibria in which at lower-level managers may separate, whereas at intermediate levels they may pool, and at higher levels they may return to separation. That said, other equilibria also exist to this game. In fact, as our intent is simply to provide sufficient conditions for the dynamic we describe above, we show there are also equilibria in which low-cost firms diversify and high-cost firms do not.[8]

Lemma 2. *There exists an equilibrium in which for sufficiently low costs, managers will diversify and otherwise will stay focused.*

We now turn to our primary result. In the appendix, we construct an equilibrium such that managers with very low returns in the first period all stay focused, managers with very high level of returns diversify, and managers in the "middle" diversify only when their costs are sufficiently low. Such an equilibrium—along with the fact that higher-quality managers in any equilibrium with diversification diversify at higher *rates* given their track record—allows us to establish the existence of an equilibrium to the game with three testable properties. Result 1 summarizes the characteristics of this equilibrium.

Result 1. *There exists an equilibrium in which the following three properties hold*:

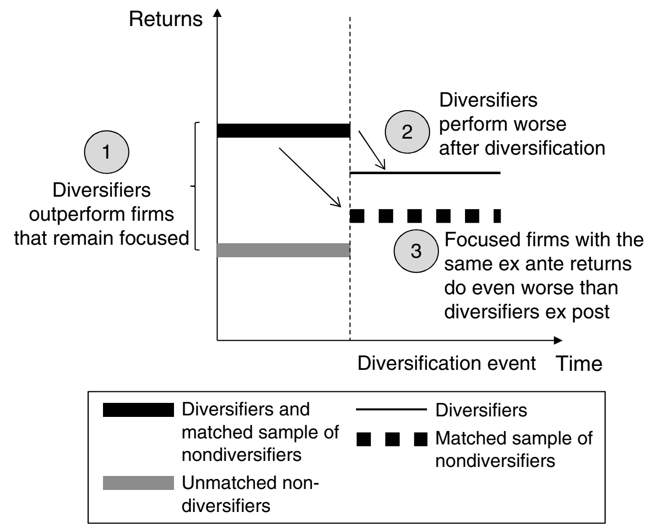
(i) *Diversifiers will outperform nondiversifiers in the prediversification period*: $E_j(r_1 \mid d_j = 1) \geq E_j(r_1 \mid d_j = 0)$.

(ii) *In expectation, the performance of diversifiers will fall after diversification*: $E_j(r_1 \mid d_j = 1) \geq E_j(r_2^1 \mid d_j = 1)$.

(iii) *Conditional on first period returns, diversifiers will outperform nondiversifiers*: $E_j(r_2^1 + r_3^1 \mid r_1, d_j = 1) \geq E_j(r_2^1 + r_3^1 \mid r_1, d_j = 0)$.

At this point, the intuition behind each component of Result 1 follows straightforwardly from the earlier results. The first result that nondiversifiers will underperform diversifiers, prior to diversification, is driven by two facts: cost cutoffs are weakly increasing in first period returns, and the more skillful managers are more likely to diversify conditional on any r_1. 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 postdiversification return must fall. Finally, the last component—conditional on first period returns, the returns of diversifiers will fall less in expectation than nondiversifiers—follows directly from Lemma 1. Because highly skilled types will be more likely to diversify conditional on first period returns, they will have a higher expected return after diversification than nondiversifiers. This, in turn, makes investors' beliefs about the diversifiers rational. Figure 1 illustrates our three predictions graphically.

Figure 1 **Skill, Luck, and Performance**



Our theory predicts a pattern of returns that is broadly consistent with a set of stylized facts, reported in the literatures on diversification and investment firms. 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 et al. 1998); yet, firms with the best track record tend to launch new funds, and their performance tends to persist relative to a control group (Kaplan and Schoar 2005). Our model explains these stylized facts in a simple testable equilibrium framework.[9] Neither agency effects nor capabilities alone can explain the full set of results demonstrated.

[8] Although the equilibria is not unique, the equilibrium we study is a natural one to study. If we confine the analysis to look at the *maximally separating* equilibrium, then the cutpoints will be increasing, assuming they exist. The intuition for this result is that both the maximum cutpoints of both types are increasing in r_1. Moreover, as we show in the appendix, these can both hold simultaneously, which means maximal separation occurs when cutpoints are increasing.

[9] 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. That said, Cabral (2006) provides

Other theories might explain some of our results, but cannot generate the full set of results predicted either. For example, Roll's (1986) hubris argument might explain why firms that experience an idiosyncratic performance shock diversify and then suffer declining returns because they develop excessive pride based on their track record. However, hubris cannot explain why diversifiers outperform firms that remain focused. Similarly, while management of returns around diversification events or anticipation of falling returns may explain parts (i) and (ii) of Result 1, they cannot explain part (iii).

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. Although 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 as volatile in industrial markets, agency costs 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 general, and the hedge fund industry is interesting to study as we discuss below.

3. Data and Institutional Context

Hedge funds are closed to the general public and are not required to publicly report their returns. However, a large number of funds do choose to report their returns to one or more private companies that make their data available by subscription. Our data on hedge funds, from Lipper-TASS (TASS) and Hedge Fund Research (HFR), were provided to us for research purposes by a major financial institution. The data series begins in 1977, but only includes "graveyard" funds, funds that stopped reporting to the data providers for any reason, including fund failure, from 1994. We use the survivor-bias-free subsample of the data 1994–2006 as our main sample, though our results are robust to using the full sample as well. Taking TASS and HFR data together, we have coverage on 3,102 firms over the period 1994–2006, representing approximately 25% of the firms in the industry.

Consistent with the standard definition of diversified firms as multiproduct firms 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 and currency twin funds, which we consider a single fund in our sample, hedge funds generally launch new funds with distinct investment objectives and/or trading strategies compared to their existing funds. Thus, diversification is usually distinct from expansion in the context of hedge funds.

Among all the data sets used in the hedge fund literature, TASS and HFR are considered the most comprehensive (Li et al. 2011). Whereas most researchers rely on either one or the other, we believe this is the first paper to integrate these two data sets, making our data set the largest survivor-bias-free data set assembled to date on hedge funds. However, the data do have some important limitations. Firms choose whether to report their data to HFR and TASS, presumably out of self-interest; therefore, the data may be subject to selection bias. Although we do not know what decision making processes lead firms to self-report their data, based on our discussions with hedge fund managers, we believe hedge funds are more likely to self-report to TASS and HFR when they are interested in raising capital at some future date for expansion of their existing fund and/or for expansion through product diversification. Thus, although our results may not generalize to hedge funds that do not require external capital to expand, this limitation does not represent a major problem for our research because we are explicitly interested in studying firms that require external capital to expand.[10]

a modification of his model to apply specifically to unrelated diversification and shows that, in this context, lower-skilled managers may have greater incentives to diversify given that their "anchor" product is not that valuable. MacDonald and Slivinski (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 returns, and investors invest rationally; however, in equilibrium, investment managers' decisions result in little persistence in outperformance. Our model also has some similarities to Bar-Isaac (2003), who develops a model in which reputations of sellers are learned slowly. He analyzes an equilibrium in which good sellers who know their quality may continue to sell in the face of a bad reputation to have more "draws" to reveal their true type, but bad types may stop selling in the face of a bad reputation.

[10] Annual returns reported to investors are audited, which limits the scope for misrepresentation for most firms. However, firms might manipulate monthly returns within a year for strategic reasons. We rely on our empirical design to deal with these effects. Fortunately, the most obvious self-reporting bias is not a problem

Because small variations in spelling and abbreviations, integrating the two data sets also requires some manual comparisons across data sets. We had two research assistants perform the manual comparisons independently, and then resolved the few discrepancies through inspection.

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 1,876 firms that entered the data set as focused firms, 1,186 firms that remained focused, and 690 firms that subsequently diversified,[11] excluding firms that entered as diversified firms, which we define as becoming a diversified firm within the first 12 months of entering the data set, and funds that reported less than 12 months of returns or did not report returns continuously. After matching diversified firms to firms that remained focused (described in detail below), our test sample consists of 37,657 fund-months from 1,353 firms, of which 676 are diversified firms and 677 (one tie) are a matched set of focused firms.

We test the predictions of the model using risk-adjusted excess returns as our baseline measure of firm performance. 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 nonsystematic 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 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 exposed to nonsystematic risks that are not priced by standard market benchmarks. If funds take on significant nonsystematic risks, perhaps through aggressive use of leverage, they may appear to generate higher average excess returns that are really an artifact of model mispricing. We account for the nonsystematic riskiness of a fund's underlying investments using a dynamic version of the information ratio. We also control for biases that may arise because of self-reporting, including serial correlation in the time series of returns using an autoregressive lag one correction, and for backfill bias by dropping the first reported monthly return.[12]

Our baseline performance benchmark follows the emerging standard for assessing hedge fund performance (Sadka 2010). The performance measure is developed based on Fung and Hsieh's (2001) seven-factor asset pricing model, which is specifically designed for pricing risk in hedge funds by controlling for exposures to linear and nonlinear equity, bond, commodity, and option-based risk factors. We augment Fung and Hsieh's (2001) model by including a "traded liquidity factor" from Pástor and Stambaugh (2003), which controls for a fund's exposure to illiquidity risk. Excess returns are the sum of a time-invariant fund-specific term a plus a mean zero residual e from the regression

$$R_{it} = a_i + R_{ft} + \mathbf{X}_t \mathbf{B}_i + e_{it}, \tag{5}$$

where i and t index funds and time (in months), respectively; R_i is a fund's raw return from TASS and HFR, and the vector $\mathbf{X}$ contains the seven risk factors from Hseih's data library and the traded liquidity factor from Stambaugh's website.[13] The term a_i is the time-invariant component of a fund's performance, and e is the residual. We compute a, the coefficients on $\mathbf{X}$, and e by running 1,876 fund-level longitudinal regressions. Excess returns Y for firm i in any period t are defined as $Y_{it} = a_i + e_{it}$, where excess return captures the combination of a fund's skill and luck relative to a market benchmark. We call the resulting measure "eight-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% levels to control for extreme values, though doing so has no meaningful impact on our results. We also

for our tests on firm skill, because strategic manipulation in anticipation of diversification would bias the results against our third prediction (e.g., returns would fall more after diversification than without manipulation). We address the possibility that diversified firms inflate their ex post returns using multiple years of lagged excess returns as our ex ante performance measure, which firms could only manipulate through more aggressive multiyear fraudulent behavior and by verifying that the results are robust to eliminating firms in the right tail of the returns distribution.

[11] 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. We also treat funds that have identical trading strategies in different currencies as a single fund.

[12] Posthuma and van der Sluis (2003) drop the first 36 months of returns to control for backfill bias. We drop the first month of recorded return data, because we found that only the first reported monthly return was significantly different from long-run average returns. Dropping additional months has little effect on our point estimates but does lead to noisier estimates because most firms in the sample diversify within the first 36 months of their existence.

[13] The Pástor-Stambaugh series is available at http://finance.wharton.upenn.edu/~stambaug/liq_data_1962_2008.txt (accessed July 5, 2009). Hseih's data library can be found at http://faculty.fuqua.duke.edu/~dah7/HFData.htm (accessed August 4, 2009).

Table 1 Key Descriptive Statistics for the Main (Matched) Sample

	Mean	Std. dev.	Min	Max
Raw returns (%)	0.87	5.19	−70	116
Eight-factor monthly excess returns (%)	0.37	3.77	−11.18	13.35
Standard deviation of excess returns (%)	3.57	2.78	0.39	13.89
Eight-factor information ratio	0.17	1.00	−2.48	3.01
Diversified (fraction)	0.53	n/a	0	1
Fund assets under management ($M)	100	238	0.2	1,890
Firm assets under management ($M)	147	372	0.9	8,310
Missing AUM (fraction)	0.11	n/a	0	1
Age (months)	47	34	2	345
Year: 1994	0.01	n/a	0	1
Year: 1995	0.03	n/a	0	1
Year: 1996	0.06	n/a	0	1
Year: 1997	0.08	n/a	0	1
Year: 1998	0.08	n/a	0	1
Year: 1999	0.09	n/a	0	1
Year: 2000	0.09	n/a	0	1
Year: 2001	0.08	n/a	0	1
Year: 2002	0.08	n/a	0	1
Year: 2003	0.09	n/a	0	1
Year: 2004	0.10	n/a	0	1
Year: 2005	0.12	n/a	0	1
Year: 2006	0.09	n/a	0	1
Headquarters in the United States	0.67	n/a	0	1

Notes. The main (matched) sample includes the fund-months from the diversification date (or match date) until 35 months after diversification (or match date) for 676 diversifiers and 677 matched focused firms (there is one tie). $N = 37{,}657$ fund-months from 1,353 firms.

replicated all of our results using Fung and Hsieh's (2001) seven-factor asset pricing model without the Pástor and Stambaugh (2003) traded liquidity factor, as well as using a more traditional passive benchmark commonly employed for evaluating mutual funds, the Fama and French (1996) three-factor model plus a momentum factor (Carhart 1997).[14]

We use excess returns as a dependent variable in our regressions of performance on diversification. We also use excess returns to compute the 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 the average two-year *CAR* as our key performance variable predicting the launch of a new fund. We verify that we obtain similar results with longer lagged *CAR* measures and measures of *CAR* that give more recent observations more weight than older observations.

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 37 basis points of risk-adjusted (excess) returns per month with a standard deviation of about 4% per month. Adjusting for nonsystematic risk exposure, using the information ratio, the average fund generated 17 basis points of excess returns per unit of risk with a standard deviation of about 1% per month.

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 $100 million of AUM, whereas the average firm held $147 million of AUM. The size distribution of AUM is skewed right, with the top 1% of funds growing to $1.9 billion.[15] We take the nonnormality of AUM into account by using 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. Eleven percent of fund-months had missing AUM, which we control for using a missing AUM dummy variable.[16]

[14] Results using four-factor and seven-factor excess returns (and the corresponding information ratios) are reported as robustness checks in Table 4.

[15] AUM values are reported Winsorized at the 1st and 99th percentiles, though Winsorizing has no effect on the results.

[16] Twenty-three percent of returns come from long/short funds—a general type of fund that often has no meaningful restrictions on investment strategy. Nineteen percent of funds reported that they were fund of funds that invest in other hedge funds. The other 58% of funds were distributed over 32 additional investment strategy categories, with the largest being equity hedge (9%), managed futures (9%), and event driven (7%) strategies. No other strategy

We report the composition of the sample by calendar year in Table 1, but we use periodicity in three ways in our analysis: (i) 13 year fixed effects control for hedge-fund-specific calendar time effects; (ii) market returns for 132 calendar months control for time-series variation in market returns in our computation of excess returns; and (iii) 36 event time categorical variables control for the time path of returns 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 fund-months in our sample are based in the United States. 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

4.1. The Propensity to Diversify

Our first prediction is that diversifiers will outperform nondiversifiers in the prediversification period. To generate evidence in support of Result 1(i), we test whether firms tend to launch new funds when they experience unusually strong performance. We drop diversifying firms[17] from the analysis following the month in which they launch a new fund (although all fund-months are included for firms that remain focused) and use the probit model

$$LAUNCH^*_{it} = \mathbf{x}_{it}\boldsymbol{\beta} + \xi_{it}, \tag{6}$$

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. The vector $\mathbf{x}$ includes all observable characteristics of firms that might plausibly have an effect on the decision to launch a new fund, including *CAR*; average *CAR* for other firms in the same strategy class; 10 fund size declines, where size is measured by AUM; size of the strategy class; log firm age; 13 time (year) dummies; 10 fund investment strategy dummies; four regional geographic location dummies; and ξ as an error term, which is assumed to be normally distributed with mean zero and variance one. Standard errors are clustered by firm.

We show the result of estimates of the probit model (6), using 1,876 firms and 85,428 fund-months, in Table 2, columns (1) and (2). Column (1) shows that the marginal effect of *CAR* on the propensity to diversify without controls is 0.079%, compared to a baseline diversification rate of 0.801% (690 new fund launches in 85,428 fund-months), and is strongly statistically significant. In other words, doubling *CAR* from the mean increases the probability that the firm will launch a new fund in any given month by approximately 10%. Column (2) shows the marginal effect of *CAR* on the propensity to diversify with controls. The result continues to be statistically significant though the point estimate on *CAR* is smaller. Holding all other regressors at their mean values and doubling *CAR* increases the probability of diversifying by 0.055%, which represents a 7% increase in the baseline diversification rate. The evidence suggests that strong performance does indeed increase the probability that a hedge fund firm will launch a new fund.

We also use the empirical model displayed in Table 2, column (2), as our baseline matching model. The baseline matching model uses all of 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. Our objective is to find a matched set of focused firms that are similar to the set of diversifying firms along all observable dimensions just prior to diversification so that we can separate skill from luck effects ex post.

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 choosing to launch a new fund in any particular month, using the probit model (6). Next, we trim the sample at the 1st and 99th percentiles of the propensity score distribution and eliminate firms off the common support of the propensity score distributions 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 676 treated (diversified) and 677 control fund-month observations (there is one tie). The interpretation of the control group is that for each fund that did diversify in a particular month, we identified the fund that was most similar in terms of all observable characteristics that did not diversify.

In Table 2, columns showing differences in means give measures of the effectiveness of the matching process. The unmatched sample columns show the mean values for *CAR* for focused and diversifying firms, respectively, before matching, and test whether *CAR* and the means on the control variables are statistically different between focused and diversifying firms. Before matching, the differences in *CAR*, firm

category had more than 5% of fund-months. Fund of funds take positions in other hedge funds. Because fund of funds are somewhat different from traditional hedge funds, we verified that they are not driving the results in this paper.

[17] 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 this section.

Table 2 Predicting Diversification and Matching Statistics

	Predicting diversification		Comparison of means in matched and unmatched samples								
			Unmatched sample[a]			Baseline match[b]			Alternative match[c]		
	(1) Marginal effects %	(2) Marginal effects %	Means: Focused	Means: Diversified	Diff. in means[d]	Means: Focused	Means: Diversified	Diff. in means[d]	Means: Focused	Means: Diversified	Diff. in means[d]
Avg. eight-factor *CAR*	***0.079**** (***0.019***)	***0.055**** (***0.017***)	***0.53*** (***0.01***)	***0.77*** (***0.06***)	***−4.13****	***0.58*** (***0.06***)	***0.73*** (***0.06***)	***−1.86***+	***0.71*** (***0.06***)	***0.74*** (***0.05***)	***−0.32***
Avg. strategy eight-factor *CAR*		−0.033 (0.084)	0.50 (0.00)	0.48 (0.02)	1.47	0.46 (0.02)	0.48 (0.02)	−0.63	0.47 (0.02)	0.48 (0.02)	−0.54
Size controls[e]	N	Y*	Y	Y	*	Y	Y		Y	Y	
Age control[f]	N	Y*	Y	Y	*	Y	Y	*	Y	Y	*
Strategy fixed effects[g]	N	Y*	Y	Y	*	Y	Y		Y	Y	
Strategy size control[h]	N	Y	Y	Y	*	Y	Y	*	Y	Y	*
Year fixed effects[i]	N	Y+	Y	Y	*	Y	Y	*	Y	Y	
Region fixed effects[j]	N	Y	Y	Y	+	Y	Y		Y	Y	
Interactions[k]	N	N	N	N		N	N		Y	Y	
Unique funds	1,876	1,876	1,186	690		677	676		649	647	
N	85,428	85,428	84,738	690		677	676		649	647	
F-test on the joint difference in means					>99*			1.23			1.12

Notes. The dependent variable equals 1 if a firm launches a second fund at time (month) t, and 0 otherwise. Standard errors are in parentheses. Y, yes; N, no.
[a]The unmatched sample is the full survivor-bias-free sample of first funds from firms in TASS and HFR, 1994–2006.
[b]The baseline match sample is derived from 1:1 nearest neighbor matching on the propensity to diversity using model (2) (there is one tie).
[c]The alternative match sample modifies model (2) by including interaction effects on *CAR* with year and size (there are two ties).
[d]T-tests are reported on individual differences in means; F-tests are reported on tests of the joint differences in means.
[e]Size controls include own-fund size decile dummies (by AUM) and a dummy for missing size (except in the alternative match where size enters continuously).
[f]Log age, where age is measured as months from founding date.
[g]Strategy fixed effects include dummy variables for the 10 largest self-identified investment strategy types (by number of funds).
[h]Log *AUM* for all firms in a strategy.
[i]Year fixed effects include dummy variables for each year, 1994–2006.
[j]Region fixed effects include dummies for firms domiciled in the United States, United Kingdom, continental Europe, Asia, and all other locations.
[k]Interactions include average eight-factor *CAR* interacted with log *AUM*, (log *AUM*)^2, *missing AUM*, and the year fixed effects.
*Significant at the 5% level; +significant at the 10% level.

size, age strategy class, strategy size, year, and region between focused and diversifying firms are statistically significant, and the overall F-test on the joint significance of the differences in means very large, which suggests that the two populations are not statistically comparable.

The baseline match columns repeat this procedure for the matched sample. The statistical differences in size, strategy, and region are completely eliminated, whereas the difference in *CAR* is on the margin of statistical significance. The differences in age and year are reduced, and the joint significance of the differences in the means is eliminated ($F = 1.23$). Comparing the differences in the means in the full sample with those in the matched sample reveals that matching substantially aligns the ex ante characteristics of the firms in the diversified and focused groups. Figure 2 shows this effect graphically. Figure 2(a) 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, they are essentially identical after

Figure 2 Propensity Score Predicting Diversification Before (a) and After (b) Matching

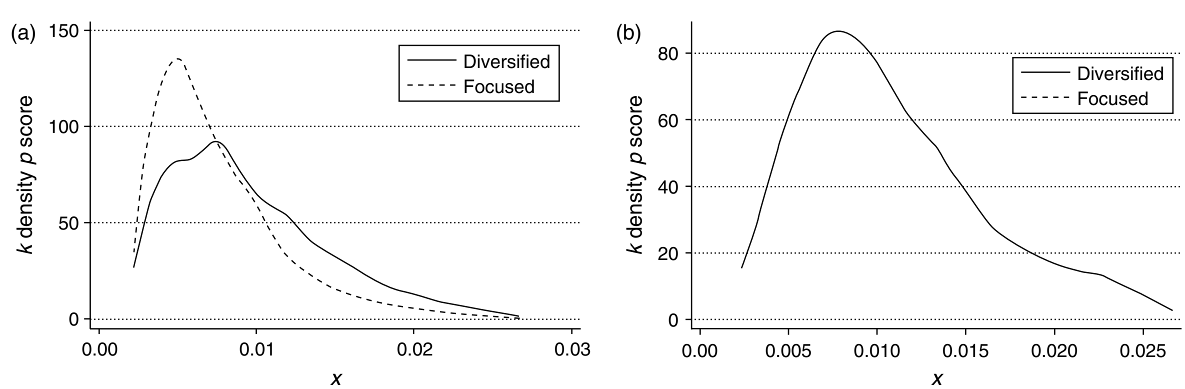
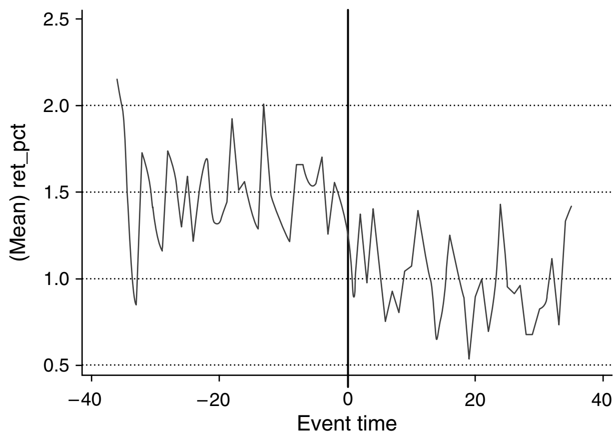


Figure 3 Time Path of Raw Returns for Diversifiers



Notes. This figure shows average raw 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 36 months before diversification to 35 months after diversification for 33,421 fund-months from 676 diversifying firms.

matching; indeed the distributions lie almost directly on top of one another (Figure 2(b)).[18]

4.2. Within-Firm Changes

Our second key prediction, Result 1(ii), is that the performance of diversifiers will fall after diversification, a result that is evident even in a simple time-series plot of excess returns. Figure 3 shows the relationship between fund performance and diversification graphically, plotting first fund average excess returns for the 676 diversifying firms in our test sample. As Figure 3 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

$$Y_{it} = \alpha + \lambda_i + DIVERSIFIED_{it} + T_t + \mathbf{X}_{it}\boldsymbol{\beta}_c + \varepsilon_{it}, \quad (7)$$

where i and t index funds and time (in months), respectively, for all first funds in firms that eventually diversify for five years before and after the diversification event; 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 1 when a fund is part of a diversified firm and 0 otherwise; T is a vector of 13 calendar year dummies; $\mathbf{X}_c$ is a vector of controls including the log of firm age, the log of AUM by market segment ("strategy") and then fund size dummies measured by deciles of AUM, plus a dummy for missing AUM; and ε is the residual. Standard errors are clustered by fund.

Table 3, columns (1) and (2), show the results of the within-fund estimator (7). Excess returns are 14 basis points per month lower following diversification. The effect is only significant at the 10% level, but the p-value is 0.054. Using the information ratio, performance is four basis points per month per unit of risk lower following diversification, and the point estimate is reliably different from zero. Altering the time window around the diversification month had no meaningful effect on the results.

Performance falls in hedge funds following diversification. However, we know from the prior literature that the relationship between diversification and performance should always be evaluated conditional on the selection process firms undergo when choosing to launch a new business unit or fund (Campa and Kedia 2002, Villalonga 2004). Table 3 and Figure 3 both show that returns are higher prior to the launch of a new fund, which might suggest that better performance causes hedge funds to launch new funds. If true, then we would expect returns to naturally revert toward the mean following diversification. 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 whether skilled firms diversify when they are lucky as our model predicts, we use the matched sample of focused firms identified by our matching model.

4.3. Matched Sample Ex Post Performance

We compare ex post performance for diversifiers relative to firms that remain focused beginning from the diversification or match date for the 1,353 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 examine the event (at time 0) and the 35 months after the event $(0, 1, 2, 3, \ldots, 35)$. Altering the number of months in the regression following the event has no meaningful effect on the results. We estimate the difference in ex post returns between diversifying firms and the matched set of focused firms using the pooled ordinary least squares model (8):

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

[18] To be sure that our ex post results are not being driven by ex ante differences in *CAR*, and that time-varying *CAR* thresholds are not driving our results, we use an alternative matching model where *CAR* is interacted with covariates that, in theory, might have a marginal effect on the relationship between performance and diversification, including firm size and calendar year. In Table 2, the alternative match columns show that the alternative matching regime eliminates the statistical differences between *CAR* and the calendar year fixed effects and slightly improves the F-test on the joint significance of the means. Our results are robust to this alternative matching regime.

Table 3 Diversification and Performance

	Within-fund changes in performance		Matched sample performance	
Dependent variable	Eight-factor excess returns	Eight-factor information ratio	Eight-factor excess returns	Eight-factor information ratio
Event window (in months)	−36 to +35	−36 to +35	0 to +35	0 to +35
	(1)	(2)	(3)	(4)
DIVERSIFIED	***−0.136***$^{+}$	***−0.037****	***0.177****	***0.061****
	(***0.071***)	(***0.018***)	(***0.050***)	(***0.019***)
Log age	−0.102^{+}	−0.044*	−0.097*	−0.065*
	(0.056)	(0.016)	(0.039)	(0.016)
Log AUM by strategy	0.068	0.001	−0.113*	−0.023
	(0.122)	(0.029)	(0.047)	(0.028)
Constant	Y	Y	Y	Y
11 size fixed effects	Y	Y	Y	Y
13 year fixed effects	Y	Y	Y	Y
36 event time fixed effects	N	N	Y	Y
5 region fixed effects	N	N	Y	Y
11 strategy fixed effects	N	N	Y	Y
676 fund fixed effects	Y	Y	N	N
Firms	676	676	1,353	1,353
N	33,421	33,421	37,657	37,657
Adjusted R^2	0.04	0.07	0.01	0.02

Notes. The "within-fund changes in performance" sample includes the fund-months from 36 months before diversification until 35 months after diversification for 676 diversifiers. The matched sample includes the fund-months from the diversification date (or match date) until 36 months after diversification (or match date) for 676 diversifiers and 677 matched focused firms (there is one tie). Standard errors are clustered by fund.

*Significant at the 5% level; $^{+}$significant at the 10% level.

where i indexes firms, and t indexes calendar time; performance (Y), *DIVERSIFIED*, and T are as above in (7); and $\mathbf{X}$ includes log firm age, log of assets under management by strategy, and fund size dummies as in (7). We also include in $\mathbf{X}$ 5 region dummies that control for location-specific effects, and 11 strategy-type dummies to control for strategy-specific return patterns, as well as a vector of event time (month) dummies for the 36 months after launching a new fund (or match date for the control group) to control for the pattern of mean reversion following the event as predicted by our theoretical model; and ε is the residual. Standard errors are clustered by fund.

Table 3 shows the matched sample eight-factor ex post returns in columns (3) and (4). Following diversification, excess returns are 18 basis points per month higher, and the information ratio is 6 basis points per month higher, per unit of risk in the first funds of diversified firms compared to a matched sample of nondiversifiers, and the coefficients are reliably different from zero. The interpretation supports our contention that diversifying firms outperform firms that remain focused ex post, conditional on being similar across observable dimensions ex ante.

We verify that our results are not sensitive to including a longer data series of lagged returns to compute *CAR* and/or by weighting recent returns more than older returns in event time (see Table 4 for the results after matching on 60-month weighted *CAR*). We also found similar results using an alternative matching model, which forces ex ante returns to be more similar between diversifiers and nondiversifiers and controls for the precise pattern of ex ante returns by calendar time (see Table 4 for the results using the alternative matching model). Similar results were obtained when matching only on *CAR*. Furthermore, we found similar results using firm-level performance as the dependent variable in (8), which implies that firms are not using their second fund to cross-subsidize the first (see Table 4 for firm-level results).

The overall pattern of evidence is consistent with a 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, with skill effects dominating luck effects.

Table 4 Robustness Checks

Regression description	n	Excess returns	Information ratio
		Dependent variables	
Alternative performance measures			
Four-factor performance	37,657	0.144*	0.054*
		(0.049)	(0.018)
Seven-factor performance	37,657	0.177*	0.059*
		(0.049)	(0.018)
Firm-level performance			
Equal weighted eight-factor firm performance	37,657	0.184*	0.065*
		(0.049)	(0.018)
Value weighted eight-factor firm performance	37,657	0.183*	0.065*
		(0.051)	(0.019)
Alternative matching regimes			
Weighted 60-month *CAR* eight-factor performance	37,501	0.123*	0.052*
		(0.053)	(0.018)
Alternative matching regime eight-factor performance	35,784	0.102*	0.064*
		(0.048)	(0.017)

Notes. Standard errors clustered by fund in the alternative performance measures and alternative matching regime robustness checks, and by firm in the firm-level performance regressions. Coefficient values for *DIVERSIFIED* are reported. All regressions contain the same controls as in Table 3. Firm-level controls are aggregated to the firm level. The "first stage" of the alternative matching regime model includes *CAR* interacted with the full set of year dummies, *size* (log *AUM*), *missing AUM*, and *size*^{2} (as shown in Table 2).

*Significant at the 5% level.

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. We test these propositions in the context of the global hedge fund industry from 1994 to 2006. The evidence supports agency theory's prediction that diversification decisions are influenced by managers' 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 findings are that when firms need external capital to expand, they will tend to diversify when they experience a positive idiosyncratic performance shock that raises their performance above that of their peers and above their long-run average, but better firms diversify in equilibrium, even though managers appear to exploit asymmetric information about their true ability to time the market. 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 consistent with these effects. 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. Finally, 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.

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Appendix. Proofs of Results

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 if and only if

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

Rearranging, we have the condition that

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

Because $E(w_{13}(r_2,1)) - E(w_{13}(r_2,0))$ is lower for a low type than a high type, it must be the case that $c_H(r_1) \ge c_L(r_1)$. Because $c_j \sim h(c)$ is the same for low and high types and is atomless, and $\mathrm{Corr}(c_j, \theta_j) = 0$, this implies that

$$\Pr(d_j=1 \mid \theta_H, r_1) = \Pr(c_j > c_H(r_1)) \ge \Pr(d_j=1 \mid \theta_L, r_1) = \Pr(c_j > c_L(r_1)). \quad (9)$$

The remainder of the result follows trivially from (9). □

Proof of Lemma 2. Note that (3) and Lemma 1 are a result of the manager's decision problem, and therefore are met in any nonpooling equilibrium. Note further that from (3) it is clear that if a manager with cost $c_j \sim h(c)$ chooses to diversify, then all managers $k \neq j$ of the same skill type θ, initial performance r_1, and $c_j < c_k$ also diversify. Because the distribution of c is atomless, we can then define the decision for all managers as defined by the thresholds in c at which diversification occurs.

To specify an equilibrium, we have to define beliefs of the investor $\phi(d, r_1) = \Pr(\theta_k = \theta_H \mid d, r_1)$. For convenience, we suppress parameters and refer to beliefs using the following simplified notation where the meaning is clear: $\phi(d, r_1) = \phi$, $\phi(1, r_1) = \phi_1$, and $\phi(0, r_1) = \phi_0$. Because the payoffs in (3) do not depend on r_1, but rather on investor beliefs ϕ, we can define the best response functions of the managers given arbitrary beliefs of the investor as $c_\theta(\phi_1, \phi_0)$. Given those beliefs and $H(c)$, the share of types θ that diversify is $H(c_\theta(\phi_1, \phi_0))$.

Next, note from Lemma 1 that if $\phi_1 = \phi_0$, then $c_H(\phi_1, \phi_0) \geq c_L(\phi_1, \phi_0)$, and strictly so if $c_H(\phi_1, \phi_0) > 0$. This implies

$$E(w_{12}(r_1, 1) + w_{22}(r_1, 1) \mid \theta_H) - E(w_{12}(r_1, 1) + w_{22}(r_1, 1) \mid \theta_L) > E(w_{12}(r_1, 0) \mid \theta_H) - E(w_{12}(r_1, 0) \mid \theta_L).$$

In any separating equilibrium, beliefs of the investor in the second period are governed by Bayes' rule and the best responses of managers:

$$\phi_1 = \frac{H(c_H(\phi_1, \phi_0))q(r)}{H(c_H(\phi_1, \phi_0))q(r) + H(c_L(\phi_1, \phi_0))(1 - q(r))},$$

$$\phi_0 = \frac{(1 - H(c_H(\phi_1, \phi_0)))q(r)}{(1 - H(c_H(\phi_1, \phi_0)))q(r) + (1 - H(c_L(\phi_1, \phi_0)))(1 - q(r))},$$

where $q(r) = \text{Prob}(\theta_H \mid r_1)$, or the share of managers with return history r who are high types.

The above beliefs form a mapping over beliefs of the investor that are consistent with the best responses of managers. All interior equilibria are fixed points of this mapping. However, to show the existence of a diversification equilibrium, we define the following modified mapping:

If $c_H(\phi_1, \phi_0) \geq c_L(\phi_1, \phi_0)$, then

$$\phi_1 = \frac{H(c_H(\phi_1, \phi_0))q(r)}{H(c_H(\phi_1, \phi_0))q(r) + H(c_L(\phi_1, \phi_0))(1 - q(r))},$$

$$\phi_0 = \frac{(1 - H(c_H(\phi_1, \phi_0)))q(r)}{(1 - H(c_H(\phi_1, \phi_0)))q(r) + (1 - H(c_L(\phi_1, \phi_0)))(1 - q(r))}.$$

Otherwise,

$$\phi_1 = q(r) \quad \text{and} \quad \phi_0 = q(r).$$

This is clearly a continuous mapping. To show the existence of diversification we need to show that that same mapping is defined over the set $[0, 1]^2$, where $\phi_1 \geq \phi_0$ (i.e., a convex and closed, compact set). If $\phi_1 \geq \phi_0$ and $c_H(\phi_1, \phi_0) \geq c_L(\phi_1, \phi_0)$, it maps to another pair where $\phi_1 \geq \phi_0$. If $\phi_1 \geq \phi_0$ and $c_H(\phi_1, \phi_0) < c_L(\phi_1, \phi_0)$ it maps to $\phi_1 = \phi_0$. By Brouwer's fixed point theorem we have a fixed point in the set $[0, 1]^2$, where $\phi_1 \geq \phi_0$. By Lemma 1, $\phi_1 = \phi_0$ is not an equilibrium, so it is not a fixed point, so it must be that $\phi_1 \geq \phi_0$. So this must also be a fixed point of the unmodified problem above.

It is also a partial pooling equilibrium such that some, but not all, of both high and low managers diversify for all r_1; namely, note that $\phi_1 = 1$ is not an equilibrium, because then there would be no updating, so the expected utilities from diversifying for high types and low types are the same, but those from not diversifying are weakly higher for high types, so we would have $c_H(\phi_1, \phi_0) < c_L(\phi_1, \phi_0)$. This implies that $\phi_1 < 1$, so some low-type managers diversify. Because $c_H(\phi_1, \phi_0) \geq c_L(\phi_1, \phi_0)$, then some high-type managers also diversify. □

Lemma 3. *Define $\bar{c}$ such that a high-type manager with cost type $\bar{c}$ is indifferent between diversifying and staying focused if the investor has beliefs $\phi_1(\bar{r}) = q(\bar{r})$, $\phi_0(\bar{r}) = 0$. Then for all $r_1 > \bar{r}$, there exists an equilibrium where all high-type managers diversify and some low-type managers diversify. Furthermore, $c_L(\phi_1, \phi_0)$ is weakly increasing in r_1; strictly increasing over $[\bar{r}, \hat{r}]$, where $\hat{r}$ is defined such that a low-type manager with cost type $\bar{c}$ is indifferent between diversifying and staying focused if the investor has beliefs $\phi_1(\bar{r}) = q(\bar{r})$, $\phi_0(\bar{r}) = 0$; and constant above $\hat{r}$.*

Proof of Lemma 3. Given $\bar{c}$ and $r_1 > \bar{r}$, diversification is a best response for all high-type managers. This implies that $\phi_1 = q(r_1)/(q(r_1) + H(c_L(\phi_1, 0))(1 - q(r_1))) \geq q(r_1)$, $\phi_0 = 0$. Because the return from staying focused is zero for low types, $c_L(\phi_1, 0) = E(\pi \mid \theta_L, d = 1, \phi_1, 0)$, where we denote the manager's payoff as π. Note that ϕ_1 is decreasing in $c_L(\phi_1, \phi_0)$ within the range $[q(r_1), 1]$, and $c_L(\phi_1, 0)$ is increasing in ϕ_1. It follows that a unique equilibrium exists. By construction, for $r_1 > \hat{r}$, $c_L(\phi_1, \phi_0) = \bar{c}$. All that remains is to show that $c_L(\phi_1, \phi_0)$ is increasing over $[\bar{r}, \hat{r}]$.

The equilibrium defines thresholds as functions of $q(r_1)$:

$$E(\pi \mid \theta_L, d = 1, \phi_1, 0) - c_L^* = 0,$$

$$\frac{q(r_1)}{q(r_1) + H(c_L^*)(1 - q(r_1))} - \phi_1^* = 0,$$

where the asterisks indicate equilibrium quantities. From the implicit function theorem, we have

$$\begin{bmatrix} \dfrac{\partial c_L^*}{\partial q(r_1)} \\[2mm] \dfrac{\partial \phi_1}{\partial q(r_1)} \end{bmatrix} = \left[\frac{1}{1 + \dfrac{q(r_1)(1-q(r_1))}{(q(r_1)+H(c_L^*)(1-q(r_1)))^2} \dfrac{\partial H(c_L^*)}{\partial c_L^*} \dfrac{\partial E(\pi \mid \theta_L, d=1, \phi_1, 0)}{\partial \phi_1^*}} \right] \cdot \begin{bmatrix} \dfrac{\partial E(\pi \mid \theta_L, d = 1, \phi_1, 0)}{\partial \phi_1^*} \dfrac{H(c_L^*)}{(q(r_1) + H(c_L^*)(1 - q(r_1)))^2} \\[2mm] \dfrac{H(c_L^*)}{(q(r_1) + H(c_L^*)(1 - q(r_1)))^2} \end{bmatrix}.$$

Because

$$\frac{\partial E(\pi \mid \theta_L, d = 1, \phi_1, 0)}{\partial \phi_1^*} > 0,$$

$$\frac{q(r_1)(1 - q(r_1))}{(q(r_1) + H(c_L^*)(1 - q(r_1)))^2} \frac{\partial H(c_L^*)}{\partial c_L^*} > 0, \quad \text{and}$$

$$\frac{H(c_L^*)}{(q(r_1) + H(c_L^*)(1 - q(r_1)))^2} > 0,$$

this implies that $\begin{bmatrix} \partial c_L^*/\partial q(r_1) \\ \partial \phi_1/\partial q(r_1) \end{bmatrix} > 0$. □

Lemma 4. *There exists an equilibrium with diversification such that the derivative $\partial c_k(\phi_1, \phi_1)/\partial r_1$, $k \in \{H, L\}$, is weakly positive everywhere and strictly positive over some range.*

Proof of Lemma 4. This proof is by construction. For $r_1 > \bar{r}$, take the equilibrium defined in Lemma 3. For $r_1 \in [\underline{r} \in \bar{r}]$, take the equilibrium shown in Lemma 2, where $\underline{r}$ is chosen such that the thresholds are nondecreasing. Finally, for $r_1 < \underline{r}$, take the no diversification equilibrium, i.e., where beliefs are such that $\phi_1 = 0$, $\phi_2 = q(r_1)$. Note that because the equilibrium identified in Lemma 3 has the highest thresholds for an equilibrium for the given r_1, by continuity, there must exist $\underline{r} < \bar{r}$. □

Proof of Result 1. (i) The cutpoints $\{c_k\}$ are weakly increasing in r_1, and c_j is independent of r_1. This implies that conditional on θ_k, the probability of diversification is increasing in r_1. Furthermore, by Lemma 1, we have that $c_H(\phi_1, \phi_2) \geq c_L(\phi_1, \phi_2)$. Using the fact that we have $\Pr(r_{1i} > r \mid \theta_H) > \Pr(r_{1i} > r \mid \theta_L)$, we have the result. Part (ii) follows directly from the fact that the cutpoints $\{c_k\}$ are weakly increasing in r_1. Part (iii) follows directly from Lemma 1 in that $c_H(\phi_1, \phi_2) \geq c_L(\phi_1, \phi_2)$, and strictly so for returns where we have nondiversifiers. □

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