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Skill and Luck in Hedge Fund "Diversification"

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ABSTRACT

We propose that when existing firms must raise capital to fund a new venture ("diversify"), they are more likely to diversify when they are both lucky and skillful. Firms consider diversifying when they experience extraordinarily strong performance because investors are more willing to invest in a firm's new venture when the firm has performed well historically. However, when returns on new investments reveal information about firm ability, lucky but low-ability firms are less likely to diversify compared to lucky and skillful firms. We test the theory by observing the revealed behavior and performance of profit maximizing firms using a large panel dataset on the global hedge fund industry. Our findings show that firms are more likely to diversify when they experience positive risk-adjusted excess returns, yet legacy funds' returns fall significantly following diversification. We interpret the unconditional decline in returns following diversification as evidence that firms time the launch of new funds around peak historical returns. However, legacy fund returns in diversified firms fall less than do returns in a control sample of firms that are matched based on past performance and all other observable characteristics. Furthermore, new funds in diversified firms generate positive excess returns and overall returns are higher for diversified firms than in focused firms. We interpret positive conditional performance of diversified firms as revelatory evidence that firms with greater skill diversify while those with less skill choose to remain focused.

Why do firms diversify? Agency cost theorists emphasize the role of private managerial incentives (Jensen and Meckling 1974), while strategists are more likely to invoke synergies that arise from firm-specific ability (Teece 1980). Although these theories are often considered separately, together they capture the tension at the heart of diversification decisions – investors want managers to take advantage of unique firm capabilities, but they are wary of managers' private incentives. This paper takes a step toward integrating agency theory and firm-specific ability in the context of diversification by proposing and testing a model that takes both perspectives seriously. Our theoretical construct builds on the first order prediction of agency theory – firms will diversify when managers benefit from doing so – while accounting for the existence of heterogeneous firm capabilities, which implies that more capable firms are more likely to diversify.

The model makes sharp predictions about the patterns of firm performance following diversification when firms must raise capital to fund a new venture that we test using a large panel dataset on the global hedge fund industry. As in Campa and Kedia (2002) and Villalonga (2004) we control for firm heterogeneity by matching diversified firms to

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focused firms on their *ex ante* characteristics. Our key empirical contribution is to use the information embedded in the pattern of returns *ex post* to shed some light on the causes of diversification.

We find that firms diversify when they experience positive risk-adjusted excess returns that do not persist after diversification, suggesting that managers time their diversification moves around peak performance. We interpret the unconditional decline in excess returns following diversification as evidence that firms diversify when they are lucky. However, legacy fund returns in diversified firms fall less than do returns in a control sample of firms that are matched based on past performance and all other observable characteristics. Meanwhile, new funds in diversified firms generate positive excess returns and overall value-weighted returns are higher for diversified firms than in focused firms. Consistent with heterogeneous firm ability, we interpret the superior performance of diversified firms *ex post* compared to the matched set of focused firms as a selection effect – firms choose to diversify when they are better at identifying new opportunities. Taken together the results paint a picture of diversification as a process where managers exploit private information for private reasons, yet market forces constrain their choice set to include strategies that also benefit shareholders.

We analyze the context where a firm must raise new capital to fund a diversification effort and consider the role of skill and luck on the decision to diversify. Our baseline assumption is that diversification increases managers' short-run payoffs, but may not increase their long-run payoffs or overall firm value. Thus, the decision to diversify is only contingent on the manager's ability to convince shareholders to contribute capital to the new venture and on the potential for long-term repercussions from launching a fund that performs poorly. We further assume shareholders' expected returns are a function of perceived managerial investment ability, a perception that is updated each period. Managers' payoffs are a function of investment ability and cost management ability, which are determined exogenously from a common distribution, and a random time-specific shock that influences returns on investments. Managers are perfectly informed about their own quality – past, present and future – but investors only observe historical firm performance as a noisy but informative signal of managerial investment ability. Under these conditions, our first hypothesis predicts that firms will be more likely to diversify when they experience positive past performance, since this facilitates new investment from investors.

> (H1) When firms require new capital to fund their diversification strategy, they will tend to diversify when they experience positive short-term performance

The first hypothesis predicts that shareholders will be more likely to contribute capital to a new venture when a manager's past performance has been good, which directly implies that firm performance will tend to exhibit unconditional mean-reversion following diversification.

> (H2) When firms require new capital to fund their diversification strategy, legacy business unit performance will fall following diversification

When firms diversify when they experience positive short-term performance that is unlikely to persist we say firms diversify when they are lucky. Note that firms can be both lucky and good, as we shall argue below, and investor willingness to invest when firms are lucky is not based on investor mistakes. Mean reversion in the firm's legacy business unit may be fully anticipated by investors since they are assumed to care only about levels of risk-adjusted expected returns, not changes in returns.

The foregoing assumed managers will always want to diversify when they experience positive historical returns, however, if returns from the firm's new fund generate a second observable signal of managerial quality, managers will not always wish to diversify since lower quality managers will be wary of sending a bad signal to the market as investors may withdraw their funds from the firm's legacy business unit.[1] Under these conditions, the model predicts that firms with the greatest ability to exploit new opportunities will diversify and firms with the lower investment ability to exploit new opportunities will remain focused.

> (H3) When firms require new capital to fund their diversification strategy firms with greater skill will diversify.

The testable implication of this prediction given H1 and H2 is that diversified firm performance will fall less following diversification than at comparable firms, which remain focused. We refer to firms with higher risk-adjusted returns as having greater skill than other firms. Thus, our central prediction is that firms that are both lucky and skillful are more likely to diversify. Our tests of this prediction revolve around within-firm changes in legacy business unit performance in diversified firms and within-firm changes in overall firm performance in diversified firms relative to within-firm changes in performance in a matched control group of firms that do not diversify.

I. Data and Variables

A. Institutional Background

Hedge funds are investment vehicles that, like mutual funds, pool capital contributed by investors for the purpose of investing in securities and other investment assets. Some aspects of the hedge fund industry are regulated by the Securities Exchange Commission (SEC), but unlike mutual funds, hedge funds are legally permitted to short sell, use high leverage ratios and can compensate their managers using non-linear performance-based measures. In order to be exempt from the stricter investment and compensation restrictions that mutual funds face, hedge funds must be open only to qualified investors.

The hedge fund industry is a good place to examine luck and skill effects in diversification as the properties of the data are well suited to measuring the intertemporal relationship between diversification and fund performance. The industry is composed of

[1] Our approach is similar to Cabral (2000) who shows how new product launches using an existing brand name risks the brand equity of existing products.

more than 10,000 firms, of which approximately 60% are diversified, affording the econometrician a large sample to work with. Moreover, fund performance is easy to measure as many firms in the industry self-report fund-level returns monthly to private companies that monitor the industry. Although monthly returns to industry groups are self-reported, annual returns reported to investors are audited and strong anecdotal evidence suggests that investors carefully compare annual returns to self-reported monthly returns. Thus, firms have limited ability to manipulate reported earnings to industry associations.

B. Data and Sample

Hedge funds are closed to the general public and are not required to publicly report their returns. However, a large number of funds do report their returns to one or more private companies that make their data available by subscription to researchers. Our data on hedge funds are obtained from Lipper TASS and Hedge Fund Research (HFR). Among all the datasets used in the hedge fund literature TASS and HFR are considered the most comprehensive (Li, Zhang and Zhao, 2007). 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.

Our analysis focuses on 2,175 firms that enter as focused firms (see Figure 1). We exclude funds from firms that enter as diversified firms, which we define becoming diversified within the first twelve months of entering the industry, as these firms have limited *ex ante* characteristics to match to potential control funds. For similar reasons we confine our analysis to firms' first diversification event as we match firms exactly on their *ex ante* diversification status in our econometric specification. After excluding 43 funds from firms that enter as focused firms either because they reported less than twelve months of returns or did not report returns continuously our baseline test sample contains 156,762 fund-months from 2,132 firms. The baseline test sample also excludes the first month of returns from all funds to reduce backfill bias (Posthuma and Jelle van der Sluis, 2003).

B. Excess Returns

Our dependent variable is risk-adjusted excess return – a measure of fund returns adjusted for the riskiness of the fund's underlying investments relative to a market benchmark. We follow the standard approach for measuring fund-level excess returns using the Fama-French three-factor model (1996), computing excess returns as the residual *e* from the regression:

$$(1)\ R_{it} = a_i + R_{ft} + B_{1i}(R_{mt} - R_{ft}) + B_{2i}(HML_t - R_{ft}) + B_{3i}(SMB_t - R_{ft}) + e_{it},$$

where i and t index funds and time (in months) respectively; R_i is a fund's own return, R_f is the risk-free rate, R_m is the market equity return, HML is the return on value relative to growth stocks, SMB is the return on small stocks relative to big stocks, and *e* is the residual. We take the factors HML, SMB, R_f, and R_m from Ken French's data library,[2] R_i from TASS and HFR, and compute B_1, B_2, B_3 and *e* by running 3,137 fund-level regressions. We then compute $\hat{e}$ by adjusting excess returns *e* for serial correlation that may arise due to self-reporting using an AR1 correction and winsorize the overall distribution of returns at the 1% level to control for outliers. Finally, we construct equal weighted average category-level ("strategy") returns $\dot{e}_{-ijt}$ for all other (e.g., excluding *i*) *n-1* funds in category *j* for each period *t* based on self-reported investment strategy categories (e.g., long/short fund, global macro fund, etc.) using (2).

$$(2)\ \dot{e}_{-ijt} = \Sigma\, \hat{e}_{-i}/(\text{n-1})$$

We then subtract category-level excess returns $\dot{e}_{-ijt}$ from fund-level excess returns $\hat{e}_{it}$ to compute a measure of excess returns adjusted for overall category performance, as shown in (3).

$$(3)\ Y_{it} = \hat{e}_{it} - \dot{e}_{-ijt}$$

For simplicity we call the resulting measure *Y* "excess returns" for the remainder of the paper. We use excess returns *Y* as our key dependent variable in our OLS regressions and also use excess returns to compute average cumulative abnormal returns (CAR), where $CAR = \Sigma\, Y_{it}$, a standard measure of a fund's cumulative historical performance, in our probit model predicting diversification. We use average 24-month *CAR* as our key performance variable predicting diversification 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. We use average CAR to account for the fact that some funds diversify before their twenty fourth month (our sample criteria requires that they are focused for at least one year). Our results are not sensitive to the number of months used in the average *CAR* calculation.

Table 1a shows descriptive statistics for excess returns and for our right hand side variables: assets under management for the fund and firm, firm age, self-reported strategy, period, and region, which are also drawn from TASS and HFR, for the 156,762 fund-months in our baseline test sample.

On average the funds in our baseline sample generated a negative five basis point monthly risk-adjusted return relative to all other hedge funds in the full TASS and HFR database with a standard deviation of 4% per month. All of the funds in our sample are the first fund launched by a firm, but 37% of fund-months in our baseline sample came from funds in firms that were diversified in the month the fund reported its returns. On average the funds in our sample were in firms with 2.18 funds, reflecting the fact that some firms in our sample diversified extensively after entering the hedge fund industry with a single fund, with one firm managing 114 funds simultaneously.

C. Controls

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

The average fund had $174 million of assets under management (AUM), while the average firm held $318 million of AUM. The size distribution of AUM is skewed right with the largest fund growing to $233 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, although our results are unchanged when we use log(AUM). 14% of fund-months had missing AUM, which we control for using a missing AUM dummy variable.

The average observation in the baseline sample was five years old. We begin tracking firms after their first month of reported returns to control for back-fill bias, which we found to be pronounced in firms' first reported monthly return. Thus, the youngest fund in our analysis is two months old. We experimented with later cutoffs to control for back-fill bias and found that alternative cut-offs did not change our results.

18% of funds reported that they were fund-of-funds that invest in other hedge funds. 23% were long/short funds – a general type of hedge fund that often has no meaningful restrictions on investment strategy. The other 59% of funds were distributed over 32 additional investment strategy categories with the largest being managed futures (12%), equity hedge (8%), and event driven (8%) strategies. No other strategy category had more than 5% of fund-months in part because many strategies emerged in the late 1990s and so reported relatively few fund months compared to more traditional hedge funds like long/short funds.

The growth of the hedge fund industry is also reflected in the time weighting of returns, as 49% of reported fund-month returns in our baseline sample came in the last five years of the data set. We only report calendar year averages, but we use periodicity in three ways in our analysis: calendar year controls for timing effects in the propensity to diversify, calendar months controls for time series variation in market returns in our computation of fund excess returns, and event time, the number of months before or after the month in which a firm first diversifies, controls for the time path of returns before and after diversification (or match date) in our statistical tests.

The hedge fund industry is dominated by U.S. domiciled funds and our data reflects this with 70% of fund-months coming from U.S.-based funds. 15% of fund-months come from European firms (7% U.K. and 8% from mainland Europe), 2% from Asia-based firms and 13% from the rest of the world.

II. Empirical specification and results

A. Raw Excess Returns and Diversification

In the statistical tests below we control for fund and firm characteristics shown in Table 1, but our key results are evident in simple time-series plots of excess returns. Figure 2 shows one fundamental relationship between diversification and fund performance graphically, plotting average excess returns for all 963 first ("legacy") funds from focused firms that subsequently diversify. The figure shows five years of monthly returns before and after the diversification event. Note that not all funds are represented in every month since many funds diversified before their fifth year, and others' experience is right censored as they diversified after 2001. A small number of funds' experience is right censored because they exited after diversifying.

Figure 2 shows a large drop in average excess returns for legacy funds in firms that subsequently diversified. However, the figure also raises questions about the selection process firms undergo when choosing to diversify, as it is clear that excess returns are large and trending upward prior to diversification, suggesting that higher excess returns may cause firms to diversify.[3] Most importantly, the returns in Figure 2 are not benchmarked against a control group. To address each of these concerns we turn to our empirical specification.

B. The Propensity to Diversify

Our main objective is to understand how skill and luck influence the decision to diversify. To do so we use both *ex ante* and *ex post* information embedded in returns and other observable characteristics of firms and funds. Our baseline approach follows the standard event study methodology developed by Fama, Fisher, Jensen and Roll (1969) to measure of the relationship between diversification and fund returns, and follow Campa and Kedia (2002) and Villalonga (2004) in using propensity score matching to develop a valid control group of focused firms against which to measure diversified firm performance *ex post*. Our key methodological contribution is to use *ex post* information to make inferences about unobservable firm characteristics *ex ante*.

We estimate a probit model to test our first hypothesis, that diversifiers are more likely to be strong performers when they must tap the capital markets for funds to diversify, and to use observable *ex ante* firm and market factors that influence firms' decisions to diversify for the first time to create a valid control group, as in (4):

$$(4)\ \mathrm{DIV}_{it}^{*} = \mathbf{x}_{\mathbf{it}}\boldsymbol{\beta} + \xi_{it},$$

where the unit of observation is the fund-month for fund *i* in month *t*. We estimate the latent variable DIV* using DIV = 1 [DIV*>0] when the firm diversifies; **x** includes all observable characteristics of firms that might plausibly have an effect on the diversification decision including two-year average monthly cumulative abnormal returns (CAR) and two-year average CAR squared, a vector of firm size deciles measured by assets under management (including a dummy variable for missing values of assets under management), firm age and age squared, an interaction between two-year average CAR and firm age, 21 time (year) dummies, 30 fund investment strategy dummies, five geographic location dummies, and ξ - an error term, which is assumed to be normally distributed with mean zero and variance one in a probit specification.

[3] A change in the variability of returns before and after diversification is also evident in Figure 2, raising the possibility that diversified firms may be trading off lower average returns for lower variability in returns after diversification.

Our objective is to estimate the factors influencing the firm's decision to diversify for the first time so we drop diversified firms from (4) in the month following the month in which they diversify, while all fund months are included for firms that remain focused. This leaves us with 97,713 fund months from 2,045 firms.

We show the result of estimate of (4) using all 2,045 firms and 97,713 fund months in Table 2 columns 1-2. Column 1 shows the raw coefficients and standard errors from the probit estimation and reveals that the model predicts 2.8% of the variation in diversification, which is a good fit considering the incident of diversification is 0.8% (826/97,713). Column 2 shows the more easily interpretable marginal effects of each explanatory variable as the partial derivative at the average value of each regressor. From column 2 we can see that average 24-month cumulative abnormal return (CAR), firm age and size have a statistically significant impact on the firm's propensity to diversify. In terms of economic significance, average 24-month CAR has the largest effect, with a 10% increase in average 24-month CAR increasing the propensity to diversity by 1%, while a 10% increase in firm age reduces firms' propensity to diversify by only 0.1%. With the exception of the largest focused firms, firms with larger first funds one month before the diversification date were more likely to diversify. Firms in the smallest two size declies are 0.5% less likely to diversify (combined) than firms in the largest decile, while firms in the 7th and 8th largest decline were each 0.4% more likely to diversify, although the statistical significance of the 7th and 8th size decile is marginal. None of the year or strategy dummies were statistically significant (detailed results omitted) and only the "other" region fixed effect was statistically significant relative to U.S. domiciled firms, reducing the propensity to diversity by 0.2% (detailed results omitted).

The probit model produces evidence consistent with our first hypothesis, and importantly generates an overall propensity to diversify score for each fund-month, which facilitates the creation of a matched control group that we use to understand the implication of information about luck and skill embedded in *ex post* returns. Our propensity score matching approach builds on Rosenbaum and Rubin (1983), who show that matching on propensity scores using all relevant observable characteristics allows the econometrician to make casual inferences from comparing treatment and control groups in the absence of unobservable characteristics that are correlated with both assignment to experimental groups and outcomes.

Columns 3-4 in Table 2 show the mean values for each regressor by diversification status, while column 5 shows a t-test on the differences in means between these two values. Inspection of columns 3-5 immediately reveals why propensity score matching is so important in this context as all of the statistically significant factors predicting diversification are systematically different between the 826 fund-months where firms diversify and the 96,887 months in which focused firms remain focused even though the latter group includes these 826 funds just one month earlier. Indeed, the comparison between these two groups immediately gives rise to fundamental questions about what an appropriate control group is for a diversifying fund.

We find and exploit a valid control using standard propensity score matching techniques. First, as in Rosenbaum and Rubin (1983), we calculate the propensity score of the probability of a fund selecting the binary treatment diversificaiton in any particular month, using the probit model (4). Next, we trim the sample to include only firms on the common support of the propensity score of the probability of diversifying and match treatments to controls using nearest neighbor matching without replacement to create a balanced sample of 798 treated (diversified) and control fund-month observations. The interpretation 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 diversify. Columns 6-8 in Table 2 replicate columns 3-5 for only the matched and trimmed sub-sample of 798 fund-months for diversifiers and the 798 most similar fund-months from the set of controls. After matching and trimming, the only repressor that has a statistically significant impact on a firm's propensity to diversify is firm age – all historical return characteristics embedded in average 24-month cumulative abnormal return and all size characteristics are statistically indistinguishable.

The 1,596 unique funds identified in our propensity score matching algorithm represent the fund-months around which we shall construct our event study. We call the period in which these funds diversified or were matched "the event" and refer to the months around the event in terms of event time, with the event taking place at event time zero. To construct our matched test sample we include the twenty-four months before (-24, -23, -22, . . ., -1) and fifty-nine months after the event (1, 2, 3. . ., 59). Altering the window around the event had no qualitative effect on our results, although the results were generally more precise the wider the window. Table 1b shows descriptive statistics for the matched test sample of firms. Fund-level summary statistics in Table 1b are quite similar to those in Table 1a, but firm-level summary statistics vary somewhat as we restrict the sample to months that are near in time to the event leaving less time for firms that experienced events before 2001. In particular, in the matched test sample firms are fourteen months younger, have $97 million less assets under management and have a maximum of 23 total funds (versus 114 in the unmatched sample).

C. Diversification and Ex Post Returns

After developing a valid control group, we next estimated the relationship between diversification and changes in fund and firm returns versus all matched focused firms using the OLS model (5):

$$(5)\ Y_{it} = \alpha + \lambda_i + DIV_{it} + T_t + \mathbf{X_c B}_c + \varepsilon_{it},$$

where i and t index funds and time (in months) respectively; is our calculation of excess returns from (3) above; λ is a fund or firm fixed effect, depending on the specification; DIV 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 event time (month) dummies from twenty-four months before diversification (or match date for the control group) to sixty months after diversification (or match date for the control group); and $\mathbf{X_c}$ is a vector of controls including the age of the firm (in months) and a vector of size fund or firm dummies measured by assets under management; and ε is the residual. Funds and firms are weighted in (5) by the inverse probability of diversifying at the event date to eliminate treatment on the treated bias (Imbens, 2004).

For comparison purposes we also estimate this relationship using the unmatched control group of focused firms. When the control group is not matched calendar time dummies are extraneous because the effect of calendar month on returns is already accounted for in the calculation of excess returns Y in equations (1) and (3). Once the control group is properly matched we use event time (month) dummies. Since the effect of calendar month on returns is already accounted for in (1) and calendar year effects of selection on diversification are accounted for in (4), only the effects of event time are left to be explained in (5).

By including firm and time fixed effects in our OLS specification (5) we absorb all time-invariant firm-specific characteristics and all time-varying market characteristics that may influence the returns to diversification, thus our main econometric concerns with the causal impact of diversification on *ex post* returns are related to heterogeneous time-varying firm-specific characteristics. By matching we control for observable time-varying firm-specific differences, but do not control for unobservable time-varying firm-specific heterogeneity.

Table 3 shows the relationship between diversification and changes in excess returns generated by the first fund a firm launched for both the unmatched (column 1) and matched test samples (column 2). Compared to the unmatched control group legacy fund excess returns fell by almost 19 basis points per month after diversification. However, once legacy funds that diversified are matched to a valid control group their *ex post* diversification excess returns are almost 18 basis points higher than the control group. We interpret these results, in combination with the probit results, as evidence that firms with strong *ex ante* excess returns tend to diversify and then experience mean reversion following diversification. In this sense firms appear to diversify when they are lucky. However, diversified firms' legacy funds outperform a control group of firms with similarly strong *ex ante* excess returns who did not diversify, suggesting that diversified firms either had greater unobservable skill in terms of identifying new opportunities *ex ante* or created value through synergy. However, the synergy story is less credible in the presence of falling excess returns for the treatment (diversified) group. Indeed, it is only because the control group experiences even stronger mean reversion than the treatment group that the correlation between diversification and excess returns is positive. We therefore find that the evidence favors the selection on skill explanation.

Table 4 shows the results of firm-level OLS regressions of diversification on excess returns. Whereas the differences-in-difference estimate of the correlation between diversification and value weighted firm excess returns is essentially zero when comparing diversifiers to unmatched controls (column 1), the change in value weighted diversified firm excess returns is nearly 33 basis points per month compared to changes in the control group's excess returns *ex post*. The evidence suggests that diversified firms outperform focused firms that are similar along all observable dimensions. The fact that the coefficient estimate on diversification is larger in the firm-level regressions compared to the legacy fund regressions provides some scope for an interpretation that diversification creates value through synergies. However, this explanation cannot explain why some firms fail to diversify. We find it more plausible that firms with higher levels of unobservable skill, as evidenced by the legacy fund regressions, are also better at identifying and, in particular, exploiting new opportunities using existing corporate resources like managerial talent, process and information technology systems. Thus, overall value weighted firm excess returns increase following diversification precisely because the firm has greater ability to recognize new opportunities and to create synergies by operating multiple funds within a single corporate structure.

D. Robustness Checks

We interpret both the coefficient on diversification and unobservable time-varying firm-specific differences broadly as skill effects, but we cannot definitively disentangle the selection effects of skill, that induce firms to diversify because they are more skilled at identifying and/or exploiting new opportunities, from causal effects of skill on *ex post* returns. Clearly, in the absence of unobservable time-varying firm-specific heterogeneity the relationship between diversification and returns would be a causal effect. However, this interpretation is problematic in equilibrium since all firms should diversify if diversification caused returns to increase. A more subtle causal interpretation might ascribe skill effects to dynamic capabilities, where the causal effect of skill is contingent on the arrival of new opportunities that were previously unforeseen, which simultaneously create opportunities for the firm to diversify and cause the firm's future returns to increase. We admit that it would be interesting to distinguish between causal effects and selection effect, but as the mechanisms behind the dynamic capability interpretation are nearly synonymous with our selection interpretation we cannot completely rule out the causal story.

We can rule out other leading alternative explanations that have testable implications contrary to our predictions. To see how alternative explanations may manifest themselves we model how skill effects are captured in our econometric specification using (6), where γ_{it} represents time-varying firm-specific characteristics that may are correlated with DIV and η_{it} are time-varying firm-specific characteristics that are uncorrelated with DIV.

$$(6)\ Y_{it} = \alpha + \lambda_i + DIV_{it} + T_t + \mathbf{X_c B_c} + \gamma_{it} + \eta_{it},$$

We argue that the coefficient on DIV should be positive because firms choose to diversify when they posses greater skill in identifying new opportunities. However, we may be concerned that there are other firm-specific time-varying factors γ_{it} that may be correlated with DIV and returns. Therefore, a concern with our approach is with the interpretation of γ_{it} as a skill parameter. If γ_{it} is a skill parameter we are not concerned that it may be correlated with DIV since omitting γ_{it} biases our estimate of DIV toward zero, but if γ_{it} represents another time-varying firm-specific factor that is correlated with both DIV and returns, then it would bias the coefficient estimate on DIV upward.

To influence the interpretation of our results the effects we are concerned with would have to influence both the propensity to diversify and future returns in the same direction (e.g., would have to increase or decrease both) without being related to skill, time-invariant firm characteristics, time-varying market characteristics or observable differences between firms (both time-varying and static). For example, one could be concerned that all firms plan to diversify whenever they are lucky, but as the time to launch a new fund takes 18-24 months, only firms that receive positive productivity shocks close to the diversification date actually diversify. If the positive productivity shock is unrelated to the skill of the firm, for example if highly skilled managers sort into lucky firms randomly, then the interpretation that diversification signals better quality will be conflated with the "correct" interpretation that lucky firms diversify.

We believe it is unlikely that productivity shocks unrelated to skill close to the diversification date are driving our results, but nevertheless address the concern in two ways. First, we discussed with hedge fund managers about how frequently firms planned to launch a new fund only to scuttle the plan close to the launch date because of time-varying firm-specific factors. Second, we used an alternative specification of our matching model that replace CAR with lagged monthly abnormal returns so that the specific time-path of historical returns were explicitly weighted in our selection equation.

III. Conclusion

Understanding the relationship between diversification and firm performance is of great importance to scholars and practitioners alike. While academic research on diversification has focused on how diversification influences performance, less attention has been given to the factors that cause firms to diversify. This paper attempts to make some headway toward understanding the causes of diversification. We propose that both skill and luck play a role in the decision to diversify and test our propositions in the context of the global hedge fund industry. The paper shows that firms diversify when they experience extraordinary short-term positive returns that do not persist, suggesting that firms tend to diversify when they are lucky. However, comparing firms that experience similar *ex ante* short-term performance reveals that diversifiers outperform firms that remain focused *ex post*, which we interpret as evidence that diversifiers are more skilled than non-diversifiers.

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Figure 1 Number of firms by entry and diversification status

	Enter	Subsequently	
Focused	2,175	Stay focused	1,212
		Diversify	963
Diversified	962	Stay diversified	859
		Switch to focused	103

Figure 2 Time Path of Diversified Firm's First Fund's Excess Returns

This figure shows average excess returns for diversified firms' first funds on the vertical axis versus event-time on the horizontal axis. Event time is measured in months around the event (e.g., diversification) at time 61. The chart shows the time path of returns from five-years before diversification (time 1 to time 60) to five years after diversification (time 61 to time 121). n=963 firms over ~75,000 fund-months. Due to entry and exit not all funds are represented at teach time period.

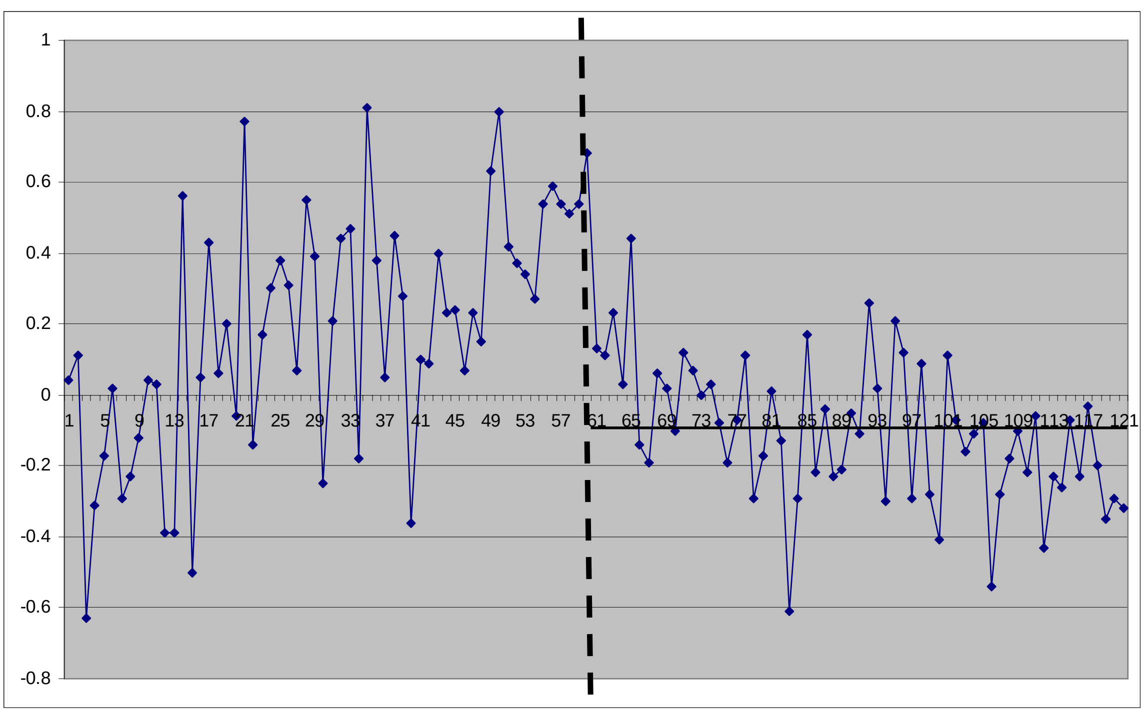


Figure 3 Legacy funds versus matched set of focused funds (n=1,596)

This figure shows average excess returns on the vertical axis versus event-time on the horizontal axis for legacy funds in firms that diversified (treatment group in blue) versus funds in firms that did not diversify (control group in red). Event time is measured in months around the event (e.g., diversification) at time 0 for the treatment group. The control group was matched to the treatment group based on the *ex ante* characteristics of the treatment group at time 0. (Table 2 shows the results of the matching algorithm). Returns from the matched control group were then cast forward and backward to create comparable event time for the control group. The chart shows the time path of returns from two-years before diversification, or match, (time -20 to time 0) to five years after diversification, or match, (time 0 to time 60). n=1,596 firms over, 798 firms that diversified and 798 firms that did not diversify, representing ~88,000 fund-months. Due to entry and exit not all funds are represented at teach time period. Table 3 shows the regression results, with controls, that correspond to this figure.

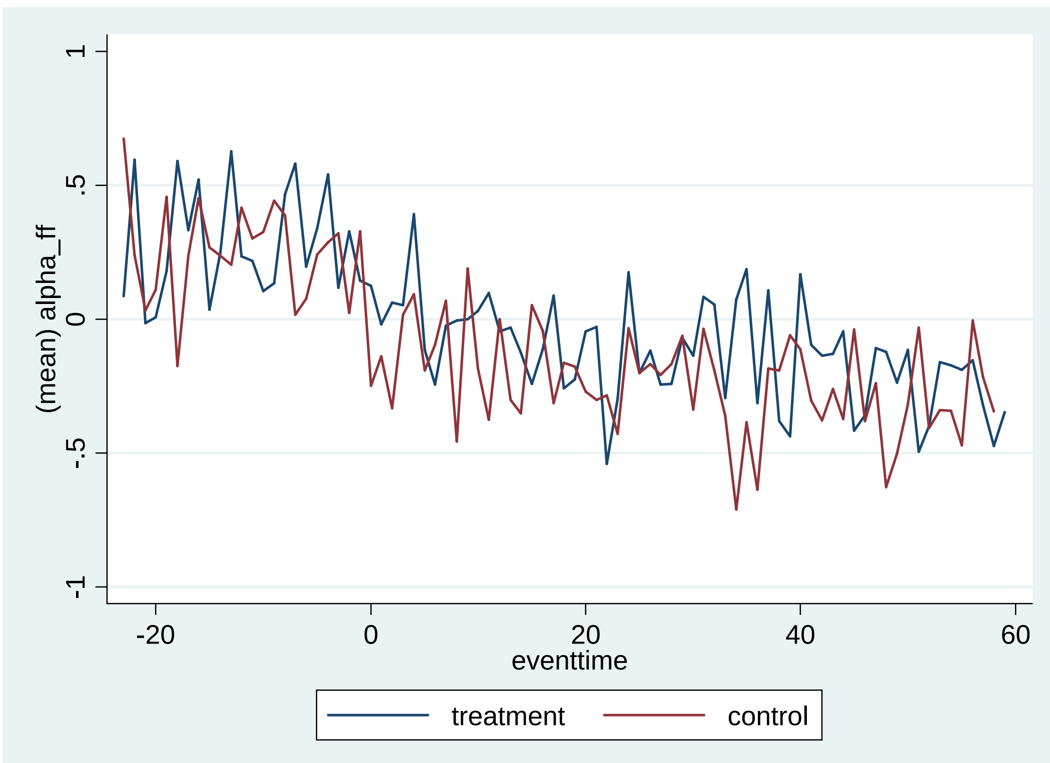
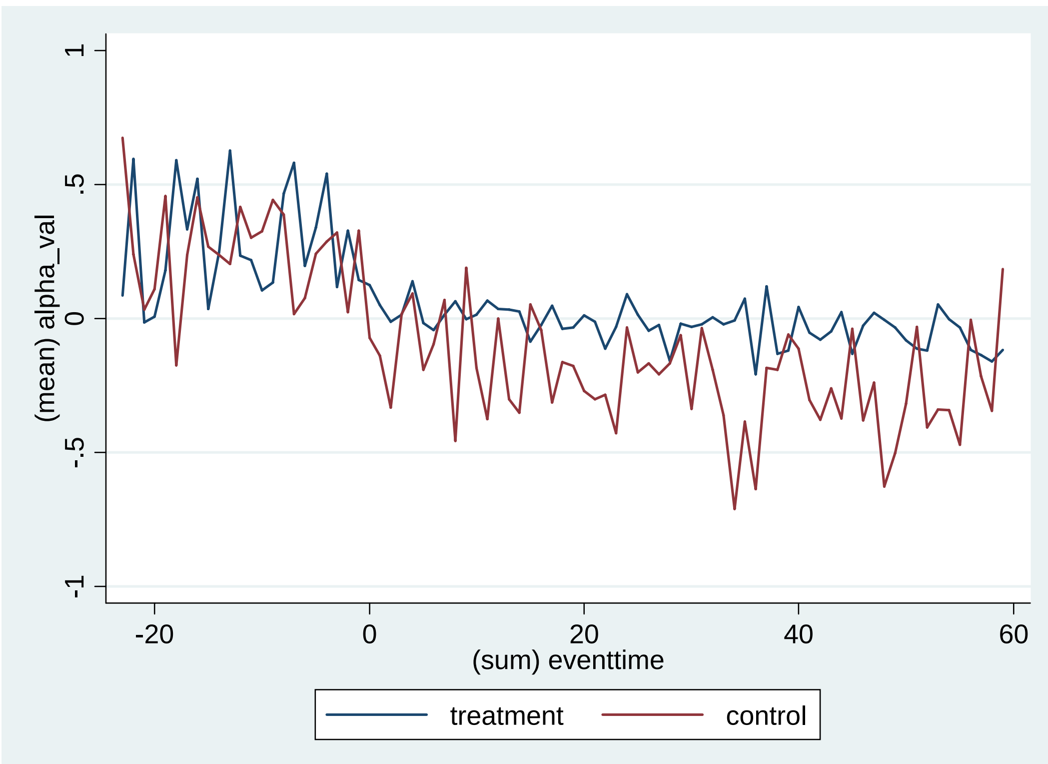


Figure 4 Diversified firms versus matched set of focused funds (n=1,596)

This figure shows average excess returns on the vertical axis versus event-time on the horizontal axis firms that diversified (treatment group in blue) versus firms that did not diversify (control group in red). Event time is measured in months around the event (e.g., diversification) at time 0 for the treatment group. The control group was matched to the treatment group based on the *ex ante* characteristics of the treatment group at time 0. (Table 2 shows the results of the matching algorithm). Returns from the matched control group were then cast forward and backward to create comparable event time for the control group. The chart shows the time path of returns from two-years before diversification, or match, (time -20 to time 0) to five years after diversification, or match, (time 0 to time 60). n=1,596 firms over, 798 firms that diversified and 798 firms that did not diversify, representing ~88,000 fund-months. Due to entry and exit not all funds are represented at teach time period. The pattern of returns from the control group is identical to Figure 3 as is the *ex ante* returns for the treatment group. Only *ex post* returns for the treatment group differ in this figure compared to Figure 3. Table 4 shows the regression results, with controls, that correspond to this figure.



Preliminary and Incomplete

Table 1a Descriptive statistics – Full Sample

N=156,762 fund months	Mean	Std dev	Min	Max
Monthly excess returns	-0.05	4.08	-11.69	12.75
Total funds in firm (count)	2.18	3.66	1	114
Fund assets under management ($M)	174	1,790	0.001	223,000
Firm assets under management ($M)	318	2,360	0.001	223,000
Fraction missing AUM	0.14	0.35	0	1
Fraction diversified	0.37	0.48	0	1
Age (in months)	61	52	2	356
Strategy 1: Fund of funds	0.18	0.38	0	1
Strategy 2: Long/short fund	0.23	0.42	0	1
Strategy 3: Equity hedge	0.08	0.27	0	1
Strategy 4: Managed futures	0.12	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	0.04	0.21	0	1
Strategy 8: Global macro	0.03	0.18	0	1
Strategy 9: Convertible arbitrage	0.02	0.14	0	1
Strategy 10: Fixed income arbitrage	0.02	0.15	0	1
All other strategies	0.15		0	1
Year 1- 10 (1977-1986)	0.01		0	1
Year 11: 1987	0.01	0.07	0	1
Year 12: 1988	0.01	0.08	0	1
Year 13: 1989	0.01	0.09	0	1
Year 14: 1990	0.01	0.11	0	1
Year 15: 1991	0.02	0.13	0	1
Year 16: 1992	0.02	0.15	0	1
Year 17: 1993	0.03	0.17	0	1
Year 18: 1994	0.04	0.19	0	1
Year 19: 1995	0.05	0.21	0	1
Year 20: 1996	0.05	0.22	0	1
Year 21: 1997	0.06	0.23	0	1
Year 22: 1998	0.06	0.24	0	1
Year 23: 1999	0.07	0.26	0	1
Year 24: 2000	0.07	0.26	0	1
Year 25: 2001	0.08	0.27	0	1
Year 26: 2002	0.08	0.27	0	1
Year 27: 2003	0.08	0.28	0	1
Year 28: 2004	0.09	0.28	0	1
Year 29: 2005	0.09	0.29	0	1
Year 30: 2006	0.07	0.25	0	1
USA	0.70	0.46	0	1
U.K.	0.07	0.26	0	1
Mainland Europe	0.08	0.26	0	1
Asia	0.02	0.15	0	1
All others	0.13	0.34	0	1

Table 1b Descriptive statistics – Matched Sample

N=88,912 fund months	Mean	Std dev	Min	Max
Monthly excess returns	-0.03	4.00	-11.69	12.75
Total funds in firm (count)	1.83	1.67	1	23
Fund assets under management ($M)	162	2,140	0.001	223,000
Firm assets under management ($M)	221	2,580	0.001	223,000
Fraction missing AUM	0.15	0.36	0	1
Fraction diversified	0.39	0.49	0	1
Age (in months)	47	33	2	356
Strategy 1: Fund of funds	0.18	1.67	0	1
Strategy 2: Long/short fund	0.21	0.39	0	1
Strategy 3: Equity hedge	0.09	0.41	0	1
Strategy 4: Managed futures	0.11	0.29	0	1
Strategy 5: Equity market neutral	0.05	0.32	0	1
Strategy 6: Event driven	0.08	0.21	0	1
Strategy 7: Emerging markets	0.05	0.27	0	1
Strategy 8: Global macro	0.04	0.21	0	1
Strategy 9: Convertible arbitrage	0.02	0.19	0	1
Strategy 10: Fixed income arbitrage	0.03	0.15	0	1
All other strategies	0.14		0	1
Year 1- 10 (1977-1986)	0.01		0	1
Year 11: 1987	0.00	0.06	0	1
Year 12: 1988	0.00	0.07	0	1
Year 13: 1989	0.01	0.08	0	1
Year 14: 1990	0.01	0.09	0	1
Year 15: 1991	0.01	0.12	0	1
Year 16: 1992	0.02	0.14	0	1
Year 17: 1993	0.03	0.17	0	1
Year 18: 1994	0.04	0.19	0	1
Year 19: 1995	0.05	0.22	0	1
Year 20: 1996	0.06	0.23	0	1
Year 21: 1997	0.06	0.24	0	1
Year 22: 1998	0.07	0.25	0	1
Year 23: 1999	0.07	0.26	0	1
Year 24: 2000	0.08	0.27	0	1
Year 25: 2001	0.08	0.27	0	1
Year 26: 2002	0.08	0.27	0	1
Year 27: 2003	0.09	0.28	0	1
Year 28: 2004	0.09	0.29	0	1
Year 29: 2005	0.09	0.28	0	1
Year 30: 2006	0.06	0.23	0	1
USA	0.67	0.47	0	1
U.K.	0.08	0.27	0	1
Mainland Europe	0.08	0.27	0	1
Asia	0.03	0.16	0	1
All others	0.14	0.35	0	1

Table 2 Propensity Score

Dependent variable = diversify for the first time at time t, t = {0,1}

				Full Sample			Matched/Common Support		
	(1)	(2)		(3)	(4)	(5)	(6)	(7)	(8)
	Coef.	$\partial y/\partial \mathbf{u}$ at $\bar{\mathbf{u}}$		Focus.	Div.	t on Δ	Focus	Div.	t on Δ
Avg. 24-month CAR $_{t-1}$	0.049	0.001	***	0.142	0.377	-5.9	0.343	0.371	-0.5
	(0.018)	(0.000)		(0.004)	(0.041)		(0.042)	(0.040)	
Avg. 24-month CAR^2 $_{t-1}$	-0.004	-0.000		1.332	1.551	-1.3	1.406	1.514	-0.5
	(0.003)	(0.000)		(0.016)	(0.183)		(0.138)	(0.187)	
Size decile 1 $_{t-1}$	-0.200	-0.003	***	0.134	0.090	3.7	0.109	0.088	1.4
	(0.080)	(0.001)		(0.001)	(0.010)		(0.011)	(0.010)	
Size decile 2 $_{t-1}$	-0.139	-0.002	**	0.117	0.086	2.8	0.083	0.088	0.4
	(0.080)	(0.001)		(0.001)	(0.010)		(0.010)	(0.010)	
Size decile 3 $_{t-1}$	0.005	0.000		0.110	0.110	0.0	0.130	0.114	1.0
	(0.078)	(0.002)		(0.001)	(0.010)		(0.012)	(0.011)	
Size decile 4 $_{t-1}$	0.085	0.002		0.094	0.110	-1.6	0.114	0.107	0.5
	(0.078)	(0.002)		(0.001)	(0.011)		(0.011)	(0.011)	
Size decile 5 $_{t-1}$	0.050	0.001		0.088	0.090	-0.1	0.100	0.093	0.5
	(0.080)	(0.002)		(0.001)	(0.010)		(0.010)	(0.010)	
Size decile 6 $_{t-1}$	0.083	0.002		0.075	0.082	-0.8	0.094	0.085	0.6
	(0.081)	(0.002)		(0.001)	(0.010)		(0.010)	(0.010)	
Size decile 7 $_{t-1}$	0.169	0.004	*	0.063	0.082	-2.3	0.066	0.083	-1.2
	(0.081)	(0.002)		(0.001)	(0.010)		(0.009)	(0.010)	
Size decile 8 $_{t-1}$	0.179	0.004	*	0.054	0.067	-1.6	0.050	0.063	-1.1
	(0.084)	(0.002)		(0.001)	(0.009)		(0.008)	(0.009)	
Size decile 9 $_{t-1}$	0.138	0.003		0.050	0.057	-0.9	0.044	0.055	-1.0
	(0.086)	(0.002)		(0.001)	(0.008)		(0.007)	(0.008)	
Size decile 10 $_{t-1}$	excluded	excluded		0.053	0.038	1.9	0.035	0.035	0.0
				(0.001)	(0.007)		(0.007)	(0.007)	
Missing size $_{t-1}$	0.065	0.001		0.162	0.189	-2.1	0.174	0.190	-0.8
	(0.074)	(0.002)		(0.001)	(0.014)		(0.013)	(0.014)	
Age (months) $_{t-1}$	-0.005	-0.0001	***	47.055	33.370	9.1	27.4	33.1	-4.3
	(0.001)	(0.0000)		(0.139)	(1.064)		(0.84)	(1.06)	
Age^2 $_{t-1}$	0.000	0.000		4076.7	2047.4	7.2	1317.6	1986.7	4.1
	(0.000)	(0.000)		(26.0)	(140.9)		(87.2)	(137.0)	
(Avg. 24-month CAR x Age) $_{t-1}$	0.000	0.000		-1.363	5.613	-3.9	3.347	5.988	1.6
	(0.000)	(0.000)		(0.163)	(1.320)		(1.033)	(1.339)	
Constant	Y	n/a		n/a	n/a		n/a	n/a	
21 year f.e.	Y	Y		Y	Y		Y	Y	
30 strategy f.e.	Y	Y		Y	Y		Y	Y	
4 region f.e.	Y	Y		Y	Y		Y	Y	
Pseudo R^2		0.028							
N		97,713		96,887	826		798	798	

Table 3 First Fund Returns Following Diversification

Dependent Variable = Excess returns				
	(1)		(2)	
	OLS		P-score	
Diversified firm	-0.188	***	0.178	**
	(0.042)		(0.075)	
Firm age	-0.004	***	-0.012	***
	(0.000)		(0.003)	
Total funds In firm (count)	0.004		-0.004	
	(0.003)		(0.016)	
Constant	Y		Y	
Size fixed effects	11		11	
Period fixed effects	N		129	
Fund fixed effects	2,045		1,596	
N	156,762		88,531	
Within	0.004		0.008	
Between	0.001		0.013	
Overall R^2	0.002		0.003	

Standard errors clustered by fund
The unit of analysis is the fund-month. The firm's first month is excluded from the analysis.
Set (1) includes all first funds from all firms that entered as focused firms, reported returns continuously and reported at least 12 months of performance.
The matched set (2) includes 24 months of returns before and 60 months after a diversification event, or matched event, from all matched firms that entered as focused firms, reported returns continuously and reported at least 12 months of performance.

Table 4 Overall Firm Returns Following Diversification

Dependent Variable = Excess returns	(1) OLS		(2) P-score	
Diversified firm	-0.030		0.326	***
	(0.036)		(0.068)	
Firm Age	-0.003	***	-0.011	***
	(0.000)		(0.003)	
Total funds in firm (count)	0.014	***	0.029	***
	(0.004)		(0.009)	
Constant	Y		Y	
Size fixed effects	11		11	
Period fixed effects	N		129	
Firm fixed effects	2,045		1,596	
N	156,762		88,531	
Within R^2	0.003		0.009	
Between R^2	0.015		0.015	
Overall R^2	0.001		0.003	

Standard errors clustered by firm
The unit of analysis is the value weighted firm-month return. The fund's first month is excluded from the analysis.
Set (1) includes all first funds from all firms that entered as focused firms, reported returns continuously and reported at least 12 months of performance.
The matched set (2) includes 24 months of returns before and 60 months after a diversification event, or matched event, from all matched firms that entered as focused firms, reported returns continuously and reported at least 12 months of performance.