THE EFFECT OF PARENT FIRM LOCATION ON THE PERFORMANCE OF ENTREPRENEURIAL SPAWNS: EVIDENCE FROM HEDGE FUNDS*

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Abstract: We examine how parent firm location influences the performance of subsequent entrepreneurial spawns into the hedge fund industry. We find that hedge fund managers who previously worked for parent firms located in the industry hubs—New York and London—outperform their peers, regardless of where the hedge fund is located. These results are robust to controls for selection into job spells in New York/London based on all observable individual and parent firm characteristics. The evidence suggests that agglomeration effects influence entrepreneurial spawns' performance by increasing the value of individuals' human and social capital when they are still nascent entrepreneurs working for established firms.

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1. Introduction

Entrepreneurial spawning—the founding and managing of new external companies by employees of established ("parent") firms—is thought to be a key driver of entrepreneurial activity in the economy (Bhide 2000), and an emerging stream of literature has shed light on entrepreneurial spawning and its antecedents (Agarwal, Echambadi, Franco and Sarkar 2004; Gompers, Lerner and Scharfstein 2005). Yet relatively little is known about how parent firm attributes influence the financial performance of their spawns, perhaps because objective measures of spawn performance are often difficult to observe. This paper examines one parent firm attribute of particular interest: whether parent firm location in an industry's geographical hub positively influences subsequent spawns' performance. While there is a significant body of literature examining agglomeration effects and firm performance, including several studies examining the impact of agglomeration of entrepreneurial firms on the founding rates and performance of new firm located in these centers (Bell 2005; Saxenian 1994a, 1994b), little is known about how agglomeration effects pre-founding impact on the post-founding performance of new firms. However, it would seem important to the study of entrepreneurship to better understand the pre-founding factors influencing new venture performance.

This paper builds on and integrates research on parent firm determinants of entrepreneurial spawn performance with research on agglomeration effects. In particular, we examine how agglomeration effects at the parent firm level increases the commercial value of the human and social capital of nascent entrepreneurs when they are still employees of incumbent firms, ultimately leading to improved performance outcomes when those individuals found and lead entrepreneurial spawns. As such, our study makes a contribution to the entrepreneurship literature on the pre-founding determinants of new venture performance. Furthermore, by studying the origins of firm performance differences this work also contributes to the strategy literature on firm capabilities, and thereby helps to explain the underlying heterogeneity in firm performance.

We propose and test a straightforward implication of the agglomeration economics literature in the context of entrepreneurial spawning: *ceteris paribus* entrepreneurial spawns should perform better if their founder or key manager previously worked for a parent firm that is located in the relevant industry's geographical hub. Agglomeration effects increase the value of an individual's human capital when working at the center of an industry exposes one to valuable ideas and techniques that others on the periphery cannot observe (Marshall 1920/1890; Glaeser, et al. 1992). Furthermore, agglomeration effects increase the value of an individual's social capital when working in an industry hub allows one to develop relationships with leading customers and suppliers who can critically influence the success of a new venture (Saxenian 1994a; Hellmann, 2007). Agglomeration effects obtain at the level of the parent firm when individuals who have worked in industry hubs leave their parent firms to lead an entrepreneurial spawn, as these individuals take their unique knowledge and contacts with them, and can potentially exploit these resources to improve the performance of their new venture. Thus, the location of an individual's parent firm influences the commercial value of their human and social capital with clear implications for new venture performance when those individuals leave the parent firm to found or manage and entrepreneurial venture.

We test the proposition that agglomeration effects positively influence the performance of entrepreneurial spawns by constructing a unique dataset on hedge fund performance, hedge fund managers and their employment histories. The hedge fund industry provides a good setting for testing agglomeration theories in the context of spawning, as the industry is characterized by two obvious focal industry hubs, and high rates of entrepreneurial activity over the last three decades, and hedge fund performance measures are well-defined and objectively measureable even for young firms.

Our empirical tests show that hedge funds whose key managers were previously employed by parent firms located in financial services industry hubs—New York or London—outperform other hedge funds, regardless of the location of the hedge fund. Hedge fund spawns from parent firms based in financial services hubs generate 1.2-1.7% higher abnormal returns per year for their investors net of fees. Furthermore, parent firms located in New York or London are 40% more likely to produce a spawn, even after controlling for firm size and industry, and spawn more managers who subsequently lead hedge funds compared to equivalent firms outside of industry hubs. The results are robust to alternative measures of performance, sample specification and controls for selection effects through propensity score matching. The evidence suggests that agglomeration effects improve spawn performance by increasing the value of nascent entrepreneurial managers' human and social capital.

2. Theory development

Several studies suggest that incumbent organizations are often the starting point for the formation of new ventures: Bhide (2000) finds that over 70% of entrepreneurs replicated or modified an idea encountered in previous employment. Braun and MacDonald (1982) document that between 1957 and 1976 over a third of all entrants in the semi-conductor industry were founded by previous employees of Fairchild, nicknamed "Fairchildren" (Klepper, 2001).

The extant literature has developed some intriguing insights on parent firm determinants of entrepreneurial spawning: for instance, Gompers et al. (2005) find evidence that entrepreneurial spawning rates are higher for innovative and entrepreneurial firms ("Fairchild view") compared to large bureaucratic firms ("Xerox view"). Their findings suggest that both human and social capital mechanisms drive entrepreneurial performance, as individuals who work for entrepreneurial incumbent firms are exposed to a network of suppliers, customers, and venture capitalists, and participate in the entrepreneurial processes during their employment appear to be better equipped to found and manage their own businesses. Other research focusing explicitly on human capital mechanisms has shown that both technical and non-technical knowledge gained through previous employment can positively influences spawning rates (Agarwal, Echambadi, Franco and Sarkar 2004; Klepper and Sleeper, 2005; Chatterji 2009). Moreover, Klepper and Sleeper (2005) find evidence that parent firm location in the industry's geographical hub positively impacts the magnitude of entrepreneurial spawning. While the foregoing literature suggests that agglomeration effects should contribute to spawns' performance we are not aware of any papers that have explicitly tested this implication of the theory. This paper takes a step toward filling this gap in the literature by investigating the link between agglomeration effects at the parent firm level and subsequent spawn performance

This research also contributes to a literature on the origins of firm heterogeneity. Several studies have suggested that knowledge inherited from parent firms influences the performance of spawn (Helfat and Lieberman, 2002); for example, in the hard disk drive industry spawns exploited technological knowledge gained at their previous employers to outperform firms that entered from outside the industry (Christensen and Bower, 1996; Franco and Filson 2006). A similar pattern was observed in the laser, television receiver and automobile industries, where lateral entrants with less related experience performed poorly compared to spawns from closely related industries (Carroll, Bigelow, and Seidel, 1996; Eisenhardt and Schoonhoven 1990; Klepper and Simons 2000). While these studies have yielded evidence that parent firm attributes influence the performance of entrepreneurial spawns, there is less evidence about the parent level determinants of spawn performance. We build on and extend two seminal papers on the antecedents of spawn performance: Agarwal, Echambadi, Franco and Sarkar's (2004) work shows that spawns' survival rate is positively related to parent firms' technical knowledge, and Chatterji's (2009) research finds that the parent firm's non-technical knowledge positively influences the performance of spawns. Our research extends this research by focusing on the impact that the location of the parent firm has on the operational financial performance of the spawn, as opposed to the survival of the spawn or its implied market capitalization upon receipt of venture capital. While survival and market capitalization are relevant measures of firm performance they are quite coarse. For example, firm survival might be influenced by deep pockets as much as by firm quality. Thus, focusing on actual operational performance has the potential to provide a tighter connection between theory and evidence on spawn performance.

Industry activities are often concentrated in certain regions or geographic industry hubs, potentially because firms are able to derive performance benefits from locating in clusters (Krugman, 1991; Porter, 1998). Agglomeration benefits can stem from firms being more deeply embedded in an industry's customer, supplier, and support networks, thereby allowing the firm to benefit from better access to knowledge flows (Marshall 1920/1890; Glaeser, Kallal, Scheinkman and Shleifer 1992). Firms in geographic hubs can also benefit from social capital effects (Bell, 2005). Several studies have shown that agglomeration effects are particularly important for innovation and new venture formation as well as the performance of new ventures conditional on the new venture locating in the industry hub (Audretsch and Feldman, 1996; Jaffe, Tratjenberg, and Henderson, 1993; Saxenian, 1994a, 1994b). However, in the context of entrepreneurial spawning little is known about whether pre-founding agglomeration effects at the level of the entrepreneur's parent firm, affect the post-founding performance of the spawn.

Integrating the existing research on agglomeration effects and entrepreneurial spawning gives rise to a clear testable proposition: when managers work in industry hubs they are exposed to valuable knowledge, information, and ideas as well as people that managers on the periphery of the industry are less likely to encounter, which positively influences the performance of new ventures led by such managers. Thus, the unique access to critical drivers of human and social capital that geographic proximity provides not only makes a manager more likely to form or join a new venture; it also gives them a competitive edge over their peers who work outside of industry hubs when they decide to found and lead new ventures. We, therefore, propose that when a manager leaves a parent firm located in an industry's geographical hub in order to lead a new venture, this entrepreneurial spawn will outperform other spawns whose managers previously worked for parents located outside of the industry hubs, irrespective of the location of the spawn itself.

> *Hypothesis 1. Entrepreneurial spawns will perform better if their principal managers were previously employed by parent firms located in the relevant industry's geographical hub.*

Hypothesis 1 applies the fundamental idea at the heart of agglomeration economics—that knowledge and relationships are more easily transmitted and developed over short physical distances—in the context of spawn performance. The intersection of agglomeration economics and entrepreneurship also has implications for the volume of spawning activity a parent firm creates. Following Gompers, Lerner and Scharfstein (2005), and Klepper and Sleeper (2005) we also explicitly consider whether agglomeration effects influence the magnitude of spawning activity, proposing that centrally located parent firms will be more likely to produce entrepreneurial spawns and will generate more spawns than parent firms located outside of industry centers. Thus our second hypothesis predicts that agglomeration effects will also impact the rate of entrepreneurial spawning:

> *Hypothesis 2. Incumbent firms located in an industry's geographical hub are more likely to generate entrepreneurial spawns and will generate a larger number of spawns than peripherally located incumbents.*

Although the existing literature has previously tested whether the volume of spawning activity is related to agglomeration measures, it is important to connect this result with spawn performance in a single study to buttress the claim that agglomeration effects are a causal driver of spawning activity and performance. Moreover, the second hypothesis provides support for a theory of agglomeration effects that does not rely on systematic mistakes by investors or entrepreneurs. In particular, if investors have better information about local entrepreneurs and are subject to search frictions, investors need not compete away the excess returns predicted in Hypothesis 1 in equilibrium. For example, if investors follow a cutoff rule for making new investments, which fully specifies their portfolio allocations to investment managers as in Sharpe (1964), and face search costs in locating managers outside of their geographic area, then investors will "satisfice" by investing in firms that generate positive abnormal returns without attempting to maximize gross investment returns globally. An equilibrium theory of agglomeration with search costs has three important implications in the context of a competitive market for investment. First, the theory predicts that that (risk neutral) entrepreneurs will always launch new ventures when their expected returns are positive, second more entrepreneurs will spawn from firms located in industry hubs, and third entrepreneurs that spawn from firms in industry hubs will have higher expected returns on average. In the empirical context section below we discuss why the hedge fund industry is consistent with our assumption that search frictions effectively segment geographic markets.

3. Empirical context: the hedge fund industry

Hedge funds are private investment vehicles that raise capital from high net worth individuals and institutional investors to exploit investment opportunities. As private investment vehicles, hedge funds are not subject to the same rules and regulations that mutual funds are subject to, which gives them more investment flexibility. However, as private investment vehicles hedge funds are also not allowed to market their services to the general public. Thus, the private nature of the industry tends to create frictions between geographically distinct markets as discussed above.

The first hedge fund was founded in 1946 by Alfred Winslow Jones, but the hedge fund industry emerged as an important sub-sector of the financial services industry in the 1980s. The industry has subsequently undergone rapid growth with compound annual growth in assets under management above 15% (Alternative Investment Management Association 2008). In 2008 assets under management were estimated to be approximately $1.9 trillion. It is particularly noteworthy that the hedge fund sector has witnessed significant entrepreneurial activity over the past three decades: our estimates, based on industry data and discussions with hedge fund managers, suggest that 10,000-12,000 hedge fund firms have been founded since 1978.

Part of the reason for the remarkable number of new ventures formed in the hedge fund industry is undoubtedly the lack of intellectual property (IP) protections over investment strategies, which allows individuals to appropriate the value of the knowledge gained while working at their parent firm by spawning a new venture. For example, Julian Robertson's hedge fund Tiger Management Corporation has seen analysts and traders leave to spawn the large number of "Tiger Cubs", including Maverick, Lone Pine, Touradji, Sumway, Lone Pine, and Millgate, amongst others; while traders at Goldman's risk arbitrage desk famously led by Robert Rubin spawned Farallon, TPG-Axon, Eton Park, Taconic, Och Ziff, and Perry amongst others.

Another key driver of spawning activity in the hedge fund industry is its attractiveness to entrepreneurs: hedge fund managers are amongst the most highly remunerated professionals in the world. The conditions in the hedge fund industry fit closely with Hellmann's (2007) "entrepreneurial equilibrium”—firms do not own IP and the external environment is very attractive to potential entrepreneurs—where in equilibrium individuals explore their entrepreneurial ideas through external ventures. Thus, our emphasis on individuals’ opportunities to learn and network while employees of parent firms as key drivers of spawning performance in the hedge fund industry (e.g., the Fairchild view) seems warranted.

Broadly, hedge funds are classified into four broad investment styles, each of which encompass a wide array of strategies and specializations: “Macro funds” invest in financial securities based on global macro-economic trends or events; “equity long/short funds” invest in equity securities that are expected to increase in value while short selling equity securities that are expected to fall in value; “event-driven funds” invest in financial securities based on corporate events, such as mergers and acquisitions or bankruptcy; “relative value funds” exploit mispricing of financial securities. However, within each investment style a wide number of trading strategies exist, which tends to moot the relevance of a firm’s stated investment strategy.

Hedge fund firms derive their revenue from management fee and incentive fees. Management fees are annual asset management fees based on the net asset value of the assets under management by the hedge fund firm. Incentive fees entitle the hedge fund firm to a percentage of the achieved return on investment. Our data on fees is consistent with the figures reported in other research on hedge funds. Management fees range between 0% and 6% but are typically close to 2% of the net asset value, and that incentive fees are typically approximately 20% of the fund’s return (Ackermann, McEnally, and Ravenscraft, 1999).[1] As a consequence of this fee structure, hedge fund firms generate more income when they have larger amounts of assets under management and when they achieve high absolute returns.

We exploit the fact that hedge funds report a substantial amount of information about their managers and performance as an indirect marketing tool—since the firms cannot directly market their products to the general public—to gather detailed data on hundreds of hedge fund start-ups. We use this

[1] The incentive fee is typically subject to a “high water mark”, which means the fund must have generated positive returns (net of fees) over the lifetime of the investment before any incentive fees are due to the fund.

information to analyze how agglomeration effects in managers' previous employment influence the performance of hedge funds.

4. Data and empirical design

4.1 Sample construction

Data on hedge fund performance (monthly returns to investors net of fees), location, size and inception date were obtained by combining the two most extensive and widely used hedge fund databases: Lipper-TASS ("TASS") and Hedge Fund Research (HFR). The data sets include data on over 12,000 individual funds from 3,113 hedge fund firms during the period 1978 to 2007. Though the datasets are self-reported they are widely believed to be broadly representative of the global hedge fund industry. While the TASS dataset is free of survivorship bias, we run our main tests on a pooled sample of TASS and HFR, and confirm that the results are robust to dropping the firms that are listed in HFR only.

We obtained detailed biographical information about the top two hedge fund managers from 684 hedge fund firms from the database provided MARhedge (subsequently acquired by CISDM), including manager name, educational history, previous two employers, and whether the manager was the founder of the firm.[2] As this data was not available in an electronic searchable database, we hired two research assistants to enter the data independently into a database. We then checked for consistency between the two entries: if the record matched exactly between the two entries, we dropped one of the entries randomly; if there was a discrepancy we double-checked the entries with the original data and only retained the correct entry.

We verified that the MARhedge data was drawn from an equivalent pool of hedge funds as the

[2] Many hedge fund firms list only one manager with MARhedge, typically the founder and CEO, though many list two co-founders. Some other firms list top executives like the CEO and CFO, or the CEO and chief portfolio manager without indicating which, if any, managers were founders. Where more than two managers are listed in MARhedge we used the associated biographical reports to distinguish which two managers were the most senior. The results obtained are consistent if we limit our test sample to the firm's top manager instead of using the firm's top two managers.

TASS and HFR datasets by comparing the means of the common variables. There were no meaningful statistical differences between the data sets with respect to firm size, location, and fees charged to investors. We then merged the MARhedge data with TASS and HFR datasets, which resulted in 1,585 unique hedge fund manager-previous employer pairs of which 1,058 pairs had complete hedge fund performance and previous employer location information.

In order to conduct our empirical tests with meaningful controls on previous employer characteristics we restricted the main test sample to include only job spells with previous employers that were listed on public stock exchanges in the United States and United Kingdom between 1978-2007, including the New York Stock Exchange (NYSE), the National Association of Securities Dealers Automated Quotations (NASDAQ), the American Stock Exchange (AMEX), and the London Stock Exchange (LSE). The resulting data set consists of 606 unique hedge fund manager job spell-previous employer pairs from managers at 414 unique hedge funds that were spawned from 95 unique previous employers. Table 1 shows the characteristics of the 25 most prolific parent firms in terms of the number managers that left the firm to become a founder, CEO, chief portfolio manager or other senior manager at a hedge fund. Citigroup was the most prolific parent in our sample with 68 managers who left to become senior managers at hedge funds. Of the top 25 most prolific parent firms 12 are headquartered in New York or London ("HQ Location"), 20 were ranked by Institutional Investor as being in the top 25 of securities trading firms ("Ranked"), and 24 are classified as having a standard industrial code (SIC) code that begins with "6".

Insert table 1 about here

4.2 Measures

We test Hypothesis 1 using two different dependent variables: 4-factor and 8-factor equal weighted average monthly excess returns (firm "alpha") to investors (net of fees). Excess returns are estimated using the standard approach, as the difference between the actual return fund *i* achieves at time (month) t and the fund's expected return controlling for the fund's risk exposure, as in equation (1):

$$(1)\quad R_{it} = a_i + R_{ft} + \boldsymbol{X_t B_i} + e_{it},$$

where R_i is a fund's raw return net of fees charged to investors and the vector $\boldsymbol{X}$ contains factors that proxy for the fund's risk exposure. In the 4-factor model we include the three Fama-French (1996) factors R_m-R_{ft}, *HML* and *SMB*, and Carhart's (1997) momentum factor *MOM* in $\boldsymbol{X}$. R_m-R_{ft} is the market equity return less the risk free rate, *HML* is the return on value relative to growth stocks less the risk-free rate, *SMB* is the return on small stocks relative to large stocks less the risk-free rate, and *MOM* is the return on one-year momentum versus contrarian stocks. The term a_i is the time invariant component of a fund's performance (fund "alpha") and e is the residual. We take the factors *HML, SMB, MOM,* R_f, and R_m from Ken French's data library,[3] R_i from TASS and HFR, and compute a, the coefficients on $\boldsymbol{X}$ and e by running fund-level longitudinal regressions. We then compute the firm's excess return, *ALPHA*, by averaging it's fund alphas on an equal weighted basis.

While 4-factor excess returns are a standard way to measure financial performance, there is substantial disagreement in the asset pricing literature about whether the 4-factor model represents the appropriate risk adjustment procedure for hedge funds (Fung, Hsieh and Naik 2008). In particular, hedge fund scholars are concerned that active trading strategies deployed by hedge funds, and the fact that hedge funds tend to hold illiquid assets, exposes them to unique risks that are not captured by the standard 4-factor model. We therefore, create an alternative excess return measure based on an 8-factor model developed specifically to measure hedge fund excess returns where the vector $\boldsymbol{X}$ in (1) contains two of the Fama-French (1996) factor: R_m-R_{ft} and *SMB*; plus five factors from Fung and Hsieh (2004): the excess returns on portfolios of straddle options on currencies, commodities, and bonds, the yield spread of the duration adjusted U.S. 10-year Treasury bond over the 3-month T-bill, the change in the credit spread of the duration adjusted Moody's BAA bond over the 10-year Treasury bond (BAA); and a liquidity factor

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

from Pastor and Stambaugh (2002).[4] Alphas are winsorized the 1st and 99th percentile to control for outliers.

We test Hypothesis 1 by comparing the performance of hedge funds spawned from parent firms in the *CENTER* (e.g., New York and London) against spawns from parent firms in the non-*CENTER* locations at the level of the job spell, conditional on the individual subsequently becoming one of the top two executives at a hedge fund. To test Hypothesis 2 we focus on the parent firm as the unit of analysis and expand the risk set to all potential previous employers that could have spun off a hedge fund. To develop this sample we counted the number of unique manager job spells spawned from each previous employer *(SPAWNCOUNT)* and merged *SPAWNCOUNT* by previous employer name to COMPUSTAT's complete set of firms listed on public exchanges in U.S. and U.K. We dropped 335 observations for which we were unable to obtain reliable information on location or industry, leaving us with 17,299 firms. We then test Hypothesis 2, using two dependent variables based on *SPAWNCOUNT*: a binary variable that indicates whether an incumbent has generated at least one spawn in addition to the count variable *SPAWNCOUNT*.

Our key independent variable captures the location of the previous employer of the hedge fund firm's principal managers. Specifically, we capture whether the headquarter location of the previous employer of the hedge funds' principal manager was in one of the geographical hubs of the financial service industry—New York or London (the cities that account for the world's largest equity, debt and derivatives markets and are ranked as the top two global financial centers by the Global Financial Centers Index and the Worldwide Centers of Commerce Index in every year the these indices were compiled). We measure parent firm location as a binary variable, *CENTER*, which is equal to 1 if the location of the previous employer is New York City or London and 0 otherwise. Although there is undoubtedly some measurement error in *CENTER* because some individuals did not work at their firm's headquarters, the effect of the measurement error is to introduce noise into our estimates—a bias that works against finding

[4] The Fung and Hsieh factors are available at http://faculty.fuqua.duke.edu/~dah7/HFData.htm. We thank Ronnie Sadka for helping us construct several of the factors from the raw data on Hsieh's web site. Pastor-Stambaugh liquidity factors are available at http://finance.wharton.upenn.edu/~stambaug/ liq_data_1962_2008.txt.

the hypothesized results.

4.3 Empirical specification

4.3.1 Spawn Performance. Our baseline test of Hypothesis 1—predicting that spawns will outperform when their parent firm was located in the geographic center of the industry—regresses *CENTER* on *ALPHA* (both 4-factor and 8-factor excess returns) for job spell *j* and hedge fund firm *i* as in:

$$(2)\quad ALPHA_i = a + \beta_1 CENTER_j + \boldsymbol{X_c \beta_c} + e_i,$$

where $\boldsymbol{X}$ is a vector of controls that might plausibly influence hedge fund performance and *c* indexes both job spell and hedge fund controls. Hedge fund controls include the location, scope and age of hedge fund firm *i*. We use two location variables "hedge fund in center," is a binary variable set equal to one if the hedge fund is based in New York or London, and zero otherwise. "Hedge fund near center", is a binary variable set equal to one if the hedge fund is within 100 miles of New York or London, and zero otherwise. Scope is measured as the log of the average number of funds in the hedge fund firm (equal weighted by month), and age is measured as years since the firm was founded.[5] Job spell *j* controls include relatedness and quality measures related to individuals' previous employers. The relatedness measure is whether the job spell was in the financial industry, measured by the first digit of the parent firms SIC code (*SIC6*)[6]. The two quality measures are whether the parent firm was ranked as a top 25 securities trading firm in any year 2000-2007 by Institutional Investor Magazine (*RANKED*), and the parent firm's long-run average Tobin's q. Standard errors are robust and clustered at the parent-firm level.

Table 2 Panel A shows the summary statistics for the variables used in tests of Hypothesis 1. 59% of the job spells in our test sample were based at parent firms located in New York or London

[5] Our age term is equivalent to including a linear time trend. In an alternative specification we included founding year fixed effects and found very similar results.
[6] The results are robust to using a full set of two-digit SIC code dummies.

(*CENTER*), while 91% of the job spells were with financial services firms (*SIC6*), and 71% of the job spells were with financial services firms that were ranked as the top 25 securities trading firms by Institutional Investor 2000-2007.

In the absence of omitted variables that are correlated with both *ALPHA* and *CENTER*, the baseline OLS regressions deliver evidence about whether agglomeration effects influence spawn performance. However, because *CENTER* is an endogenous choice variable for both managers and parent firms, the results are potentially biased due to endogenous sorting. For example the best future hedge fund managers may self-select into companies located in New York or London precisely because they want to start their own hedge fund in the future. Thus, a positive coefficient on *CENTER* will confound selection and treatment effects. To control for the effects of endogenous sorting, we follow Rosenbaum and Rubin's (1983) propensity score matching technique, which defines a valid control group of non-*CENTER* job spells that are similar to the *CENTER* job spells with respect to all observable characteristics of the job spells. Compared to the standard approach of adding controls to a linear regression, the propensity score methodology makes fewer functional form assumptions and eliminates the influence of non-comparable control and treatment group observations that are off the common support of the estimated propensity score distribution.[7]

To implement propensity score matching we estimate a probit of the individual and employers joint decision to enter into an employment relationship in New York or London (i.e. in the *CENTER*) and use fitted values from that model as estimates of the propensity score $\Pr(CENTER_i = 1|\boldsymbol{X_{ij}})$, where $\boldsymbol{X_{ij}}$ includes all observable characteristics of individuals and their employer firms that might plausibly have an effect on either party's decision to enter into the employment relationship, including all the covariates from the OLS specification (2), the median SAT score and rank of the educational institution the manager attended[8], the highest degree they obtained, and whether their previous job spell was in the *CENTER*, as well as their employer's size (log employees). We use the predicted value of the probit regression to trim

[7] Intuitively, this approach will outperform standard regression control methods when the response of *ALPHA* to *CENTER* varies with $\boldsymbol{X}$ (i.e. there is treatment heterogeneity), and $\boldsymbol{X}$ is correlated with *CENTER*.
[8] We use a full set of SAT quintiles along with an SAT missing dummy to account for non-U.S. schools.

the extreme values of the *CENTER* and non-*CENTER* distributions and drop observations off the common support of the joint distribution of the propensity score.[9] Once we obtain the matched sample, we re-run OLS model (2) on only the matched sample, weighting observations by the inverse probability of being treated to balance the control and treatment groups (Imbens 2004).

4.3.2 Spawning. To test Hypothesis 2, predicting that agglomeration effects positively influence the rate of spawning activity from a parent firm, we analyze both the impact of *CENTER* on the likelihood of any a single spawn occurring and the count of the number of spawns from a parent. We estimate a probit model for the former dependent variable and a zero inflated negative binomial for the latter,[10] controlling for factors that might plausibly influence spawning behavior at the level of the parent firm including. As in Klepper and Simons (2005) we control for how closely related the employer is to the hedge fund industry using SIC code (*SIC6*). As in Gompers, Lerner and Scharfstein (2005) we control previous employer firm quality using Tobin's q and *RANKED*. We also control for previous employer firm size (number of employees).[11] Table 2 Panel B shows summary statistics for the spawn count analysis. In contrast to the performance sample, only about 10% of the firms in the spawning sample are located in the *CENTER* and only 30% are financial services firms (SIC6=1).

Insert table 2 about here
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5. Results

5.1 Spawn Performance

Table 3 shows the results from the OLS regressions of *CENTER* on excess returns (*ALPHA*) to

[9] Following the standard approach, we trimmed observations off the joint distribution of the treatment and control groups until the F-test for the joint significance of the differences in the means of the covariates in the treatment and control groups were no longer significant at the 10% level. To do so we trim observations at the 10% and 97.5% points in the joint distribution of the propensity scores. Alternative trimming procedures, for example symmetric trimming, yielded very similar "second stage" results, but required more observations to be dropped to before statistical differences between the control and treatment populations could be eliminated.

[10] Since there is over-dispersion in the data--the variance is significantly bigger than the mean--we use a negative binomial model as our base specification (results are also robust to a Poisson specification). Moreover, as only 95 observations are non-zero observations, there is strong evidence of zero-inflation in the data. To accommodate for this zero-inflation, we chose to adopt a zero-inflated negative binomial model (ZINB).

[11] As more than 25% of the companies listed in our COMPSUTAT database have missing size and performance, we use categorical variables for the quintiles of the number of employees and for levels of Tobin's q respectively.

investors. The coefficient estimate of *CENTER* on 4-factor excess returns is 12 basis points per month, or about 1.44% per year, with or without controls and is significant at the 1% level (columns 1 and 2). Very similar results are obtained on 8-factor excess returns (columns 3 and 4). Only firm age is robustly significant as a control.[12] The negative sign on firm age suggests either that hedge fund performance tends to decline over time, or that later entrants could not match the performance of early movers in the hedge fund industry, or both. Interestingly, the physical location of the hedge fund in or near the *CENTER* is not significant in either the 4-factor or the 8-factor specification, which suggests that agglomeration effects on human and social capital are of the most importance when the managers' human and social capital development is still in a formative stage (i.e. when they employees of parent firms).

Insert table 3 about here

Since the decision for an individual to work in the *CENTER*, and/or for an employer to hire that individual in the *CENTER* is endogenous, the results shown in Table 3 can only be interpreted as correlations. We use propensity score matching to control for endogenous sorting on observable characteristics of firms and employees. The results the first stage of the propensity score matching analysis are displayed in Table 4. Column 1 shows the marginal effects from the probit estimating the likelihood a job spell would occur in the *CENTER* conditional on a manager subsequently becoming one of the top two mangers of a hedge fund, while columns 2 and 3 show the differences in the means of the covariates for the control and treatment groups before and after matching. Conditional on an individual becoming a senior leader of a hedge fund, achieving a post-graduate degree other than an MBA, PhD or JD is positively correlated with job spells occurring in the *CENTER*, and the incidence of other post-graduate degrees is significantly higher in the treatment (*CENTER*) population than in the control (non-*CENTER*) population. Also, job spells at employers that are *RANKED* by Institutional Investor as leading trading houses are far more likely to be in the *CENTER* and are much more prevalent in the treatment

[12] As expected, because the factor models, shown in equation (1) above, do a good job picking up most of the variation in *ALPHA* the R^2s are low, in the 1-3% range, and the point estimates on most of the controls are not statistically significant.

group than in the control group. No other variables are both statistically significant in predicting a job spell being in the *CENTER* and have statistically different means in the treatment and control groups before matching, though *SIC6*, Tobin's q, and number of employees (logged and missing) are statistically different between the two populations, and the F-test for the joint difference in means between the two groups before matching is statistically significant at the 1% level. Figure 1 Panel A also reveals visually that the distributions of the propensity scores are quite different between the two populations—the non-*CENTER* population's distribution is much flatter than the *CENTER* population and has much more mass in the left tail.

Insert table 4 about here

Figure 1 Panel B shows the distributions of the propensity scores predicting that a job spell occurred in the *CENTER* for the treatment and control groups after matching, revealing a much tighter visual fit between the two groups. Table 4 column 3 corroborates this result statistically. Only the difference in means on *RANKED* remains significant at the 5% level, and the F-test for the joint significance of the differences in the means between the treatment and control groups is not significant at the 10% level. In other words, the matching approach appears to work very well: job spells occurring in the CENTER are similar to those occurring outside of the CENTER along all observable dimensions.

Insert figure 1 about here

Table 5 shows the matched sample performance results for regressions on *ALPHA* and log revenue with controls. The point estimates on *ALPHA* are relatively stable compared to the unmatched OLS regressions at 11 and 14 basis points per month for the 4-factor and 8-factor excess returns respectively, though perhaps because of the smaller sample size the estimates are a bit noisier: the 4-factor estimates are significant at the 10% level while the 8-factor remains significant at the 5% level. Overall the matched sample results are consistent with the unmatched OLS estimates, and importantly, in the absence of unobservable sources of heterogeneity that are correlated with both *CENTER* and the outcome variables of interest, the propensity score matched estimates on *CENTER* can be interpreted as causal effects.

Insert table 5 about here

5.2 Spawning

Table 6 shows the results of the tests of Hypothesis 2. The first two columns show probit regressions predicting the likelihood that a parent firm located in the *CENTER* will generate at least one spawn. We present the marginal effects of a 1% change in the covariates from their mean value, holding all other variables at their means. The point estimates on *CENTER* is 0.014 without controls (column 1) and is precisely estimated, which implies parent firms in the *CENTER* are 1.4 times more likely to generate at least one spawn compared to other firms (the mean rate of spawning at least one hedge fund is 0.5%). Including a vector of controls reduces the magnitude of the point estimate on *CENTER* to 0.004, though it is still precisely estimated, and increases the pseudo R^2 substantially (column 2). The interpretation of the point estimate in column 2 is that parent firms located in financial centers are 40% more likely to spawn at least one hedge fund relative to firms that are not located in the *CENTER*.

A number of controls are statistically significant in column 2, most impressively *RANKED*, which increases the likelihood of spawning at least one hedge fund by 25 times. *SIC6* and the top and bottom quintiles of Tobin's q are also statistically and economically significant. Firms in *SIC6* are 60% more likely to spawn at least one hedge fund, and firms in the top quintile are 40% more likely to spawn at least one hedge fund compared to firms in the bottom quintile. Of course, firm size also matters: the largest firms are twice as likely to spawn compared to firms in the middle quintile, while the smallest firms are 10% less likely to spawn. The signs on the coefficients on the controls are consistent with the spawning literature, particularly the Fairchild view, in showing that relatedness and parent firm performance (a proxy for firm quality), in addition to firm size positively influence the magnitude of spawning (Klepper and Simmons 2005; Gompers, Lerner and Scharfstein 2005).

Columns 3 and 4 show the zero inflated negative binomial (ZINB) regressions of *CENTER* on the number of spawns emanating from a parent firm.[13] Without controls the point estimate on *CENTER* is 1.53, which means firms in financial centers spawn 4.6 ($e^{1.53} = 4.6$) more hedge funds than firms located outside of the financial centers. Including controls in model 4 improves the fit of the model, the χ^2 statistic jumps from 11 to 186, and reduces the point estimate on *CENTER* to 1.15 or 3.2 additional spawns ($e^{1.15}$), though the estimate remains precise. *RANKED* and *SIC6* remain economically and statistically significant in the ZINB specification, though the economic significance of these controls reverses: in the ZINB parent firms in *SIC6* generate twice as many spawns (11.9 additional spawns) as firms that are *RANKED* (5.2 additional spawns). Quintiles of Tobin's q did not produce a discernible pattern in the ZINB. Taken together the results support Hypothesis 2 that parent location positively impacts the rate of entrepreneurial spawning and offers additional support for the Fairchild view with respect to the role of relatedness and firm quality.

Insert table 6 about here
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6. Discussion

Our main results show that hedge fund managers who worked for parent firms in New York and London outperform hedge fund managers who worked on the physical periphery of the investment industry, and that parent firms in the *CENTER* are more likely to spawn and spawn more often than firms on the periphery. Agglomeration effects at the level of the parent firm need not be inconsistent with rational investors allocating their investments based on well informed, and statistically accurate, inferences about the underlying quality of investment managers. Indeed, our simple informal model assumes that the data generating process follows an equilibrium model with rational investors. However, the results are not necessarily intuitive, which raises the bar on for the empirical strategy to yield well identified results.

[13] The Vuong test indicated that the ZINB model is superior to the "regular" negative binomial model. As a robustness check we also ran a zero-inflated Poisson model (ZIP) on the magnitude of entrepreneurial spawning and found similar results. (The log-likelihood ratio test indicated that the ZINB model is superior.)

In the ideal test of Hypothesis 1, predicting that agglomeration effects at the parent firm level influence subsequent spawn performance, we would randomly assign individuals to senior management positions in hedge funds and would then compare their performances conditional on *CENTER*. Similarly, the test Hypothesis 2 we would like to randomly assign firms to locations and observe how many spawns they launch subsequently. In practice, we base our statistical tests on self-selected populations. Hedge fund managers choose their career paths and firms choose their headquarters location presumably to maximize their own welfare. If the welfare maximization decision involves higher ability managers selecting themselves into job spells in the CENTER, or higher quality firms locating in the *CENTER*, in ways that our empirical design does not control for our results will be biased.

Unfortunately, due to the cross-sectional nature of our study, we cannot include person-specific fixed effects in our specifications, and therefore cannot directly control how a manager's unobservable ability might influence their opportunities and decisions to work in the *CENTER*. We do show that our results are robust to controlling for selection effects based on observable characteristics of managers and firms, but acknowledge that matching cannot directly control for selection on unobservable differences that might bias comparisons *CENTER* and non-*CENTER* populations.

Although the matching approach does directly control for unobservable ability, we take some comfort in the fact that the coefficient estimates of *CENTER* on performance are stable across the matched and unmatched samples. If unobservable measures of ability were driving our results, one would expect that omitting observable measures of ability from the OLS estimates in Table 3, such measures of the extent and quality of managers' educational background—which capture an meaningful component of a manager's innate ability prior to their experiences with their parent firm(s)—would have a large impact on performance (Bertrand, Luttmer and Mullainathan 2000). But, including measures of educational achievement and quality of undergraduate educations in the propensity score matching procedure has little impact on the coefficient estimate on *CENTER*.[14] Therefore, a comparison of the baseline OLS and

[14] We also try including proxies for individual-specific ability directly in the OLS regressions and find that the coefficient estimate on *CENTER* is also stable in the presence of these variables.

matched sample results suggest that unobservable ability is probably not driving the results on *CENTER*.

Another alternative explanation for the performance result we find is that firms in the *CENTER* are simply better firms, and consequently, employees of such firms get better training and have access to better resources. While employer-specific treatment effects need not exclude agglomeration effects, they might confound our results. Unfortunately, we cannot rule out this explanation by including firm fixed effects because *CENTER* does not vary within firm. However, the stability of the coefficient on *CENTER* to the inclusion of observable measures of firm quality—*RANKED*, *SIC6* and Tobin's q—in the OLS results as well as in the matching algorithm suggest that this alternative explanation is probably not driving the results on *CENTER*.

In addition to issues of endogeneity, there are two other important limitations of this study. First, we do not directly observe the mechanism that we hypothesize connect agglomeration effects to outcomes. Namely, we do not directly observe a manager's human and social capital, but rather use outcome variables as proxies for the effects of a manger's stock of human and social capital. Second, our study focuses on a single-industry, which might be idiosyncratic in ways that are difficult to predict. Thus, some caution should be applied when extrapolating the results in this paper to other contexts.

7. Conclusion

This paper examines how agglomeration effects at the parent firm level (pre-founding) influence the number of spawns a firm launch as well as the post-founding performance of the firm's entrepreneurial spawns. We find evidence that hedge funds that spawn from parent firms located at the centers of the financial industry—New York or London—generate 1.2-1.7% higher annual abnormal returns to investors net of fees compared to hedge funds that spawn from parent firms located outside of New York and London, regardless of the location of the hedge fund. Furthermore, parent firms in New York and London produce more hedge fund spawns and are 40% more likely to produce at least one hedge fund spawn. Taken together, the results suggest that agglomeration effects associated with working in industry centers increases the value of managers' human and social capital when they leave their parent firms to lead spawns.

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FIGURE 1
Distributions of the probabilities of job spells occurring in the CENTER before and after matching

Figure 1A: Kernel density distributions of the probability of a job spell occurring in the CENTER before matching (n=606)

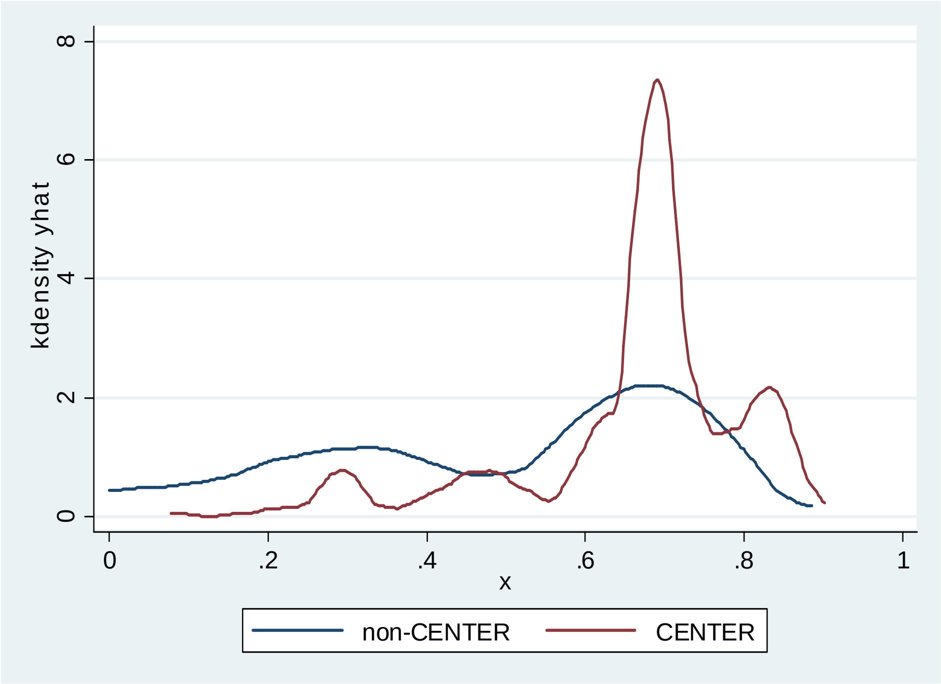

Figure 1B: Kernel density distributions of the probability of a job spell occurring in the CENTER after matching (n=464)

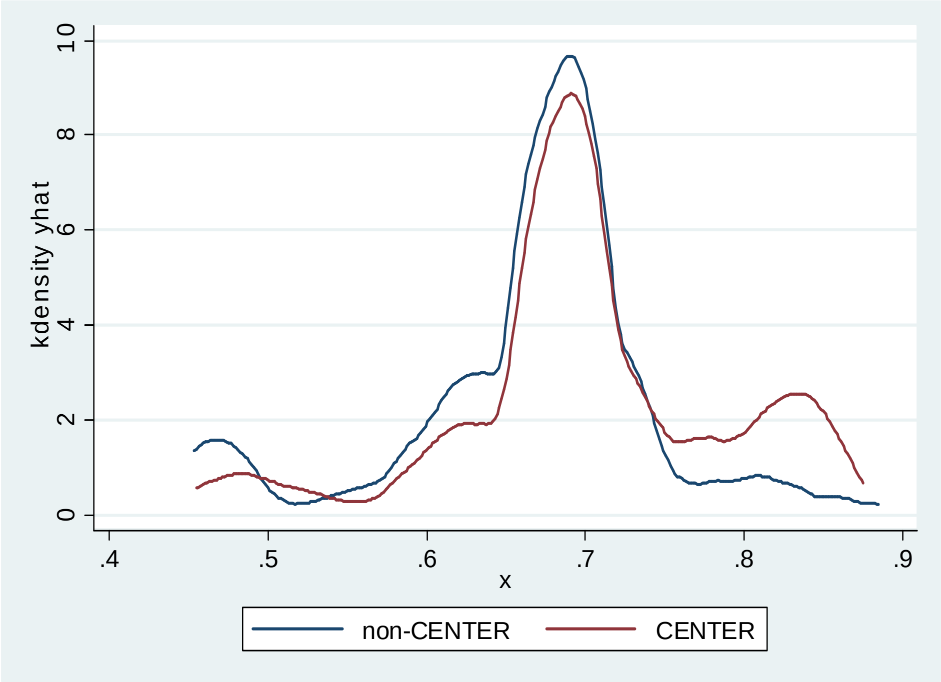

TABLE 1
Top 25 parent firms in the test sample

Firm	HQ Location	Ranked	SIC code	Employ-ees (K)	SPAWNCOUNT
Citigroup	New York	Y	61	387	68
JP Morgan	New York	Y	60	181	54
Merrill Lynch	New York	Y	62	64	50
Lehman Brothers	New York	Y	62	29	38
Deutsche Bank	Frankfurt	Y	60	78	33
Morgan Stanley	New York	Y	62	48	32
Goldman Sachs	New York	Y	62	31	31
UBS	Zurich	Y	62	84	29
Bear Stearns	New York	Y	62	14	25
BT Group	London	N	48	112	21
Bank of America	Charlotte	Y	60	210	21
Credit Suisse	Zurich	Y	62	48	18
RBS	Edinburgh	Y	60	200	17
Oppenheimer	Toronto	N	62	3	12
ING	Amsterdam	N	63	120	12
Wells Fargo	San Francisco	Y	60	160	10
Schroders	London	N	62	3	10
Barclays	London	Y	60	156	10
Allianz	Munich	N	63	181	9
RBC	Montreal/Toronto	Y	60	65	6
Alliance Bernstein	New York	Y	67	6	6
Prudential Financial	Newark	Y	63	41	6
CIB	Toronto	Y	60	41	6
HSBC	London	Y	60	313	5

Hedge fund spinoffs are measured as counts of the number of managers who left the parent firm to become hedge fund founders or senior managers.

TABLE 2
Summary statistics

Panel A: Performance analyses (n=606)

	mean	SD	min	max
Alpha 4-factor model (%/month)	0.38	0.54	-2.40	2.83
Alpha 8-factor model (%/month)	0.54	0.64	-1.33	3.47
CENTER	0.59	0.49	0	1
SIC6	0.91	0.29	0	1
Tobin's q	1.23	0.62	0.88	8
RANKED in the top 25 by Institutional Investor '00-07	0.71	0.45	0	1
Hedge fund location in fin. center	0.45	0.50	0	1
Hedge fund location near fin. center	0.14	0.35	0	1
Hedge fund age (years)	7.46	4.27	2	24
Avg. number of hedge funds	3.85	3.80	1	33

Panel B: Spawncount analyses (n=17,299)

	mean	SD	min	max
SPAWNCOUNT	0.04	1.04	0	68
At least 1 spawn	0.005	0.074	0	1
CENTER	0.10	0.30	0	1
SIC6	0.30	0.46	0	1
Tobin's q	1.88	5.43	0.04	523
Number of employees (K)	6.50	29.86	0	2100
Ranked in the top 25 by Institutional Investor '00-07	0.002	0.042	0	1

TABLE 3
Excess returns to investors

Dependent variable: Equal weighted average monthly excess returns (%)

	(1) 4-factor ALPHA		(2) 4-factor ALPHA		(3) 8-factor ALPHA		(4) 8-factor ALPHA	
CENTER	***0.12***	******	***0.12***	******	***0.10***	******	***0.12***	*****
	(0.04)		***(0.05)***		***(0.05)***		***(0.06)***	
SIC6			0.08				-0.04	
			(0.08)				(0.11)	
RANKED by Inst. Investor			0.03				0.06	
			(0.05)				(0.07)	
Tobin's q			0.01				0.05	
			(0.04)				(0.04)	
Tobin's q missing			0.08				-0.08	
			(0.07)				(0.11)	
Hedge fund in center			-0.02				0.01	
			(0.05)				(0.05)	
Hedge fund near center			-0.05				0.02	
			(0.10)				(0.12)	
Hedge fund firm age			-0.06	***			-0.02	**
			(0.01)				(0.01)	
Log avg. number of funds			-0.06	*			-0.04	
			(0.03)				(0.03)	
Constant	0.31	***	0.33	***	0.47	***	0.56	***
	(0.03)		(0.11)		(0.04)		(0.15)	
N	606		606		606		606	
R^2	0.01		0.03		0.01		0.03	

* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level
Standard errors are robust and clustered at the parent-firm level.
Monthly 4-factor abnormal returns are measured net of Fama and French's three factors (Fama and French 1993), as well as Carhart's momentum factor (Carhart 1997). The monthly 8-factor abnormal return is measured net of the seven factors proposed by Fung and Hsieh (2004), including exposure to: the S&P 500 index; a firm size factor; returns to portfolios of straddle options on currencies, commodities, and bonds; the yield spread of the duration adjusted U.S. 10-year Treasury bond over the 3-month T-bill; the change in the credit spread of the duration adjusted Moody's BAA bond over the 10-year Treasury bond), as well as Pastor and Stambaugh's liquidity factor (2002). Abnormal returns are averaged over time to compute the standard measure of persistent excess returns (fund "alpha") at the fund level. Alphas are then averaged on an equal weighted basis by fund to compute the firm's equal weighted average monthly abnormal return (e.g., firm "alpha").

TABLE 4
Propensity score matching

Dependent variable: Job spell in CENTER

	Probit coefficients		Δ means pre-match (t-stats.)		Δ means Matched (t-stats)	
MBA dummy	0.01		0.80		-0.73	
PhD dummy	0.02		-0.42		0.06	
JD dummy	-0.13		0.70		0.37	
Other postgraduate degree dummy	0.19	***	-2.39	**	-1.84	*
Graduate degree information missing	0.15		-0.61		0.00	
Avg. SAT undergrad.—quintile 5 (top)	-0.11		0.35		0.09	
Avg. SAT undergrad.—quintile 4	0.06		-1.31		-1.42	
Avg. SAT undergrad.—quintile 2	-0.03		0.23		0.19	
Avg. SAT undergrad.—quintile 1	0.02		0.79		-0.79	
Avg. SAT score missing	-0.06		-0.28		1.24	
Rank undergrad. institution quint5 (top)	-0.08		1.26		1.00	
Rank undergrad.—quintile 4	-0.06		1.26		-1.05	
Rank undergrad.—quintile 2	-0.01		-0.90		-0.86	
Rank undergrad.—quintile 1	0.02		-0.43		-0.75	
Rank missing	0.03		-0.65		1.18	
SIC6	-0.49		-2.02	**	-1.78	*
RANKED by Institutional Investor	0.39	***	-8.33	***	-2.59	**
Tobin's q	-0.02		3.07	***	-0.20	
Tobin's q missing	0.13		-0.10		0.18	
Number of Employees (logged)	0.00		-3.81	***	-0.66	
Number of Employees missing	-0.33	*	4.07	***	0.00	
Previous job spell in CENTER	0.75	***	-1.27		-0.93	
Previous job spell missing	0.85	***	-0.75		0.93	
N	606		606		464	
Pseudo-R^2	0.14					
F-stat. for joint test of differences			5.32	***	1.13	

* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level
Marginal effects displayed for probit model

Δ means are calculated as non-CENTER population means minus CENTER population means.

TABLE 5
Matched sample results

Dependent variable: Equal weighted average monthly excess returns (%)	(1) 4-factor ALPHA		(2) 8-factor ALPHA	
CENTER	***0.11***	*	***0.14***	**
	(0.06)		***(0.07)***	
SIC6	0.19		-0.22	
	(0.12)		(0.21)	
RANKED by Institutional Investor	-0.08		0.17	
	(0.10)		(0.17)	
Tobin's q	-0.11		-0.10	
	(0.10)		(0.08)	
Tobin's q missing	0.05		0.20	**
	(0.07)		(0.09)	
Hedge fund in center	-0.03		-0.05	
	(0.06)		(0.06)	
Hedge fund near center	-0.05		0.03	
	(0.10)		(0.13)	
Hedge fund firm age	-0.01	*	-0.03	***
	(0.01)		(0.01)	
Log average number of funds	-0.06		0.03	
	(0.04)		(0.04)	
Constant	0.51	***	0.85	***
	(0.13)		(0.15)	
N	464		464	
R^2	0.04		0.04	

* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level
Standard errors are robust and clustered at the parent-firm level.
Observations are weighted by the inverse probability of selection (Imbens 2004).
Monthly 4-factor abnormal returns are measured net of Fama and French's three factors (Fama and French 1993), as well as Carhart's momentum factor (Carhart 1997). The monthly 8-factor abnormal return is measured net of the seven factors proposed by Fung and Hsieh (2004), including exposure to: the S&P 500 index; a firm size factor; returns to portfolios of straddle options on currencies, commodities, and bonds; the yield spread of the duration adjusted U.S. 10-year Treasury bond over the 3-month T-bill; the change in the credit spread of the duration adjusted Moody's BAA bond over the 10-year Treasury bond), as well as Pastor and Stambaugh's liquidity factor (2002). Abnormal returns are averaged over time to compute the standard measure of persistent excess returns (e.g., fund "alpha") at the fund level. Alphas are then averaged on an equal weighted basis by fund to compute the firm's equal weighted average monthly abnormal return (e.g., firm "alpha").

TABLE 6
Likelihood and magnitude of spawning

	Dep. Var.: at least one spawn				Dep. Var.: *SPAWNCOUNT*			
	(1) Probit		(2) Probit		(3) ZINB		(4) ZINB	
CENTER	***0.014***	*******	***0.004***	******	***1.53***	*******	***0.91***	*******
	(0.003)		***(0.001)***		***(0.46)***		***(0.34)***	
SIC6			0.006	***			2.48	***
			(0.002)				(0.93)	
RANKED by Instit. Investor			0.251	***			1.64	***
			(0.093)				(0.44)	
Employees quintile 5 (top)			0.010	**			-0.40	
			(0.004)				(1.22)	
Employees quintile 4			0.002				-1.04	
			(0.002)				(1.42)	
Employees quintile 2			0.000				0.34	
			(0.001)				(0.98)	
Employees quintile 1			-0.001	***			0.39	
			(0.000)				(0.81)	
# of employees missing			0.000				-1.11	
			(0.001)				(1.88)	
Tobin's q quintile 5 (top)			0.003	**			-0.98	
			(0.001)				(1.25)	
Tobin's q quintile 4			0.001				2.28	*
			(0.001)				(1.196)	
Tobin's q quintile 2			-0.000				1.04	
			(0.000)				(0.64)	
Tobin's q quintile 1			-0.001	**			-2.90	
			(0.000)				(1.72)	
Tobin's q missing			-0.001	**			2.26	**
			(0.000)				(1.03)	
Constant					-3.02	***	-2.10	
					(0.37)		(1.83)	
N	17,299		17,299		17,299		17,299	
Log-likelihood	-569.47		-390.04		-798.02		-577.20	
Chi-squared	45.48	***	281.17	***	10.96	***	186.25	***
Pseudo R^2	0.03		0.34		N/A		N/A	

* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level
Standard errors are robust and clustered at the parent-firm level.
Marginal effects displayed for probit models.