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Abstract

We examine how parent firm location influences the performance of entrepreneurial spawns in 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. Interestingly, we do not find evidence that the actual location of the spawned hedge fund significantly impacts on its performance when controlling for the location of its parent firm. The evidence suggests that pre-founding agglomeration effects increase the value of individuals' human and social capital when they are still nascent entrepreneurs working for established firms, and that the entrepreneurs' pre-founding experience at the parent firms critically "imprints" the new spawns and influences the spawns' capabilities and post-founding performance.

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 (e.g. Agarwal, Echambadi, Franco and Sarkar 2004; Gompers, Lerner and Scharfstein, 2005). Yet relatively little is known about how parent firm attributes influence the performance of their spawns (Chatterji, 2009), perhaps because objective measures of spawn performance are often difficult to observe. One such parent firm attribute is the parent firm location and in particular the degree to which parent firms are embedded in an industry's geographical hub. While there is a significant body of literature

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examining agglomeration effects and firm performance, and while several scholars have examined post-founding agglomeration effects and the impact of new ventures' location in an industry hub on their performance (e.g. Audretsch and Feldman, 1996; Saxenian, 1994a, 1994b; Stuart and Sorenson, 2003), little is known about how agglomeration effects pre-founding and the location of parent firms impact on the post-founding performance of new firms. However, given that initial founding conditions and resources "imprint" new ventures and influence future resource acquisition as well as capability development (Cohen and Levinthal, 1990; Johnson, 2007; Stinchcombe, 1965), it seems highly important to better understand the pre-founding determinants of a new venture's founding conditions and resources.

We build on and integrate research on parent firm determinants of entrepreneurial spawn performance with research on agglomeration effects. In particular, we fill the aforementioned gap by examining how agglomeration effects at the parent firm level increase 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. We propose that entrepreneurial spawns perform better if their founder or key manager previously worked for a parent firm that is located in the relevant industry hub[1]. In particular, when individuals work at the center of an industry they are exposed to valuable (new) ideas, techniques, and other knowledge that others cannot observe (Marshall 1920/1890; Glaeser, Kallal, Scheinkman and Shleifer 1992). Furthermore, working at firms in industry hubs exposes individuals to customers and suppliers who may be critical to the success of a new venture (Saxenian 1994a, 1994b; Hellmann, 2007). When individuals who have worked in industry hubs leave their parent firms to lead an entrepreneurial spawn they take their

[1] Industry hub refers to a significant concentration of firms of a particular industry in a geographical area such that the concentration of firms in this area is significantly higher than that of most other areas.

unique knowledge and contacts with them, and exploit these resources to improve the performance of their new venture. Thus, the location of an individual's parent firm critically influences the commercial value of their human and social capital when those individuals leave the parent firm to manage a new venture. In this regard, the entrepreneurs' pre-founding experience at the parent firm, and the initial resources and conditions of the entrepreneurial spawn at founding crucially "imprint" the spawn, and hence, have a lasting influence on its capabilities and post-founding performance.

We test the proposition that agglomeration effects pre-founding influence the post-founding performance of entrepreneurial spawns using a unique international dataset on hedge funds, hedge fund managers and their employment histories. The hedge fund industry provides an ideal setting as the industry is characterized by 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. The data underlying our analysis comes from merging data on hedge funds sourced through two largest and most respected hedge fund performance databases, Lipper-TASS and Hedge Fund Research (HFR), with data on hedge fund managers' biographies sourced through MARHedge (now CISDM) database, and data on parent firm characteristics sourced through COMPUSTAT North-America and Global.

The results show that hedge funds whose key principal 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 the nascent entrepreneurs' human and social capital when they are still working for parent firms. Interestingly, we do not find evidence for post-founding agglomeration effects of entrepreneurial spawns when controlling for pre-founding agglomeration effects. This accentuates the relative importance of pre-founding agglomeration effects, and suggests that entrepreneurs' experience and human and social capital accumulated pre-founding critically "imprints" the new spawns and shapes its capabilities.

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. Moreover, Braun and MacDonald (1982) documented 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 given some insights on the parent firm level determinants of entrepreneurial spawning: for instance, Gompers, Lerner, and Scharfstein (2005) find evidence that entrepreneurial spawning rates are higher for innovative and entrepreneurial firms ("Fairchild view") compared to large bureaucratic firms ("Xerox view"), suggesting that individuals who work for entrepreneurial incumbent firms are exposed to a network of suppliers, customers, as well as venture capitalists, and participated in many entrepreneurial processes during their employment, thereby equipping them for the founding of their owning business. Other research has shown that technical and non-technical knowledge gained through previous employment also positively influences spawning rates (Agarwal, Echambadi, Franco and Sarkar 2004; Klepper and Sleeper, 2005). Moreover, Klepper and Sleeper (2005) find indicative evidence that parent firm location in the industry's geographical hub positively impacts on the magnitude of spawning. We build on and extend the above literature, by focusing our analysis on spawn performance.

Helfat and Lieberman (2002) suggest that the heterogeneity in new firms' capabilities is related to the prior affiliation and the pre-founding knowledge of firm's entrepreneurs. Moreover, several studies have suggested that knowledge inherited from parent firms influences the performance of spawns: for example, in the disc 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, as well as across several industries in Brazil where lateral entrants with less related experience performed poorly compared to spawns from closely related industries (Carroll, Bigelow, Seidel, and Tsai, 1996; Eisenhardt and Schoonhoven 1990; Hirakawa, Muendler, and Rauch, 2010; Klepper and Simons 2000). While these studies have yielded suggestive evidence of the impact that parent firms level attributes have on the performance of entrepreneurial spawns, only few studies have empirically identified such parent level determinants of spawn performance: Aggarwal, Echambadi, Franco and Sarkar (2004) show that the spawn's survival rate is positively related to the parent's technical knowledge; moreover, Chatterji (2009) finds that the parent firm's non-technical knowledge positively influences the performance of spawns. While this stream research has demonstrated that knowledge transferred from parent to spawn shapes the performance of the spawn, relatively little is known about observable parent level determinants of the magnitude of knowledge, as well as social capital, that entrepreneurial spawns are able to accumulate and extract pre-founding. Our paper builds on and extends this research by focusing on the location of the parent firm and pre-founding agglomeration effects on the performance of the spawn.

Economic activity is often found to be concentrated in certain regions or geographic industry hubs as firms can derive significant performance benefits from locating in clusters (Krugman, 1991; Porter, 1998); several studies have demonstrated positive effects of agglomeration on the performance of firms locating within the cluster (Carlton, 1983; Head, Ries, and Swenson, 1995). Agglomeration benefits can stem from firms in industry hubs being more centrally embedded in an industry's customer, supplier, and support networks and hence, thereby benefiting 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 to improve their performance (Bell, 2005; Stuart and Sorenson, 2003). 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). Moreover, several studies have provided evidence that clusters are maintained and reinforced by new firms locating close to existing agglomeration of incumbent firms (Sorenson, 2003; Sorensen and Audia, 2000; Stuart and Sorenson, 2003). Consequently, the existing literature posits that entrepreneurial spawns are able to benefit from knowledge spillovers and from enhanced social capital, and thereby achieve a higher performance, if they locate themselves in the industry hub (Figure 1, models 1 and 3).

While the extant literature has provide insights into the effect of spawn location on their performance, relatively little is known about how agglomeration effects at the parent firm level, i.e. pre-founding of the new venture, affect the post-founding performance of the spawn. Yet, given the findings from the entrepreneurial spawning literature that suggest that capabilities and performance of spawns are shaped in the formative years of the venture and critically impacted by the characteristics of the parent firm, it would seem highly important to consider pre-founding agglomeration effects at the parent level when analyzing the determinants of spawn performance. This paper fills this gap by analyzing how pre-founding agglomeration effects affect performance of the entrepreneurial spawn while controlling for the actual location of the spawn.

Integrating the extent research on agglomeration effects and entrepreneurial spawning, we propose that pre-founding agglomeration effects critically shape the capabilities and performance of the entrepreneurial spawn. In particular, 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. The unique access to such 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. The human and social capital of the principal manager becomes a crucial resource of the new venture that critically influences the new venture's capabilities and performance.

The pre-founding conditions, experiences and resources of a new venture critically shapes the venture's future performance as they "imprint" the new ventures and shape their capabilities: the "imprinting hypothesis", originally developed by Stinchcombe (1965), posits that organizations are critically shaped by the historical resources on which their founders draw;

several studies have provided empirical evidence for founding conditions, initial resources, and founder's history imprinting on a new venture's strategy and future performance (Bamford, Dean, and McDougall 1999, Boeker, 1990; Harris and Ogbonna 1999; Johnson, 2007). The concept of imprinting seems particular important for a new firm's social capital and knowledge resources. Gulati, and Gargiulo (1999), Marquis (2003) and Milanov and Fernhaber (2009) demonstrate the size of and the firm's centrality in its initial network critically determines the size of and the firm's centrality in its future networks, and thereby its social capital that is crucial to its success. Similarly, Cohen and Levinthal (1990) show that a firms initial knowledge critically its ability to effectively absorb future knowledge and information. Consequently, the stock of knowledge resources and social capital that founders of entrepreneurial spawns are able to extract from their parent firm's shapes the spawn's post-founding capabilities and ultimately its performance. This critically accentuates the impact of pre-founding agglomeration effects at the parent level vis-à-vis the impact of post-founding agglomeration effects on the performance of entrepreneurial spawns.

Hence, since agglomeration effects pre-founding can be expected to increase the value of an individual's human and social capital, we propose that when managers leave their parent firm located in an industry's geographical hub in order to lead an entrepreneurial spawn, 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 contrasts with the extant agglomeration literature on entrepreneurship literature as it focuses on the location of the parent firm and pre-founding agglomeration effects as opposed to the location of the actual spawn and post founding agglomeration effects on spawn performance. In figure 1, Hypothesis 1 predicts a positive performance effect for models 1 and 2 while the extant literature predicts positive performance effects for models 1 and 3.

Insert figure 1 about here

Following Gompers, Lerner and Scharfstein (2005), and Klepper and Sleeper (2005) we also explicitly consider whether agglomeration effects influence the magnitude of spawning activity. We do this for two reasons: firstly, the idea that agglomeration effects at the parent level impact the magnitude of entrepreneurial spawning is a logical implication of our focal Hypothesis 1. Namely, if working in an industry hub increases the human and social capital of nascent entrepreneurs, we would expect individuals that intend to eventually start a hedge fund to prefer employment with incumbents firms in an industry hub over employment with non-centrally located firms. Moreover, the central embeddedness of the nascent entrepreneur in existing networks of customers and suppliers pre-founding facilitates the formation of relationship-specific investments that are critical to the formation of new ventures (Hellman, 2007). Hence, the enhanced value of the human and social capital of potential entrepreneurs working for incumbent firms located in industry hubs positively impacts on their chances of successfully starting a new venture. Thus, as logical implication of Hypothesis 1, we would expect that, ceteris paribus, more spawns are produced by parent firms in the industry hubs. Secondly, testing Hypothesis 2 will be crucial in assessing whether our focal Hypothesis 1 is consistent with equilibrium notion of investors making inferences about the quality of the fund manager and rationally allocating their funds.

> *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.*

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, and the private nature of the industry tends to create frictions between geographically distinct markets, which may magnify the importance of agglomeration effects.

While the first hedge fund was founded in 1946 by Alfred Winslow Jones, the hedge fund industry only 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 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.

Aside from factors such as more entrepreneurial autonomy and flexibility, the key driver of individuals leaving their jobs with incumbent financial services firms to found and manage hedge funds is the attractiveness of the external environment; hedge fund managers are amongst the most highly remunerated professionals in the world: the average annual compensation for a partner of a hedge fund in 2009 was estimated to be between $5m and $20m, compared to the annual salary of an investment banking managing director/ partner of approximately $1m (Institutional Investor, 2010). The conditions in the hedge fund industry fit closely with Hellmann's (2007) "entrepreneurial equilibrium"—employees own the IP and the external environment is very attractive—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 five 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. "Fund-of-Funds" invest in other hedge funds and thereby often represent heterogeneous strategies. However, within each investment style a wide number of trading strategies exist, which tends to moot the relevance a firms stated investment strategy.

Hedge funds 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. Hence, hedge fund firms generate high income if they have a large amount of assets under management or if they achieve high absolute returns. However, over time performance critically influences the assets under management hedge funds are able to attract. A hedge fund's performance is transparent and objectively measureable, and the predominant measure of performance is the abnormal return (Alpha).

We exploit the fact that hedge funds report a substantial amount of information about their managers and performance as an indirect marketing tool to gather data on hundreds of hedge fund start-ups. We use this information to analyze how agglomeration effects in managers' previous employment influence the post-performance of hedge fund spawns.

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 funds managers from 684 hedge fund firms from the MARhedge database, 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 a consolidated database but only in an on-screen format, we had two individuals enter the data independently into a database program, and afterwards 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 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

[2] Many hedge fund firms list only one manager, 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 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.

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 658 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, and 19 were ranked by Institutional Investor as being in the top 25 of securities trading firms.

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 based on several *factors,* as in equation (1):

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

where R_i is a fund's raw return net of fees charged to investors and the vector $\boldsymbol{X}$ contains factors that form the fund's expected return. In the standard 4-factor model we include the three Fama and 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 AUM 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, researchers 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 abnormal 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

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

factor from Pástor and Stambaugh (2002).[4] We windsorised the obtained 4- and 8-factor model alphas at the 1st and 99th percentile to avoid distortions due to extreme values.

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 a risk set of 17,299 firms. We then tested Hypothesis 2 using two dependent variables based on *SPAWNCOUNT*: a binary variable that indicates whether an incumbent has generated at least one spawn and *SPAWNCOUNT* itself.

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 the geographical hubs of the financial service industry—New York or London (New York and London 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.

Given the lack of more detailed information on the exact location of the entrepreneur's previous employment, the previous employer's headquarter location is a frequently used proxy in

[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 entrepreneurial spawning literature for the location of the entrepreneur's previous employment (e.g. Gompers, Lerner and Scharfstein, 2005; Klepper and Simons, 2000). In our sample, the vast majority of individuals worked for wholesale, corporate and investment banking divisions of financial institutions, and a large proportion of these divisions is traditionally co-located with the institutions' headquarter. 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 the hypothesized results. Moreover, it is plausible that even if the entrepreneur did not work actually in the *CENTER*, a headquarter location of the parent firm in the *CENTER* can still have a positive effect on the parent firm's knowledge and social capital resources that the entrepreneur can extract and leverage for the entrepreneurial spawn.

4.3. Empirical specifications and models

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:

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

where $\boldsymbol{X}$ is a vector of controls that might plausibly influence hedge fund performance and *c* indexes both job spell, hedge fund, and individual level controls. Hedge fund controls include the location, scope, size and age of hedge fund firm *i*. We use two location variables to control for post-founding agglomeration effects evidenced by the extant literature discussed earlier:

"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 average number of funds in the hedge fund firm (equal weighted by month), size is measured as the average firm-level aggregate AUM a hedge fund firm managed in the entire period of our analysis, 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]. In this regard, Chatterji (2009) provides indicative evidence for a positive relationship between industry relatedness and spawn performance. 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. On the individual hedge fund manager level we control for the ability of the hedge fund manager through dummy variables indicating the highest educational level achieved as well as the median SAT score of the highest educational institution attended[7]; in this regard, Chevalier and Ellison (1997) demonstrate that a fund manager's performance is correlated with the median SAT score of the educational institution attended suggesting that this is a good measure of a fund manager's ability. Standard errors are robust and clustered at the parent-firm level.

Table 2, Panel A shows the summary statistics for the variables used to test Hypothesis 1.

[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.
[7] As we do not have the median SAT scores for every observation (since we do not have the educational record for every individual in the sample and since some individuals went to non-US schools), we use binary variables for the quintiles of the institution's SAT score alongside missing information dummy variables.

58% of the job spells in our test sample were based at parent firms located in New York or London (*CENTER*), while 94% of the job spells were with financial services firms (*SIC6*), and 74% of the job spells were with financial services firms that were ranked as the top 25 securities trading firms by Institutional Investor 2000-2007. There are no significant correlations between the variables used to test Hypothesis 1. Interestingly, the correlation between parent firm location in the CENTER and hedge fund location in the CENTER is only 0.06.

In the absence of endogeneity, 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 selection effects. 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 deal with selection effects we use a propensity score matching approach to develop a valid control group.

Propensity score matching allows one to control for selection bias by creating a matched sample of treatment and control observations that are similar with respect to all observable characteristics (Rosenbaum and Rubin 1983). 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 size of parent firm (as measured by the logarithm of the number of employees), the rank of the university attended, as well as whether a manager's previous job spell was in the *CENTER*[8]. In particular, our set of control variables allows us to control for the quality of the parent firm and the ability of the hedge fund manager in particular, which we would expect to be important drivers in the selection bias of job spells involving the best parent firms and the best hedge fund manger occurring in the CENTER. In this regard, the past performance and ranking of parent firms are established measure of firm quality, and Chevalier and Ellison (1997) suggest that the median SAT score of the educational institution that fund managers attended is a good measure of their ability.

We use the predicted value of the probit regression to trim 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 run the 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). Compared to the standard approach of adding controls to a linear regression, the propensity score methodology is superior in that it 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. 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.

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[8] We included these variables in the first stage regression to further saturate the probit model and to predict the propensity score of a job spell occurring in the CENTER; we did not include these variables in the unmatched or matched OLS regression due to their correlation with other explanatory variables and their low explanatory power in the OLS analysis. Including these variables in the OLS analysis produced almost identical results.

[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 99% 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.

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: industry relatedness (*SIC6*), firm quality (Tobin's Q, and *RANKED*), and 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 this sample are located in the *CENTER* and 30% are financial services firms.

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 investors. The coefficient estimate of *CENTER* on 4-factor excess returns is 11 and 13 basis points per month (or 1.32% and 1.44% per year) without and with controls respectively, 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)[12]. Because the factor models, shown in equation (1)

[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 binary variables for the quintiles of the number of employees and for Tobin's Q respectively.
[12] We also tested whether our results are sensitive to outliers; when dropping to 5 observations with the highest and lowest performance, we obtained similar results.

above, do a good job picking up most of the variation in *ALPHA* the R^2s are low, and the point estimates on most of the controls are not statistically significant[13]. In this regard, it is important to note that a low R-squared does not mean that there is no meaningful relationship between the independent and dependent variable or that the effect found is of little empirical or theoretical relevance (Allison, 1999; Wooldridge, 2009). We take comfort in the fact that our estimates on *CENTER* are quite stable across specifications—that is the simple correlation between *CENTER* and *ALPHA* is not sensitive to observable omitted variables.

Notably, 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 most important when entrepreneurial spawns are in the formative stages with their founders still working for parent firms. Only firm scope is robustly significant as a control. The negative sign on firm scope suggests that firms with a larger scope generate lower returns than their more focused peers. It is worth noting that none of the individual level control variables measuring a manager's innate ability is robustly statistically significant.

Insert table 3 about here

Since the decision for an individual to work in the *CENTER*, and for an employer to hire that individual in the *CENTER* is endogenous, the results shown in Table 3 are potentially confounded. To adjust for endogenous sorting in our sample we rely on propensity score matching to control for selection on observables. The results of the propensity score matching analysis are displayed in Table 4. Column 1 shows the coefficients (marginal effects) from the probit model estimating the likelihood a job spell would occur in the *CENTER* conditional on a

[13] Low R^2s are common in regression analyses of the multi-factor abnormal market returns as the predictor factors used to compute them already capture a significant portion of the variance.

manager subsequently becoming a senior member 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. Interestingly, 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. Less surprisingly 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 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. The F-test for the joint difference in means between the two groups before matching is statistically significant at the 1% level. Figure 2A also reveals visually that the distributions of the propensity scores before matching are quite different between the two populations.

Insert table 4 about here

Figure 2B, which shows the distributions of the propensity scores predicting that a job spell occurred in the *CENTER* for the treatment and control groups after matching, reveals a much tighter 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 observable dimensions.

Insert figure 2 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; moreover, the coefficient estimates remain significant at the 5% level. Overall the matched sample results are consistent with the unmatched OLS estimates.

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. 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*. Interestingly a number of controls are statistically significant in column 2, particularly

RANKED, which increases the likelihood of spawning at least one hedge fund 25 times. *SIC6* firms with Tobin's Q in the top quintile (compared to the 2nd quintile) are 60% and 30% more likely to spawn at least one hedge fund, respectively, while firms in the bottom quintile of Tobin's Q are 10% less likely to spawn. Unsurprisingly 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. These results are consistent with Gompers, Lerner, and Scharfstein (2005) and Klepper and Simmons (2005). Taken together the controls suggest parent firm quality and relatedness increase the likelihood that the parent will spawn, which is consistent with the Fairchild view.

Columns 3 and 4 show zero inflated negative binomial regressions of *CENTER* on the number of spawns emanating from a parent firm without controls. Without controls the point estimate on CENTER is 1.53, which means firms in financial centers spawn 4.6 (exponential 1.53) more hedge funds than firms located outside of the financial centers. Including controls in model 4 improves the fit of the model while reducing the point estimate to 1.15 or 2.5 additional spawns, though the estimate remains quite precise. *RANKED* and *SIC6* remain economically and statistically significant in the zero inflated negative binomial (ZINB) specification, though 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). This is consistent with Gompers, Lerner, and Scharfstein (2005) and Klepper and Simmons (2005). Thus, the ZINB provides further confirms the prior literature in offering additional support for the Fairchild view with respect to the role of relatedness and firm quality, and provides evidence that the parent location positively impacts the rate of entrepreneurial spawning.[14] Furthermore, the empirical support for Hypothesis 2

[14] We also ran a zero-inflated Poisson model (ZIP) on the magnitude of entrepreneurial spawning and found similar results, though the log-likelihood ratio test between the ZINB and the ZIP indicated that the ZINB model is superior.

confirms Hypothesis 1 as it logically follows from it and as it indicates that our main finding in favor of Hypothesis 1 is consistent with the notion of rational investors making inferences about the quality of investment managers and committing investment funds.

Insert table 6 about here
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6. Discussion

We checked whether our results are robust to different forms of operationalization of our variables. Firstly, we constructed an alternative dependent variable to measure hedge fund firm accounting profits. In particular, we measure the average monthly amount of revenue a hedge fund firm is able to generate through management and incentive fees[15]. This is a function of the overall investment performance, the amount of the hedge fund's assets under management it is able to raise, and its fee pricing. Our qualitative research with hedge fund managers suggests that there is relatively small variance in the cost of hedge funds firms across firms and over time. However, we control for the cost of the hedge fund firms through the size and scope of the fund firm as well as its location. Ideally, we would have liked to directly measure the hedge fund firm's accounting profits; however, in the absence of data on the operating cost of hedge funds, given that we control for the main factors influencing the cost of hedge funds, we consider our measure a good representation of profit[16]. As the results of model i) in Table 7 show, we obtain support for our initial results when using this alternative measure of performance: the CENTER

The Vuong test indicated that the zero-inflated negative binomial model is superior to a regular negative binomial model so we present the ZINB results here.

[15] We take into account an investor's "watermark" hurdles when computing incentive fee revenues, i.e. we base the incentive fee revenue only on the return above the watermark. We perform this calculation separately for new funds committed in each year to accommodate for different investment time-spans and their corresponding watermarks.

[16] We were not able to obtain fee information for 52 observations, and hence, we conducted this analysis on 606 observations. We also control for the level of the incentive and management fees that funds charge, in addition to the control variables contained in $\boldsymbol{X_c}$ in equation 2; our dependent variable is transformed by the logarithm.

coefficient is positive and significant at the 10% level; the R-squared for this model is much higher at 83.8% which is consistent with our argument that the low R-squared for the main alpha regression is low to the inclusion of 4 and 8 factors to compute the abnormal return alpha.

Secondly, we test whether our results are robust to a different operationalization of our focal independent variable. In particular, we test whether splitting out the CENTER dummy variable into a New York and a London binary dummy variable confirms our results. As model ii) in Table 7 shows, our results are confirmed with the New York dummy being positive and significant at the 1% level and the London dummy being significant at the 10% level.

Thirdly, we test whether our results are robust to additional control variables. In model iii) Table 7, we include strategy fixed effects (six dummy variables that indicate whether the hedge fund firm operates at least one hedge fund with the strategy equity long/short, macro, arbitrage, event-driven, fund-of-funds, and other), and our results are fully confirmed with the CETNER coefficient positive and significant at the 5% level. Moreover, in model iv) Table 7, we include a variable that captures the pre-founding industry experience of the manager; as we only have this information for a part of the managers we use the average pre-founding experience for the missing observations and include a missing information dummy variable. Our results are fully confirmed with the CENTER coefficient being positive and significant at the 1% level[17].

Our analysis might still suffer from a biased sample as we only include public spawners in our analysis to test for Hypothesis 1 due to the lack of parent-level control data for private spawners. In order to test for such sample bias, we conducted an analysis that includes public and

[17] We did not include the strategy dummies in the main regression due to their correlation with other variables and their low explanatory power; we did not include the pre-founding experience variable in the main regression due to a higher number of missing information; it is noteworthy that our results are robust to different operationalization of our control variables including two digit SIC dummies (instead of SIC6), a linear scope variable, or time-fixed effect dummies of firm founding (in addition to or instead of a continuous age variable), as well as when using continuous operationalizations of the attended university's median SAT and ranking variables instead of quintile variables.

private spawners. We collect the information on the location of the headquarters of the private firms and we hand-coded the primary industry of the private firms using 4 categories[18]. In model v) in Table 7, we conducted an OLS analysis based on this sample (we had to exclude the Tobin's q variable as this information was not available for the private firms), and obtained support for our results with a positive CENTER coefficient being significant at 5%.

Insert table 7 about here

There are several possible alternative explanations for our main findings. Firstly, in the ideal experiment we would randomly assign individuals to job spells and to senior management positions in hedge funds. In practice, we must base our statistical tests on self-selected populations. Though we show that our results are robust to controlling for selection on observables, matching cannot control for unobservable differences between the treatment and control populations. In particular, we are unable to control for a manager's unobservable ability and how unobservable ability might influence an individual's decision to work in the *CENTER*. Heterogeneity in manager ability is important to the extent that it is observable to the managers themselves and/or to their parent firm but it is unobservable to the econometrician. In our case, our results might be confounded by managers with higher ability selecting themselves into job spells in the CENTER while weaker ability managers working for non-CENTER firms. There are two reasons that speak against this alternative explanation: firstly, our OLS analysis and matching model contains educational background covariates as well as covariates about the quality of the educational institution a manager attended; both should capture an important component of a manager's innate ability prior to their experiences with their parent firm(s); the

[18] The four hand coded categories are: Hedge funds & Alternative Investments; Banks; all other financial service firms; all non financial service firms.

fact that our OLS results are robust to controlling for these proxies of an individual's ability, and that the propensity score matching analysis fully confirms our initial findings provides evidence against the two alternative explanations. Secondly, we ran two separate sets of regressions, one set with only the CENTER variable against the 4- and 8-factor alphas, and one set with the CENTER variable and individual level characteristic variable (education and quality of educational institution attended) against the 4- and 8-factor model alphas. Following Bertrand, Luttmer, and Mullainathan (2000), if the individual level characteristics are correlated with the unobservable characteristics of the innate ability of the managers, then if the magnitude of the coefficient estimates of the CENTER variable does not change across the two regressions, it is unlikely that the unobservable characteristic are causing an endogeneity problem; in our case the coefficient estimates are almost identical and we fail to reject the Null hypothesis that there is a difference in the estimates between the regressions at the 10% level. However, while our analysis provides evidence against this alternative explanation, we cannot rule this out, and it is possible that some elements of the selection process remain outside our matching model. Thus, we must interpret our results cautiously.

Secondly, another alternative explanation is that the effect of a parent firm being located in the CENTER on spawn performance is due an alternative mechanism; for instance, it might be that firms in the CENTER are simply better firms, and consequently, employees of such firms get better trained and have access to better resources. In this case, it would not be agglomeration effects that lead to an increased human and social capital of nascent entrepreneurs but simply the "treatment" of working for a better firm. However, we found no evidence that the quality or performance of the parent firm positively impacts the spawn performance: both the ranking variable and the Tobin's Q variable are not significant and in some specification even negative.

Thirdly, another possible alternative explanation is that our results are spurious due to parent firm outliers; for instance, some parent firms might spawn a large number of very successful hedge fund firms, and these parent firms also happen to be located in the CENTER. A fixed effect model would enable us to rule out this alternative explanation. However, since focal variables such as CENTER are not time variant, this is not possible. Instead, in model vi) in Table 7, we included dummy variables for the firms that we consider most likely to be such outliers, namely the 8 bulge bracket investment banks Citi, Credit Suisse, Goldman Sachs, JP Morgan, Lehman Brothers, Merrill Lynch, Morgan Stanley, and UBS. Our initial results are fully confirmed with a positive CENTER variable significant at the 5% level.

Overall, the results of our main analysis, and our robustness checks as well as the evidence against the alternative explanations provide strong support a positive effect of pre-founding agglomeration effects on the post-founding performance of the entrepreneurial spawn. Figure 4 also demonstrated this graphically: Panel A depicts the distribution of the 8-factor alpha abnormal returns for spawns originating from CENTER and non-CENTER parents; the distributions are alike but with the CENTER distribution shifted to the right. In panel B we split the CENTER and non-CETNER observations in deciles and compare their means; in all 10 deciles the CENTER mean is bigger than the non-CETNER mean with the difference being significant at the 1% level in 8 deciles[19].

Insert figure 4 about here

Our empirical findings are consistent with the proposed theory that working for parent firms in the industry hub increases the human and social capital of nascent entrepreneurs such

[19] Similar graphs are obtained for the 4-factor model abnormal return.

that when they leave the parent firm to manage their own business they can leverage this enhanced human and social capital to achieve superior performance. Contrary to the prior literature, we do not find evidence that entrepreneurial spawns achieve better performance if they locate in an industry hub post-founding when controlling for pre-founding agglomeration effects; this suggests that the pre-founding agglomeration effects and the location of the parent firm critically determines the post-founding performance of spawns, and arguably more so, than post-founding agglomeration effects or the actual location of the spawn. This is consistent with our proposed theory of "imprinting" and the concept of absorptive capacity.

Our empirical results are also relevant for research on the origin and development of firm capabilities. In particular, our findings show that the capabilities of new firms are critically linked to the pre-founding experience of its managers, and particularly the human and social capital that its managers accumulated pre-founding. Our results suggest that a manager's pre-founding experience critically imprints the new firm, its resources and its capabilities.

There are several limitations to our study. Firstly, we do not directly measure human and social capital, and, therefore, cannot prove that these are the mechanisms underlying the parent firm location effects observed. While our findings are consistent with agglomeration effects operating at the level of an individual's human and social capital, it is possible that alternative mechanisms are at work. Secondly, our data does not allow us to directly measure in which location the hedge fund manager worked pre-founding. Instead, we use the headquarter location of the parent firm as a proxy for this. However, while this proxy seems reasonable and is established in the literature, it bears some measurement error and is imprecise. Further research that measures the direct location of an entrepreneur's pre-founding employment could improve upon this paper. Finally, it is important to note that our study focuses on a single-industry. While the hedge fund sector provides an appropriate setting for our study, our findings as well as their implications might not be fully applicable to other industries. Further research could test for parent location effects on entrepreneurial spawning and spawn performance in other industries to validate our findings.

7. Conclusion

By integrating research on the parent firm determinants of entrepreneurial spawn performance and agglomeration effects, we have examined the impact of pre-founding agglomeration effects at the parent firm level on the post-founding performance of the entrepreneurial spawn. In particular, we have developed and tested the proposition that parent firms located in an industry hub generate better performing spawns due to agglomeration effects that influence the human and social capital of nascent entrepreneurs when they are still employees of the parent firm. We have found 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 a hedge fund spawn. Taken together, the results suggest that nascent entrepreneurs working for parent firms located in industry hubs can benefit from pre-founding agglomeration effects and increase their human and social capital, such that when they leave their parent firms to lead a spawn, they are able to achieve superior performance. Interestingly, we do not find evidence for post-founding agglomeration effects of entrepreneurial spawns when controlling for pre-founding agglomeration effects. This accentuates the relative importance of pre-founding agglomeration effects vis-à-vis post founding agglomeration effects, and suggests that the entrepreneurs' pre-founding experience and human and social capital "imprints" the new spawn, and influences its capabilities and post-founding performance.

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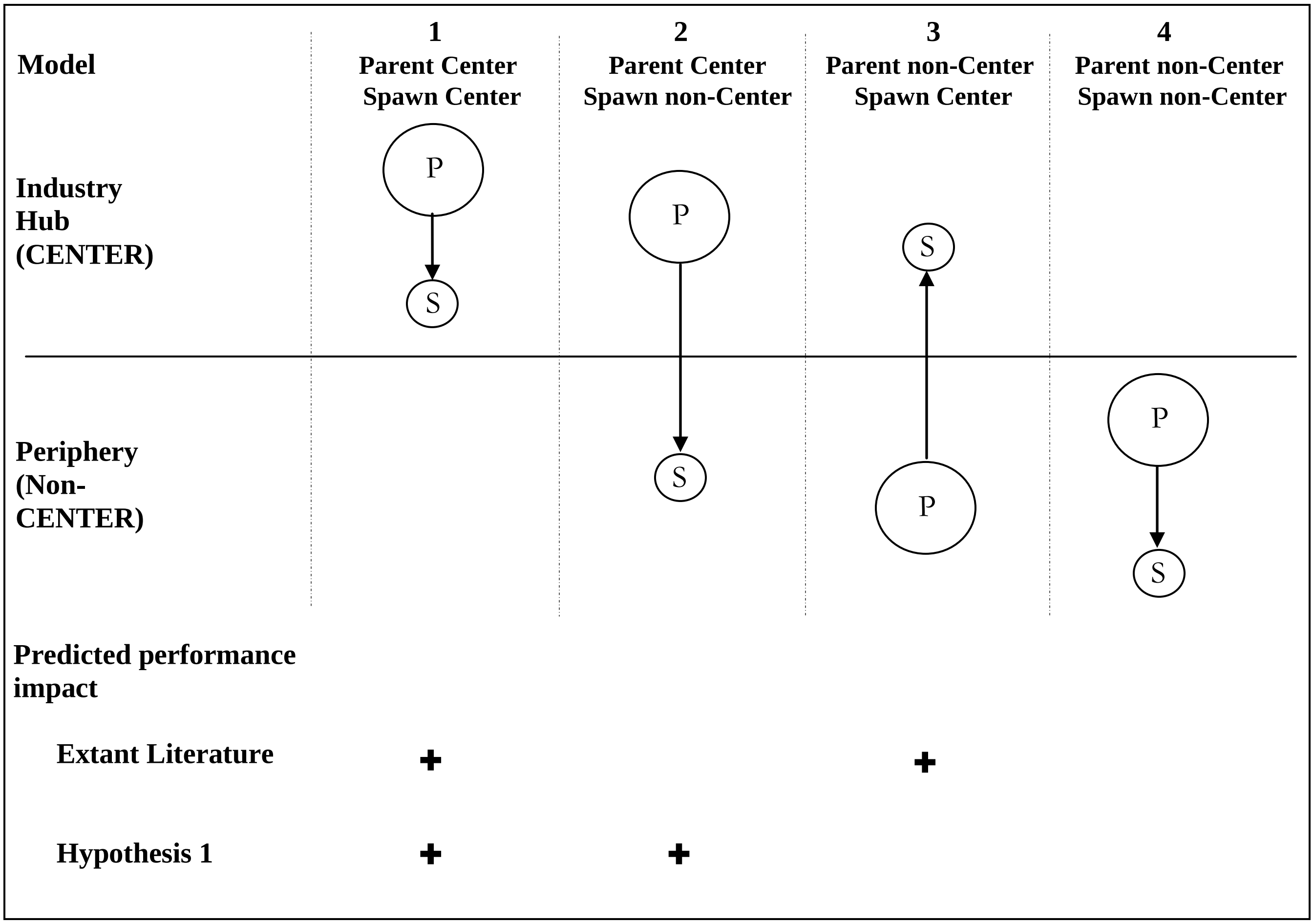
Figure 1
The geography of entrepreneurial spawning, and its impact on post-founding spawn performance



P = Parent Firm; S = Entrepreneurial Spawn

Figure 2
Distributions of the probabilities of job spells occurring in the CENTER before and after matching

Figure 2A: Kernel density distributions of the probability of a job spell occurring in the CENTER before matching (n=606)

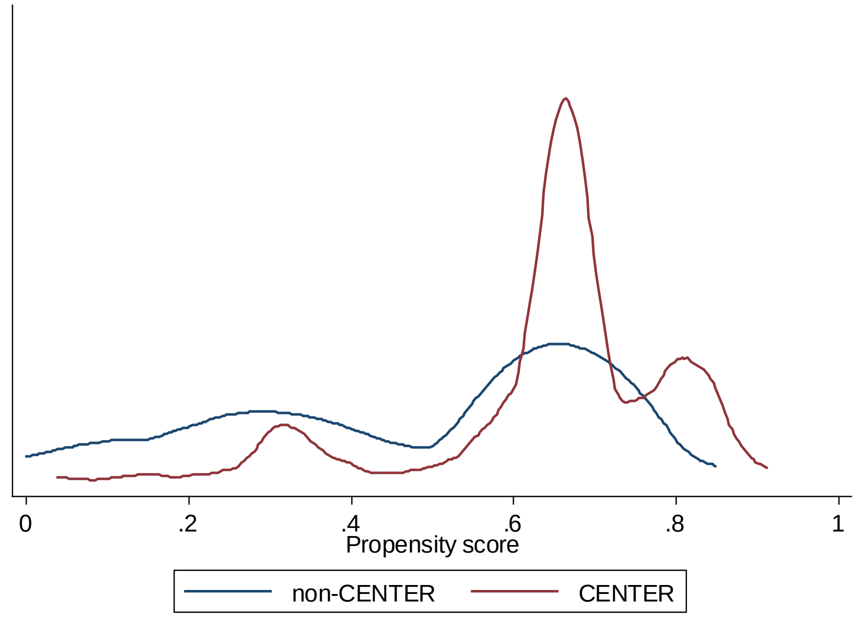


Figure 2B: Kernel density distributions of the probability of a job spell occurring in the CENTER after matching (n=464)

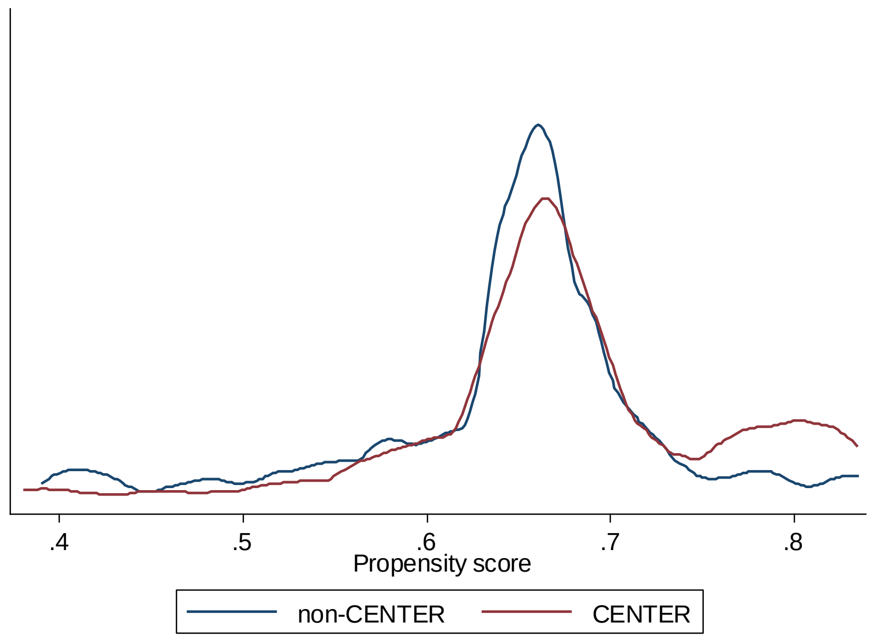


Figure 4

Distributions of the abnormal performance (alpha) by CENTER and non-CENTER distribution

Figure 4A: Kernel density distributions of the of 8-factor AUM weighted alphas by CENTER and non-CENTER distribution (n=480)

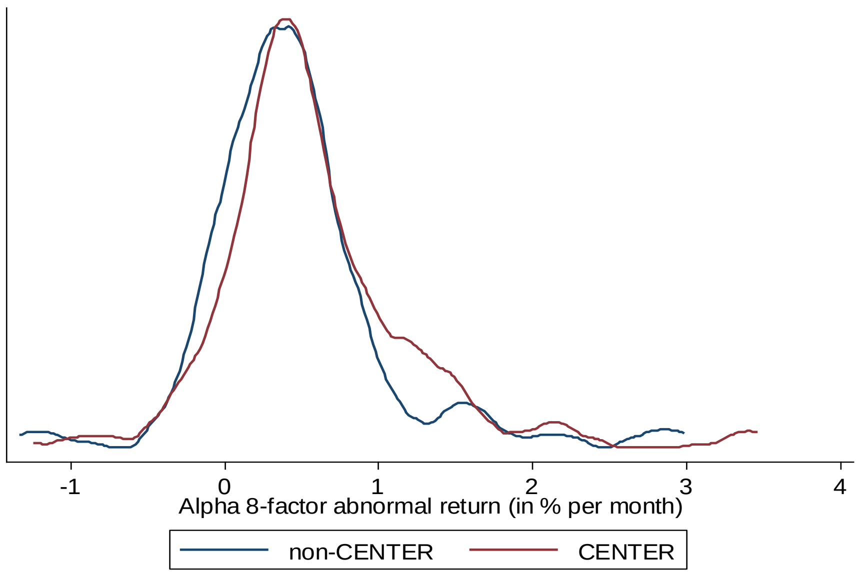
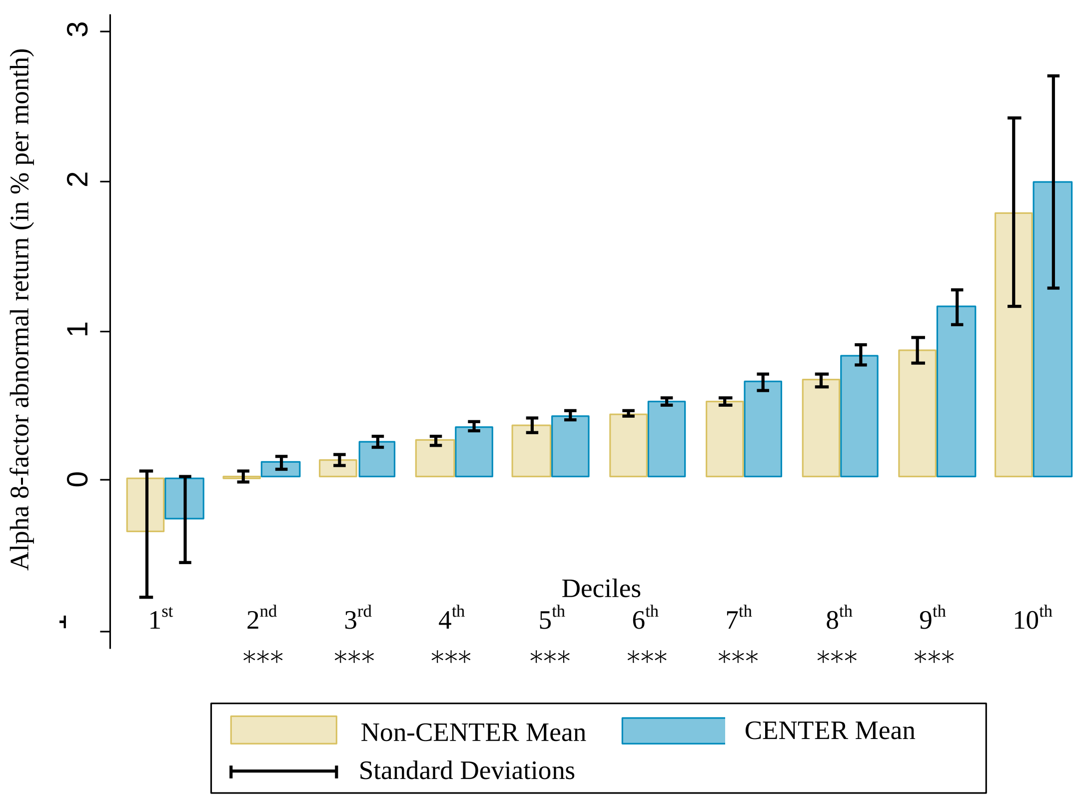


Figure 4B: 8-factor AUM-weighted alpha means and stand deviations by decile and by CENTER and non-CENTER distribution (n=480)



Statistical difference in alpha 8 factor performance means of CENTER and non-CETNER population:
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Table 1
Top 25 parent firms of the 95 parent firms in the sample

Firm	HQ Location	Ranked	SIC code	Employees (‘000)	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
Banker Trust	New York	N	60	21	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
Franklin Templeton	San Mateo	N	62	9	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=658) [20]

	mean	SD	min	max
Alpha 4-factor model (%/month)	0.42	0.57	-2.42	2.83
Alpha 8-factor model (%/month)	0.55	0.63	-1.33	3.47
CENTER	0.58	0.49	0	1
SIC6	0.94	0.23	0	1
Tobin's Q	1.21	0.59	0.88	8.11
RANKED in the top 25 by Institutional Investor '00-07	0.74	0.44	0	1
Hedge fund location in fin. center	0.46	0.50	0	1
Hedge fund location near fin. center	0.14	0.35	0	1
Hedge fund age (years)	7.35	4.24	2	24
Avg. number of hedge funds	4.14	5.19	1	53
Lifetime average AUM (in $m)	66.1	135.1	0.5	13,500
Manager: MBA dummy	0.36	0.48	0	1
Manager: PhD dummy	0.04	0.20	0	1
Manager: JD dummy	0.02	0.15	0	1
Manager: Other postgraduate degree	0.11	0.31	0	1
Manager: Median SAT score of highest education institution attended	1335.3	124	834	1495

Panel B: Spawncount analyses (n=17,299)[21]

	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

[20] There are no significant correlations between the variables used to test Hypothesis 1.
[21] There are no significant correlations between the variables used to test Hypothesis 2.

Table 3
Excess returns to investors

Dependent variable: AUM weighted average monthly excess returns (%)								
	(1) 4-factor ALPHA		(2) 4-factor ALPHA		(3) 8-factor ALPHA		(4) 8-factor ALPHA	
CENTER	***0.11***	***	***0.13***	***	***0.11***	**	***0.14***	***
	(0.04)		***(0.04)***		***(0.05)***		***(0.05)***	
SIC6			0.07				-0.11	
			(0.11)				(0.14)	
RANKED by Inst. Investor			-0.01				0.03	
			(0.05)				(0.05)	
Tobin's Q			0.00				0.04	
			(0.01)				(0.04)	
Hedge fund in center			-0.08	*			-0.03	
			(0.05)				(0.05)	
Hedge fund near center			-0.01				-0.03	
			(0.10)				(0.11)	
Hedge fund firm age			-0.01				-0.01	
			(0.01)				(0.01)	
Log avg. number of funds			-0.14	***			-0.10	**
			(0.03)				(0.04)	
Log lifetime avg. AUM (size)			0.04	**			0.03	
			(0.02)				(0.02)	
Graduate degree dummies			Included				Included	
SAT score quintile dummies			Included				Included	
Missing data dummies			Included				Included	
Constant	0.35	***	-0.27		0.49	***	0.13	
	(0.03)		(0.35)		(0.03)		(0.37)	
N	658		658		658		658	
R^2	0.01		0.07		0.01		0.07	

* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level
Standard errors (in parentheses) 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 Pástor 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 AUM 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	0.02		0.66		-0.62	
PhD dummy	-0.03		-0.32		0.35	
JD dummy	-0.08		0.63		0.15	
Other postgraduate degree dummy	0.20	***	-2.46	**	-0.80	
Graduate degree information missing	0.14		-0.86		0.39	
Avg. SAT undergrad.—quintile 5 (top)	-0.09		0.13		0.24	
Avg. SAT undergrad.—quintile 4	0.02		-1.34		-0.69	
Avg. SAT undergrad.—quintile 2	-0.04		-0.16		-0.68	
Avg. SAT undergrad.—quintile 1	0.09		1.29		0.10	
Avg. SAT score missing	-0.07		-0.13		0.61	
Rank undergrad. institution quint5 (top)	-0.04		1.05		0.12	
Rank undergrad.—quintile 4	-0.09		1.35		-0.12	
Rank undergrad.—quintile 2	-0.07		-0.30		-0.64	
Rank undergrad.—quintile 1	0.04		-0.97		-0.24	
Rank missing	-0.01		-0.41		0.63	
SIC6	0.20		-5.01	***	-1.97	*
RANKED by Institutional Investor	0.35	**	-9.10	***	-2.96	**
Tobin's Q	0.01		3.30	***	-0.52	
Tobin's Q missing	0.20		-0.40		-0.26	
Number of Employees (logged)	-0.01		-3.08	***	-0.65	
Number of Employees missing	-0.29		4.10	***	0.00	
Previous job spell in CENTER	0.76	***	-0.92		0.84	
Previous job spell missing	0.85	***	-0.96		0.84	
N	658		658		480	
Pseudo-R^2	0.14					
F-stat. for joint test of differences			5.82	***	1.21	

* 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: AUM weighted average monthly excess returns (%)				
	(1) 4-factor ALPHA		(2) 8-factor ALPHA	
CENTER	***0.11***	**	***0.14***	**
	(0.05)		***(0.06)***	
SIC6	0.32		0.03	
	(0.23)		(0.14)	
RANKED by Inst. Investor	-0.06		0.13	
	(0.11)		(0.11)	
Tobin's Q	-0.04		-0.02	
	(0.05)		(0.06)	
Hedge fund in center	-0.06		0.02	
	(0.06)		(0.07)	
Hedge fund near center	-0.02		0.05	
	(0.08)		(0.10)	
Hedge fund firm age	-0.00		-0.01	*
	(0.01)		(0.01)	
Log avg. number of funds	-0.13	***	-0.06	
	(0.03)		(0.04)	
Log lifetime avg. AUM (size)	0.01		0.01	
	(0.02)		(0.02)	
Graduate degree dummies	Included		Included	
SAT score quintile dummies	Included		Included	
Missing data dummies	Included		Included	
Constant	0.04		0.38	
	(0.27)		(0.41)	
N	480		480	
R^2	0.08		0.07	

* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level
Standard errors (in parentheses) 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 Pástor 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) <u>Probit</u>		(2) <u>Probit</u>		(3) <u>ZINB</u>		(4) <u>ZINB</u>	
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 (in parentheses) are robust and clustered at the parent-firm level.
Marginal effects displayed for probit models.

Table 7
Robustness checks

Dependent variable: AUM weighted average 8-factor monthly excess returns (%) unless otherwise specified		
Model variation	**Coefficient of focal independent variable**	
i) Alternative dependent variable: Log (hedge fund firm revenue); while controlling for factors influencing cost to proxy profit (n=606)	0.20 (0.12)	*
ii) Separating CENTER into New York and London dummies (n=658)		
NEW YORK	0.13 (0.05)	***
LONDON	0.19 (0.11)	*
iii) Including dummy variables for hedge fund strategy (n=658)	0.12 (0.05)	**
iv) Including pre-founding industry experience variable (n=658)	0.14 (0.05)	***
v) Private firm sample (n=1,058)	0.08 (0.03)	**
vi) Including dummy variables for bulge bracket investment banks (n=658)	0.15 (0.08)	**

* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level
Standard errors (in parentheses) are robust and clustered at the parent-firm level. Models i) to vi) include all covariates $\boldsymbol{X_c}$ as in equation 2, as well as additional control variables if specified. Similar results are obtained in models i) to vi) when using the 4-factor alpha as the dependent variable.

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