Dollars versus Sense: Investor Demand, Managerial Skill, and Hedge Fund Startups

Abstract

What motivates the creation of new hedge funds? New funds can either primarily cater to investor demand or offer new managerial skills. We hypothesize that skill-driven inceptions deliver better performance. Investor demand-driven funds inceptions are defined as those that follows high strategy-level returns and inflows or which are essentially clones of existing funds in the same family. In contrast, managerial supply-driven inceptions are those launched under low-demand conditions and that are not clones of existing funds. Empirically, we find that skill-driven inceptions outperform demand-driven inceptions on a risk-adjusted basis by 4–5% per year. Our findings suggest that hedge fund startups initiated by managers create more valuable investment opportunities for investors than fund startups initiated in response to investor demand. Moreover, our methodology can distinguish the two types of inceptions ex ante.

I. Introduction

The hedge fund industry has been notable for its dramatic growth over the last few decades. It was worth essentially nothing prior to the 1980s but ballooned rapidly to $3 trillion in assets under management (AUM) by 2015. During the financial crisis, the industry saw dramatic outflows but has since recovered to and surpassed its pre-crisis level. During this expansion, investors contributed capital to both existing and new funds. Although both inflows to existing funds and the inceptions of new funds are of great importance in explaining the vast growth of the hedge fund industry, the literature has focused only on the former, particularly on the relation between fund performance and subsequent fund flows (or vice versa).[1] By contrast, the literature on inceptions is relatively sparse.[2] This ignorance is surprising, given the prevalence of hedge fund inceptions in attracting capital to the industry; most currently operating hedge funds did not even exist a decade ago.

Our paper aims to fill this gap by examining the economics of hedge fund inceptions. Several important questions immediately emerge once the focus shifts from fund flows to inceptions: Are investments in new hedge funds, for instance, essentially substitutes for flows to existing funds? Or do some new funds provide valuable investment ideas and managerial skills to investors? If the answer to the second question is yes, can we identify these valuable inceptions ex

[1] See Goetzmann, Ingersoll, and Ross (2003), Agarwal, Daniel, and Naik (2004), Fung, Hsieh, Naik, and Ramadorai (2008), and Ding, Getmansky, Liang, and Wermers (2008) who examine the relations between inflows and performance. These studies are related to a vast literature on mutual fund flows. References include Chevalier and Ellison (1997), Sirri and Tufano (1998), Zheng (1999), Lynch and Musto (2003), Berk and Green (2004), Sapp and Tiwari (2004), Huang, Wei, and Yan (2007), and Keswani and Stolin (2008).

[2] The only such paper in the hedge fund literature is that of Agarwal and Jorion (2010). They examine the performance of new hedge funds and find that these funds outperform for the first two to three years of existence. In the mutual fund literature, Khorana and Servaes (1999) examine the economic determinants of mutual fund startups.

ante? We examine these issues by analyzing the incentives for fund managers to launch new funds and linking such incentives to fund performance.

Our key intuition is that the incentives to start new hedge funds may vary drastically in the cross section or over time. In particular, we argue that new fund creation is likely to be driven by two important economic factors: investor demand for known investment opportunities and the supply of new managerial skills. On the one hand, the creation of new funds can be motivated by excess demand for investment opportunities. Due to diseconomies of scale (e.g., Goetzmann, Ingersoll, and Ross, 2003; Getmansky, Lo, and Makarov, 2004; Fung, Hsieh, Naik, and Ramadorai, 2008; Teo, 2009), existing funds that grow too large may experience degraded performance. It is therefore optimal for the hedge fund industry to use new funds to absorb excess capital supplied by investors (which could otherwise trigger severe diseconomies of scale if this capital were to flow into existing funds), even if these new funds follow similar strategies to those of existing ones. We refer to hedge fund inceptions motivated by the availability of investor capital as *demand-driven* (or *investor-driven*) inceptions.

On the other hand, inceptions may be initiated by new or existing managers who have identified new investment opportunities or trading strategies. We can think of these skill-driven trading opportunities as positive shocks to the supply of managerial skills offered by the hedge fund industry. We refer to inceptions motivated by new talent or ideas as *supply-driven* (or *manager-driven*) inceptions. Supply-driven inceptions stand out especially when investor demand is low. In this case, inceptions are likely to face additional scrutiny, since the managers of new funds need to convince investors of their value before these funds can raise sufficient capital to launch. New funds that successfully go live in the latter environment, therefore, are likely to provide new skills or investment opportunities.

The above intuition allows us to not only differentiate the role of new hedge funds from that of flows to existing funds—that is, new skills can be brought to the hedge fund industry via the emergence of new funds in general and supply-driven inceptions in particular—but also to make inferences about the potential distribution of managerial skills and performance across new hedge funds. In particular, supply-driven inceptions, by offering new managerial skills and investment opportunities, are likely to deliver superior performance. Moreover, since excess demand from investors may reduce the economic rent that investors can receive vis-à-vis fund managers (i.e., Berk and Green, 2004), supply-driven inceptions are also likely to outperform peer demand-driven inceptions on a risk-adjusted basis.

We test these hypotheses using the Lipper TASS database over the period from 1994 to 2013. Our main findings are intuitively illustrated in Figure 3, which plots the long-term performance (cumulative abnormal returns) for up to 10 years of both demand- and supply-driven inceptions. We discuss the details of how to identify these two different types of inceptions below. The graph clearly shows that, in the long run, supply-driven inceptions deliver superior performance in general and outperform demand-driven inceptions in particular. The performance gap between the two types of inceptions can amount to as much as 30% over a 10-year horizon.

We rely on three identification strategies to proxy for demand- and supply-driven inceptions. First, we exploit variation in terms of "hot" and "cold" hedge fund strategy classifications. Since investors are known to chase past performance, strategy categories with superior past performance may become hot when investors chase performance, whereas others become cold due to lower return. We use past 36-month strategy return and flows to measure whether hedge fund strategy classifications are hot or not (where hot strategy categories are associated with high strategy inflows and return). When a new hedge fund is created during a hot (cold) period for that strategy, we classify it as a demand-driven (supply-driven) inception. Empirically, we find that, over the 60-month period after initial inception, supply-driven inceptions significantly outperform demand-driven inceptions by 0.295% per month, or 3.6% per year, on a risk-adjusted basis.

Second, we explore the role that hedge fund families play in launching new funds. Importantly, new funds in an existing hedge fund family may closely mimic (*clone* inceptions) or drastically differ from existing funds in the family (*non-clone* inceptions). A clone inception can happen when a fund family faces high investor demand for their existing funds and chooses to create a new yet similar fund to absorb excess capital (i.e., the inception is demand-driven). By contrast, a non-clone inception is more likely to be supply-driven, since the family lacks reputation in the proposed strategy category and needs to convince investors of the value that the new fund can deliver. We find that non-clone inceptions within families outperform clone funds on a risk-adjusted basis by about 1.5–2% per year, suggesting that non-clone funds provide valuable new ideas to the hedge fund universe relative to their clone peers.

Our final identification strategy combines the above two methods and argues that a clone inception is more likely demand-driven when it is in a hot strategy category and that a non-clone inception focusing on a cold strategy category is especially likely to be supply-driven. This combined approach has the most significant power to differentiate demand- from supply-driven inceptions. Supply-driven clone funds thus identified can deliver a risk-adjusted performance of 0.469% per month, or a compounded 5.78% per year. The performance gap between supply-driven clone funds and demand-driven non-clone funds amounts to 0.375% per month, or 4.6% per year, which is highly significant, both statistically and economically speaking. These results suggest that inceptions driven by the supply of new managerial skills are likely to deliver superior performance and outperform demand-driven inceptions.

Our paper contributes to several strands of the literature. To the best of our knowledge, we are the first to explore the economics of hedge fund inceptions in terms of demand (of investors) and supply (of managerial skills). Our results contribute to the literature on fund performance. The question of whether hedge fund managers are informed and can deliver superior performance is at the core of the hedge fund industry (Fung and Hsieh, 1997; Ackermann, McEnally, and Ravenscraft, 1999; Agarwal and Naik, 2004; Getmansky, Lo, and Makarov, 2004; Kosowski, Naik, and Teo, 2007; Agarwal, Daniel, and Naik, 2009, 2011; Aragon and Nanda, 2012; Sun, Wang, and Zheng, 2012; Cao, Chen, Liang, and Lo, 2013). Our unique contribution is to examine how new talent *enters* the hedge fund industry.

Our study also contributes to the literature examining fund flows as well as the relation between flow and performance (e.g., Goetzmann, Ingersoll, and Ross, 2003; Agarwal, Daniel, and, Naik 2004; Fung, Hsieh, Naik, and Ramadorai, 2008; Ding, Getmansky, Liang, and Wermers, 2009). We extend this literature by demonstrating that, under certain conditions, new funds can be used as a substitute for existing flows. More importantly, we show that we can predict future performance based on inception conditions. This inference suggests that, in addition to the traditional performance-flow relation, a flow-performance relation may exist in the hedge fund industry. This reverse causality has important normative implications. Investors and policy makers interested in seeking innovative and high-performing funds, for instance, can use our methodology to identify supply-driven funds.

The remainder of the paper proceeds as follows. Section II develops the testable hypotheses. Section III describes the hedge fund data we use in our analysis. Section IV examines the determinants of inception probability. Section V evaluates the performance of inceptions in times of strong and weak strategy and family demand. Section VI examines the robustness of our methods. Concluding remarks are provided in Section VII.

II. Hypothesis Development

An investor seeking exposure to the hedge fund industry has two choices. The first is to invest in an existing fund with a known track record. However, diseconomies of scale are a key characteristic of the type of "arbitrage in expectations" returns expected in the hedge fund industry. Unlike mutual funds, which, in some cases, can scale up significantly without suffering a performance penalty, hedge funds may be reluctant to accept new capital contributions, as discussed by Goetzmann, Ingersoll, and Ross (2003). A large and positive shock to investor demand, therefore, is likely to trigger hedge fund inceptions. We refer to inceptions aiming to serve investor demand as *demand-driven* inceptions. On the other hand, managers who have developed new skills or discovered new investment opportunities may be the main driving force for some inceptions. We refer to inceptions initiated to offer new managerial skills as *manager-driven* or *supply-driven inceptions*. Because this type of inception lacks the advantage of reputation and track record, it is likely subject to more intense scrutiny by investors and may face greater barriers to entry.

Demand- and supply-initiated inceptions play different economic roles and, consequently, deliver different performance. First, the impact of excess investor demand on the incentives of new funds is nontrivial. When competition among investors is high, investors' scrutiny of new funds is relatively weak (e.g., Berk and Green 2004). New funds may be launched under these circumstances that would not make a compelling enough case to investors during less favorable times. If investor discretion is effective at distinguishing promising funds from those with little potential, then funds that were able to start up only because investor demand was high are unlikely to outperform existing funds. By contrast, managers starting funds when investor demand is low will need to present a compelling case to convince investors to contribute initial capital. If investors are able to identify promising new ideas, then funds that were able to attract capital during times of low investor demand in their strategy category are likely to provide valuable new investment ideas and skills. Furthermore, new funds arising during times of low investor demand are likely to outperform new funds that have the primary objective of absorbing investor demand. This line of thought leads to the following hypothesis.

Hypothesis 1 (incentives of inceptions): Hedge fund inceptions can be driven either by investor demand (demand- or investor-driven inceptions) or by the supply of new managerial skills (supply- or manager-driven inceptions). On a risk-adjusted basis, manager-initiated inceptions are likely to deliver superior performance in general and outperform investor-initiated inceptions in particular.

The null hypothesis is that all inceptions are identical in terms of incentives and performance. To test this hypothesis, we need to identify the two types of inceptions based on solid economic grounds. It is easy to see that demand-driven inceptions are likely to arise when conditions for raising money are favorable for their investment strategies. We propose three identification strategies, which we present as testable hypotheses, based on this intuition.

First, since investors are known to chase past performance, inceptions in hot categories—those witnessing high past inflows and performance—are likely to be driven by strong investor demand. Interestingly, the supply of new managerial talent can be related to investor demand conditions as well. Although hot strategy categories and the supply of new managerial skills may not be mutually exclusive, new funds launched in cold strategy categories—that is, those with low inflows and past performance—are likely to be manager driven because there is no particular need or opportunity for funds to absorb investor demand during these periods. This observation offers one identification strategy that we will use to pin down demand- and supply-driven inceptions, which we summarize in the following hypothesis.

Hypothesis 1A (hot vs. cold strategies): Hedge fund inceptions in hot (cold) strategy categories are likely to be investor (manager) driven. Hence, inceptions in cold strategy categories are likely to deliver superior risk-adjusted performance in general and outperform inceptions in hot strategy categories.

Family structure is also related to inception motivation. When a hedge fund strategy is in high demand, management companies have two options. The first is to allow new capital to flow into its existing funds. The second is to create a new fund with the same investment objectives. While the new fund may differ from existing funds in clientele, fee structure, share restrictions, share class, currency, or other fund characteristics, it does not represent innovation in terms of investment strategy and ideas. We consider flows to these clone funds to be substitutes for flows to existing funds.

When a management company faces a shock to its supply of management skill in the form of a new manager or investment idea, it may allow the manager to create a new fund with little in common with existing funds in the family. Although the new fund may use the same legal infrastructure as existing funds, its performance and investments are distinct from those of existing funds. In terms of investment innovation, the new fund is similar to funds that start a new management company. This observation leads to our second identification strategy.

Hypothesis 1B (clones and non-clones): Clone (non-clone) inceptions in existing families are likely to be investor (manager) driven. Hence, non-clone inceptions deliver superior risk-adjusted performance in general and outperform clone funds in particular.

Khorana and Servaes (1999) and Aggarwal and Jorion (2010) argue that fund managers have the strongest incentive to deliver alpha in the early stage of their career. The manager of a clone fund does not have these same circumstances, since the clone fund's reputation depends on an already existing fund with a known track record. Investors in a clone fund are essentially looking for the returns of the existing fund the clone fund mimics.

Finally, since investing in hot/cold categories and the inception of clone/non-clone funds reflect different aspects of the same economic phenomenon, we combine the two above approaches to arrive at a sharper identification strategy: we identify demand-driven inceptions as clone inceptions in hot categories and supply-driven inceptions as non-clone inceptions in cold categories. The hypothesis associated with this identification strategy is as follows.

Hypothesis 1C (clones in hot/cold strategies): Clone inceptions in hot strategy categories are likely to be manager driven, while non-clone inceptions in cold strategies categories are likely to be investor driven. Hence, the latter type of inceptions will deliver superior performance in general and outperform the former in particular.

After we understand the economic motivations for inceptions, we take one step further and ask whether (the two different types of) inceptions create value for investors with respect to existing funds. Since demand-driven inceptions aim to provide a substitute for existing funds, the performance of this type of inception is likely to be on par with that of already existing funds. By contrast, manager-driven inceptions will outperform existing funds if this type of inception is truly driven by new talents and skills. These considerations lead to the following hypothesis.

Hypothesis 2 (value-creating inceptions): Manager-driven inceptions are likely to be value creating and associated with better performance than existing funds, whereas investor-driven inceptions are a substitute for existing funds and on par with existing funds in terms of performance.

III. Data Description

Monthly hedge fund data come from the Lipper TASS database and the sample period extends from 1994 through 2013. We use this database to identify inceptions and compute monthly inflows. Unless otherwise specified, we always report hedge fund returns in excess of the risk-free rate. Furthermore, we use the seven-factor model from Fung and Hsieh (2001, 2004) to evaluate the risk-adjusted return (hereafter *alpha*). The seven factors are constructed following the instructions from David Hsieh's Hedge Fund Data Library.[3]

Hedge funds reporting returns and AUM time series to TASS include information about their management company (family) as well as their inception dates. They also provide a broad description of their investment strategy by selecting one of the main strategies used by TASS for

[3] https://faculty.fuqua.duke.edu/~dah7/HFData.htm.

classification. We refer to this as the fund's strategy category, or simply its strategy. Table 1 presents the number of funds reporting a valid AUM at the end of each year in each of the 10 hedge fund strategies we examine, namely, convertible arbitrage (CA), dedicated short bias (DS), event driven (ED), emerging markets (EM), equity market neutral (EMN), fixed income arbitrage (FI), global macro (GM), long/short equity (LS), managed futures (MF) and multi-strategy (MS). We exclude funds reporting other, minor, strategies. In addition, we exclude funds of funds because the focus of this analysis is on the creation of individual hedge funds.

The total number of funds in our sample has steadily increased through most of its history, though the number of funds in individual strategies has grown and shrunk significantly as funds have exited and either investor demand for new funds or the supply of new managers has languished. We also report the number of distinct managers (families) reported to TASS by our hedge fund sample. Over time, the average number of funds per family has increased from 1.38 at the beginning of our sample period to 2.97 by the end. The fraction of management families with multiple funds has also increased gradually over our sample period, from 24% in 1994 to 42% at the end of 2013. Nevertheless, in all years, more than half of families manage only one fund.

Table 2 reports the number of new funds per year as well as the proportion of funds that are new that year. Since the number of live funds in the hedge fund universe has grown over time, the proportion of the universe represented by new funds has decreased from 26% in 1994 down to 3% in 2013. We also report the total AUM of new funds raised each year. Because some funds do not report a valid AUM in the month of their inception, we consider the inception AUM to be the first non-missing reported AUM in the first three months of a fund's life. Funds not reporting a valid AUM in their first three months are excluded from this investigation (and from all analyses involving inception AUM). Inception AUM grew from \$1.14 billion in 1994 to \$12.46 billion in

2007. Less was raised by new funds during 2008 and 2009, returning to about \$12.29 billion in 2011.

We also report new flows to existing funds each year, partitioned by the age of the fund in the month in which flows were received. Flows are computed based on performance and the actual or estimated AUM numbers reported to the TASS database:

$$\mathrm{Flow}_{\mathrm{n,t}} = \mathrm{AUM}_{\mathrm{n,t}} - \mathrm{AUM}_{\mathrm{n,t-1}} \cdot (1 + \mathrm{r}_{t-1,\mathrm{t}}) \tag{1}$$

where fund flows and AUM are reported in US dollars (we convert any AUM reported in another currency to its value in US dollars at that time). Later we use the normalized flow, which is the flow in month *t* divided by lagged AUM. The variable $r_{t-1,\mathrm{t}}$ represents the return to fund *n* in the month between *t* - 1 and *t*. The time-series correlation between flows to funds less than a year old and new inception AUM is 0.29, while the correlation between new AUM flows and flows to older funds is significantly lower: 0.06 for funds between one and five years old and 0.05 for funds older than five years. In contrast, flows to older funds are relatively highly correlated (0.75 between funds one to five years old and funds older than five years).

Table 3 examines the inceptions we use in our analysis (only funds with 12 valid monthly observations are included) and divides them into groups defined by whether the inception is the first fund in its reported family or a new inception in an existing family. Additionally, we report how many of the inceptions in existing families are clones of other funds in those families. A new inception in an existing family is categorized as a clone if it is in the same strategy category (long/short equity, event driven, etc.) as an existing fund in the family and if the fund has a return correlation with the previously existing fund of 90% or greater. Overall just over half of the inceptions in our sample (6,156) began new management companies and nearly half (5,335) are inceptions in existing families. Of the inceptions in existing families, about half (2583) are classified as non-clone funds. Overall, our sample contains 11,491 inceptions.

Using monthly performance information, we construct the raw and risk-adjusted performance measures of funds and portfolios of funds. In each case, we measure raw performance by finding the 60-month excess returns of each fund over the risk-free rate. Risk-adjusted returns are computed as the intercept (alpha) from a 60-month regression of fund excess returns on the seven hedge fund risk factors proposed by Fung and Hsieh (2004). The regression equation is

$$\begin{aligned} r_{p,t} = \alpha_p + \beta_{p,1} MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} YLDCHG_t + \beta_{p,4} BAAMTSY_t \\ + \beta_{p,5} PTFSBD_t + \beta_{p,6} PTFSFX_t + \beta_{p,7} PTFSCOM_t + \varepsilon_{p,t} \end{aligned} \tag{2}$$

where $r_{p,t}$ is the monthly return to portfolio *p* in month *t*, *MKT* is the excess return to the market, *SMB* is the small-minus-big size factor, *YLDCHG* is the monthly change in the 10-year Treasury constant maturity yield, *BAAMTSY* is monthly change in Moody's Baa yield less the 10-year Treasury constant maturity yield, and the other three variables are trend-following factors created by Fung and Hsieh and available on Hsieh's website: PTFSBD (bond), PTFSFX (currency), and PTFSCOM (commodity). The intercept (alpha) from these regressions provides a measure of the risk-adjusted performance of the portfolio.

IV. Inceptions and Performance: A General Analysis

Before explicitly categorizing inceptions as either demand or supply initiated, we first examine how various characteristics of hedge fund strategy classifications and fund families—especially those related to hot/cold strategies and clone funds—may affect the incentives of inceptions, as well as their performance in general.

A. Incentives for Hedge Fund Inceptions

We start with a logistic regression specification of the incidence of hedge fund inception by date, strategy category, and family, linking the incentives of launching new hedge funds to a list of category and family characteristics. The dependent variable is set to one when a family had an inception in a given year and strategy category and zero otherwise. The logistic regression equation is

$$\mathrm{Inception}_{j,k,t} = \Lambda(\beta \times X_{j,t-1} + \psi \times Y_{k,t-1}) + \varepsilon_{j,k,t} \tag{3}$$

where $\Lambda(\cdot)$ represents the logistic link function and $X_{j,t-1}$ is a vector of strategy explanatory variables for strategy category j and year t and $Y_{k,t}$ is a vector of family explanatory variables for family k and year t. Strategy return is the average monthly return of an equal-weighted portfolio of funds in each strategy category in year t - 1. Family return is similarly defined. Strategy and family volatility are computed from equal-weighted portfolios of funds over the 24 months prior to year t. Strategy and family AUM are the sum of reported AUM in December of year t - 1. Family assets in the same strategy category is the sum of reported assets in strategy category j and family k at the end of year t - 1. Normalized strategy inceptions is the number of inceptions by strategy category j in year t - 1, normalized by the number of funds in strategy category j at the end of year t - 2. Large Family Open is set to one if one of the largest eight hedge fund families had an inception in strategy category j in year t - 1. Inceptions in family is the count of inceptions in family k in year t - 1. In all models, year fixed effects are included as yearly dummy variables in the regression.

Table 4 reports the estimation results. Specifications (1) through (4) include only strategy/family/years for families that existed in the previous two years. For these specifications, the coefficients can be interpreted as effects on the probability of a new fund inception in an existing family, but they exclude hedge fund inceptions that begin new families. For specification

(5), we include the effects on the probability of a new fund inception by expanding the sample to include funds that were excluded because their families had a track record of less than two years. In this specification, we set all family-level variables to zero for these short-history funds. Additionally, we include a dummy variable to distinguish the observations included in the first four specifications from the additional data. Because of the added new-fund observations, the number of observations in specification (5) is larger than that of specifications (2), (3), and (4).

The estimation results in specification (4) show that lagged strategy category returns and lagged inceptions positively predict inceptions in a family/year/strategy with coefficients of 28.53 and 0.79, respectively (t-statistics = 6.44 and 2.97). Flow to the family also predicts inceptions in the family (estimate = 0.328, t-statistic = 6.16 in specification (4)), suggesting that, many inceptions are demand driven. High assets in a given strategy also predict inception supporting the idea that clone funds, in particular, launch because existing funds in the family are already large and unwilling to absorb more capital from investors. The results from specification (4) reveal an interaction effect: Families with high assets in the previous year in categories that had good returns in the previous year are particularly likely to have an inception (estimate = 12.18, t-statistic = 2.02).

In specification (5), we add inceptions that begin new families to the regression and zero out all family variables for these funds. This approach has the effect of including family/year/strategies for the first couple of years of the families' existence and increasing our sample size. Broadly speaking, the results of specification (5) are consistent with those of the specifications that use only data from inceptions in existing families. Strategy return, in particular, is highly predictive of inceptions in this specification (estimate = 36.19, t-statistic = 14.67). In specification (5), the strategy flow coefficient is negative (estimate = -11.07, t = statistic = -6.3) after accounting for the effects of other variables.

Taken together, family and strategy indicators of inceptions, flows, and returns positively predict future inceptions, indicating that these factors create a high-investor demand environment in which initiating a fund is relatively easy. These observations lend support to our three identification strategies, which we will use to examine the implications of the two types of inceptions.

B. Performance and Characteristics

To further understand whether characteristics related to hot/cold strategy categories and clone/non-clone conditions are directly linked to performance incentives, we now link fund performance to ex ante fund characteristics. If good performance in new funds is concentrated in funds that represent new ideas and managerial skill, then characteristics associated with new managerial skill will be positively related to performance. We examine the relation between characteristics that are potential proxies for managerial skill and both the raw and risk-adjusted performance of the associated inceptions.

In Tables 5 and 6, we investigate the strategy category and fund-level variables associated with higher inception performance (over the first 60 months of the fund's life) using a cross-sectional regression methodology. In Table 5, we regress 60-month excess returns to a given fund on its past strategy flows, inceptions, returns, and volatility, as well as a dummy variable for whether the fund is the first in its family and whether it is a non-clone inception in an existing family (with clone as the omitted dummy variable). We also include year fixed effects and a control for the size of the inception. Because a number of inceptions do not have an associated reported AUM, we examine this characteristic by creating a dummy variable that equals one if the fund is missing the inception AUM and we also set inception AUM to zero when it is missing. The regression equation is

$$
\begin{aligned}
\text{Performance}_{i,j,[1,60]} &= \alpha + \beta_1 \text{NormFlow}_{j,[-36,-1]} \\
&+ \beta_2 \text{Inceptions}_{j,[-12,-1]} + \beta_3 \text{Ret}_{j,[-36,-1]} + \beta_4 \text{Vol}_{j,[-24,-1]} \\
&+ \beta_5 \text{FirstInFamily}_i + \beta_6 \text{NonClone}_i + \beta_7 \text{InceptionAUM}_i \\
&+ \beta_8 \text{MissingInception}_i + \varepsilon_{i,j}
\end{aligned} \tag{4}
$$

where Performance_i is the cumulative return for fund i over the first 60 months after its inception; NormFlow_j is the lagged flow to the strategy category, j, containing fund i before its inception, normalized by the strategy AUM in that strategy category at the beginning of that period; Inceptions_j is the lagged number of inceptions in the strategy category, j, containing fund i before its inception, normalized by the number of funds in that strategy; Ret_j is the lagged strategy return (equally weighted) for the strategy category containing fund i prior to its inception and Vol_j is the strategy return volatility over the two years prior to the inception of fund i; FirstInFamily_i is a dummy variable set to one if fund i is the first fund in its family and NonClone_i is a dummy set to one if the fund is not the first in its family but is not a clone fund either (i.e., it is in a different strategy category than existing funds in the family or has a return correlation below 90% with existing funds in the family). The omitted dummy variable is Clone_i, representing inceptions in existing families that are clones of existing funds in the family (same strategy and a correlation higher than 90%). The variable InceptionAUM_i is the total AUM in the first reported month of fund i's life (set to zero if no AUM is reported within the first three months after inception) and $\text{MissingInception}_i$ is a dummy that is set to one when no AUM for fund I was reported in the first month (capturing the average effect for funds for which we do not know the inception AUM).

In each specification in Table 5, the lagged strategy flow (normalized by the strategy AUM) negatively predicts the subsequent performance of the inceptions in that strategy (-9.094 in specification (4), t-statistic = -4.55). In addition, in specification (3), the past strategy return negatively predicts inception performance, with a coefficient of -8.148 and a t-statistic of -1.86, though the coefficient is not significant when other variables are added in specification (4). These results suggest that inceptions in high-demand environments as measured by normalized strategy flow have lower subsequent returns. In specification (4), we also see that the dummies for being a non-clone inception in an existing family and for being the first fund in a family positively predict subsequent 60-month returns. In addition, strategy volatility positively predicts the future performance of inceptions during that period. This finding suggests that the period after high volatility in a strategy is also a period of low demand for new funds, perhaps because investors view volatile categories as less desirable.

In Table 6, we examine the relation between risk-adjusted performance and inception characteristics. Our measure of risk-adjusted performance is the alpha coefficient from a regression of the 60-month returns from hedge fund i beginning at the time of its inception on the hedge fund risk factors suggested by Fung and Hsieh (2004). The regression equation for Table 6 is

$$\begin{aligned}\alpha_{i,j} = \delta + \beta_1 \mathrm{NormFlow}_{\mathrm{j},[-36,-1]} + \beta_2 \mathrm{Inceptions}_{\mathrm{j},[-12,-1]} \\ + \beta_3 \mathrm{Ret}_{\mathrm{j},[-36,-1]} + \beta_4 \mathrm{Vol}_{\mathrm{j},[-24,-1]} + \beta_5 \mathrm{FirstInFamily}_{\mathrm{i}} \\ + \beta_6 \mathrm{NonClone}_{\mathrm{i}} + \beta_7 \mathrm{InceptionAUM}_{\mathrm{i}} + \beta_8 \mathrm{MissingInception}_{\mathrm{i}} + \varepsilon_{\mathrm{i,j}}\end{aligned}$$

After computing alpha for each fund using the Fung and Hsieh factors, we regress the cross section of alpha coefficients (α_i) on the variables from Table 4 to determine the effect of strategy and family characteristic variables as of inception on the risk-adjusted performance of hedge funds over the first five years of their life.

In specification (4), the lagged strategy return significantly and negatively predicts risk-adjusted returns, with a coefficient of -6.955 and a t-statistic of -2.24. Lagged strategy flow negatively predicts performance in specification (1) but does not achieve statistical significance when strategy returns and inceptions are added in specification (4). In addition, dummies for being the first fund in a family and for being a non-clone inception in an existing family (clone funds are the omitted dummy) are both positive and significant in each specification. The Missing Inception AUM dummy is insignificant in each specification, suggesting that some funds' lack of inception AUM in the data is not significantly related to the performance variables of interest.

Taken together, the results of these tables validate the prediction in our hypotheses that proxies for strategy demand (returns and flows) as well as family-level demand (new family and non-clone) at the time of funds' inceptions are both significantly related to subsequent raw and risk-adjusted performance.

V. Performance of Demand- and Supply-Driven Inceptions

We now move to our main analysis to use our three strategies to identify demand- and supply-driven inceptions. We then test our hypotheses by constructing portfolios of demand- and supply-driven inceptions and examine their performance.

A. Inceptions in Hot and Cold Strategy Categories

We start from the identification strategy based on hot and cold strategy categories. To identify hot and cold strategies, we examine two characteristics of the strategy in which a particular inception is observed: the 36-month (prior to inception) flows into the strategy and the 36-month (prior to inception) returns for the strategy. Each month, we rank the 10 strategies using these two lagged variables. Strategy categories with a high rank (seven or greater) in both characteristics are relatively hot, whereas strategies with a low rank (four or lower) in both are relatively cold. Inceptions in hot and cold strategy categories are interpreted, respectively, as demand driven and supply driven. We then form portfolios of demand- and supply-driven inceptions to examine their performance.

More explicitly, portfolios are constructed based on a three-month formation period, with their performance examined in a 60-month holding period. In any given month, demand- and supply-driven inceptions from the prior three-month period are included in the respective inception portfolios (and funds live during that period are included in the non-inception portfolios). Funds within inception portfolios are equally weighted, meaning that these portfolios are rebalanced to equal weights at the beginning of each month. Monthly returns are computed for the following 60-month period. Portfolio returns are then regressed on the seven hedge fund risk factors from Fung and Hsieh (2004) to obtain the risk-adjusted performance of each inception portfolio (see equition (2) for the Fung and Hsieh regression specification).

The results for the time-series regression are in the first three columns of Table 7. The portfolio of supply-driven inceptions has a significant alpha of 0.483% monthly, as exhibited in the first column, whereas that for demand-driven inceptions does not have a significant alpha. Furthermore, the monthly spread between the two portfolios is 0.295% per month, or 3.54% per year, which is both statistically and economically significant (t-statistic = 2.03). All these estimates are not only statistically significant but also economically sizable. These results lend support to our first hypothesis, suggesting that supply-driven inceptions deliver superior risk-adjusted performance in general and outperform demand-driven inceptions in particular.

The next two columns of Table 7 report the performance of all inceptions, as well as that of existing funds. Perhaps not surprisingly, the performance of all inceptions (0.362% per month) falls between that of supply-driven inceptions and that of demand-driven inceptions. Next, existing funds also deliver significant risk-adjusted performance (α=0.240% per month), which is consistent with the literature stating that the hedge fund industry can generally deliver good performance.

The last column of Table 7 compares the performance of the inception portfolio and that of existing funds. Inceptions, on average, outperform existing funds by a risk-adjusted return of 0.122% per month, or 1.46% per year, which is also statistically significant (t-statistic = 3.78). This observation suggests that inceptions, on average, outperform existing funds for the first five years. If we take a closer look, however, outperformance is mainly due to supply-driven inceptions. Indeed, demand-driven inceptions, which deliver a risk-adjusted return of 0.188% per month, slightly underperform existing funds (which have an alpha of 0.240% per month), though the underperformance is insignificant. By contrast, unreported tests show that supply-driven inceptions significantly outperform existing funds. Hence, our results support Hypothesis 1, that supply-driven inceptions do provide valuable new skills above and beyond those demonstrated by existing funds to the hedge fund universe.

B. Clone and Non-Clone Inceptions

We now examine the effect of family characteristics. Since we have already shown that new funds outperform existing funds, one could conjecture that inceptions creating new families (i.e., new funds that are not launched by any existing families) could also outperform inceptions conducted by existing families. To examine this conjecture, we decompose inceptions into new-family inceptions and existing-family inceptions and form portfolios similar to the inception and non-inception portfolios. We then estimate the Fung–Hsieh seven-factor model (see equation 2) to obtain the risk-adjusted performance measure (alpha) for each portfolio and report the results in the first two columns of Table 8.

Grouped, both new-family inceptions and inceptions in existing families have positive alphas (0.372% and 0.338%, respectively, with t-statistics of 6.06 and 4.55). Interestingly, when we examine the performance difference between the two groups, which we report in the third column, we find that, unlike the case for funds, inceptions by brand new families and inceptions by existing families does not exhibit a significant difference in performance. The insignificance suggests that new supply-driven funds that have valuable new investment ideas can arise within an existing family as well as within their own, new family. Indeed, as discussed in previous sections, clone and non-clone inceptions are likely to be demand driven and supply driven, respectively.

To investigate this issue further, we further decompose inceptions of existing families into two groups: clone inceptions and non-clone inceptions. We form clone and non-clone portfolios using the same technique as in Table 6 and compute the alphas of each portfolio and the spread portfolio between them. The results are in the last three columns of Table 8. The non-clone inception portfolio significantly outperforms the clone portfolio. The two portfolios differ by 0.129 per month, or 1.55% per year (t-statistic = 2.61), confirming that non-clone supply-driven inceptions are likely to provide new ideas that contribute to superior subsequent performance. The adjusted R^2 in the non-clone and clone specifications is quite high (53.7% and 54.7%), because the hedge fund risk factors included in the regression were designed to explain the variance in hedge fund portfolio returns. On the other hand, we note that the risk exposures of clone and non-clone funds are similar.

Figure 2 illustrates the performance difference between inceptions of different types, showing cumulative abnormal returns for 120 months after inception. Funds that represent the first fund in a completely new family and new funds that come about in existing families but are not clones of existing funds in those families (non-clone funds) have very similar performance after inception. On the other hand, clone funds significantly underperform funds of the previous types.

C. Clone and Non-Clone Inceptions in Hot and Cold Strategy Categories

Next, we then combine the previous results and identify managerial skill supply-driven inceptions as non-clone inceptions investing in cold strategy categories; we define clone inceptions investing in hot strategy categories as investor demand-driven. For each of these six partitions of inceptions, we form a portfolio using a three-month formation period and a 60-month holding period, as we did in previous tables. We then regress these portfolio returns (as well as pairwise and corner spreads) on hedge fund risk factors to obtain the risk adjusted alpha.

We summarize the matrix of alpha coefficients in Panels A and B of Table 9 and report selected parameters of these regressions of interest in Table 10. In Panel A of Table 9, the first column shows that supply-driven inceptions based on the third identification strategy (non-clone inceptions investing in cold strategy categories) can deliver a risk-adjusted return of 0.489% per month, which clearly outperforms demand-driven inceptions (clone inceptions investing in hot strategy categories), which have a return of 0.114%.

Panel B of Table 9 provides the alpha coefficients for the portfolios formed from the corners of the demand/supply matrix. The spread portfolio that is long funds formed from non-clone inceptions in existing families during times of low demand (cold strategies) and short funds formed from clone inceptions during high demand (hot strategies) has a significant alpha of 0.375% per month and a t-statistic of 2.115. Similarly, the spread portfolio that is long new-family inceptions formed during times of low demand and short clone funds arising during times of high demand earns a significant alpha ($t = 2.401$) of 0.3805 per month.

The difference between supply- and demand-driven inceptions as we have defined them using both measures is illustrated in Figure 3. Cumulative abnormal returns are plotted for inceptions that are classified as demand driven based on strategy category characteristics at the time of their inception and also by their position in a fund family (clone inceptions representing investor demand-driven inceptions). Over 120 months, inceptions motivated by the supply of managerial talent more than double the cumulative performance of their investor demand-driven counterparts.

As a robustness check for our results, we also examine new-family inceptions. Because new families, by definition, cannot contain clone funds, new families investing in cold strategies are likely to be supply-driven. These inceptions deliver a positive and significant alpha of 0.463% per month. The difference between this alternative proxy of supply-driven inceptions and our existing demand-driven inceptions is reported in the second row of Panel B of Table 9. The difference in alpha is 0.380% per month, which is economically and statistically significant. Table 10 reports the coefficients from selected regressions used to generate the alpha coefficients reported in Table 9.

Tests based on all three identification strategies point to the same conclusion: Supply-driven inceptions are associated with superior subsequent performance and can outperform demand-driven inceptions. Supply-driven inceptions, as we have identified them, contribute valuable new managerial skill to the hedge fund industry when compared to flows to existing funds or demand-driven inceptions.

VI. Robustness Checks

A. Backfill Bias

Because hedge fund data are voluntarily reported, the potential for data bias exists. Of primary concern to researchers using commercial databases to study hedge funds is the possibility of backfill bias. Many funds decide to submit their performance to a data vendor after they have been live for some time. At the time that they start reporting, they may optionally add their fund's historical performance to the database. Because managers want to portray their funds in as positive a light as possible, funds may decide not to include historical performance numbers from their inception to the date at which they started reporting if that performance was not good. Conversely, funds that have reason to be proud of their performance before the date at which they began listing will include their historical performance. Available inception performance numbers from early in funds' lives are therefore likely to have an upward bias, as described in Fung and Hsieh (2000). This potential bias is of particular concern for our analysis, because we compare the performance of inception portfolios to the portfolios of seasoned hedge funds. More generally, much of our analysis is primarily concerned with the performance of funds during the first few years of their lives.

Thankfully, TASS also includes a variable designating the date when the fund started reporting its returns to the database. By dropping out the performance for each fund previous to the date it started reporting, we can obtain a sample that is free of backfill bias; that is, in the backfill-free sample, the performance numbers were all reported on a monthly basis to TASS as they happened, precluding the reporting flexibility that drives the bias.

In Table 11, we construct portfolios of demand- or supply-driven inceptions using the same variables and methods as in Table 7, using the backfill bias-free subsample. We perform a regression of the first 60 months of returns from each fund on the Fung–Hsieh risk factors to identify the alpha. In the bias-free sample, while the portfolio of demand-driven inceptions does not have a significant alpha, the portfolio of supply-driven inceptions has a positive and significant alpha of 0.489% per month, or 6.03% per year (t-statistic = 5.26). Additionally, the risk-adjusted return difference between the two types of inceptions is positive (0.293% per month) and significant (t = 2.00). In addition, the risk exposure of the spread portfolio and the adjusted R-squared value are similar to the results reported in Table 7. Overall, these results are very close to our earlier findings for the full sample and suggest that backfill bias does not alter our main conclusion.

B. Alternative Proxy for Investor Demand

Several of our specifications suggest that past strategy category inceptions (normalized by the number of funds in the strategy) are a good proxy for investor demand. We therefore substitute the previous 12-month normalized inceptions at the strategy level for the strategy flows and returns that we used throughout the paper as proxies for investor demand. Again using a three-month formation period and a 60-month holding period, we construct the returns and compute the risk-adjusted alpha for the portfolios of supply- and demand-driven inceptions and report the results in Table 12. As in Table 7, the Fung–Hsieh hedge fund risk factors are very effective at explaining the variance in the returns of both portfolios (with adjusted R^2 values of 52.2% and 54.4%, respectively). The risk-adjusted return difference between the two types of inceptions is positive (0.154% per month) and statistically significant (t-statistic = 2.03), again confirming the outperformance of supply-driven inceptions.

C. Alternative Clone Fund Cutoff

To determine whether an inception within an existing family is a clone of a fund within that family, we require that the fund report the same strategy category as the previously existing fund and that the return correlation between the two funds be at least 90% over the period when both funds were live. The choice of high correlation is motivated by the consideration that the new inception and the existing fund are similar in terms of investment strategy and performance. As a robustness check, we create an alternative clone/non-clone measure using a lower threshold of 85% and re-examine clone and non-clone portfolios using this alternative measure.

Table 13 reports the regression results of the clone and non-clone portfolio returns on the hedge fund risk factors. Sub-portfolios are created using a three-month formation period and a 60-month holding period. Any inception in an existing family in the three-month period is included in either the clone or the non-clone portfolio, depending on its classification.

As shown in Table 13, the alpha of the non-clone portfolio using the alternative classification measure is 0.407% monthly, which is significant, with a t-statistic of 5.23. The clone portfolio alpha using this looser classification is also statistically significant (estimate = 0.302% per month, t-statistic = 3.72). The portfolio formed by the spread between these two portfolios also has a significant monthly alpha of 0.106%, with a t-statistic of 1.97. In summary, loosening the classification criteria to include funds with at least 85% correlation with existing funds in the family does not change our earlier findings.

VII. Conclusions

This paper explores the conditions under which new hedge funds are launched. We propose that hedge fund inceptions can be motivated either by investor demand for available fund capacity or by the supply of new managerial skills. We hypothesize that the latter type of inceptions can deliver superior performance in general and outperform the former type of inceptions in particular.

We propose three approaches to identify supply-driven inceptions, based on past characteristics of the funds' strategy categories and on the funds' family relationships. In particular, we identify non-clone inceptions in cold strategy categories as supply driven and find that this type of inceptions can deliver superior performance.

Our findings suggest considerable variety in the degree to which new inceptions provide new and profitable ideas and opportunities to hedge fund investors. Importantly, it is possible to distinguish ex ante new funds that provide genuine innovations to the industry from those that are simply taking advantage of investors' desire to obtain hedge fund exposure. Our results have significant normative implications and call for more attention to the entry of new funds in understanding the overall value of the hedge fund industry.

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Figure 1: Cumulative Flows to Inceptions and Existing Funds

Cumulative flows (since the beginning of the sample) to various types of funds are plotted. Initial flows to new funds are given by AUM of Inceptions, the first non-missing AUM reported to TASS within three months of the fund's inception, or zero if none are available. Flows to first-year funds are any flows to funds that, in the month of the flow, were between the age of one month and 12 months. Flows to funds 1–5 years are any flows to funds that, in the month of the flow, were between 12 and 60 months old. Flows to funds older than 5 years are any flows to funds that, in the month of the flow, were older than 60 months.

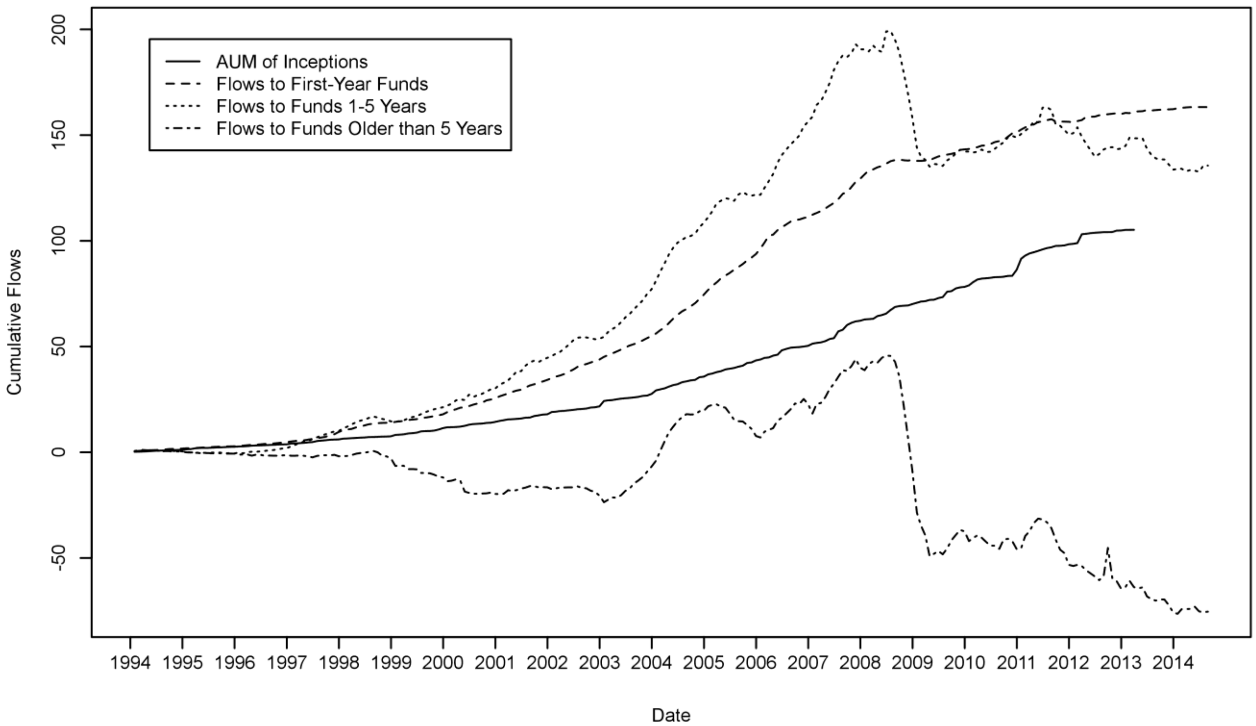

Figure **2: Cumulative Abnormal Returns for Inceptions by Type**

Cumulative abnormal returns are plotted in event time for inceptions of various types. New-family inceptions are fund inceptions that represent the first fund for their reported family. If multiple funds begin on the first date of the family, they are all considered new-family inceptions. We classify inceptions in existing families into clone and non-clone funds. Clone funds are those in the same reported strategy category as an existing fund in the family and with a return correlation with this fund of above 90%. Non-clone funds are inceptions in existing families but in a new strategy category or with a return correlation below 90% with existing funds in their family.

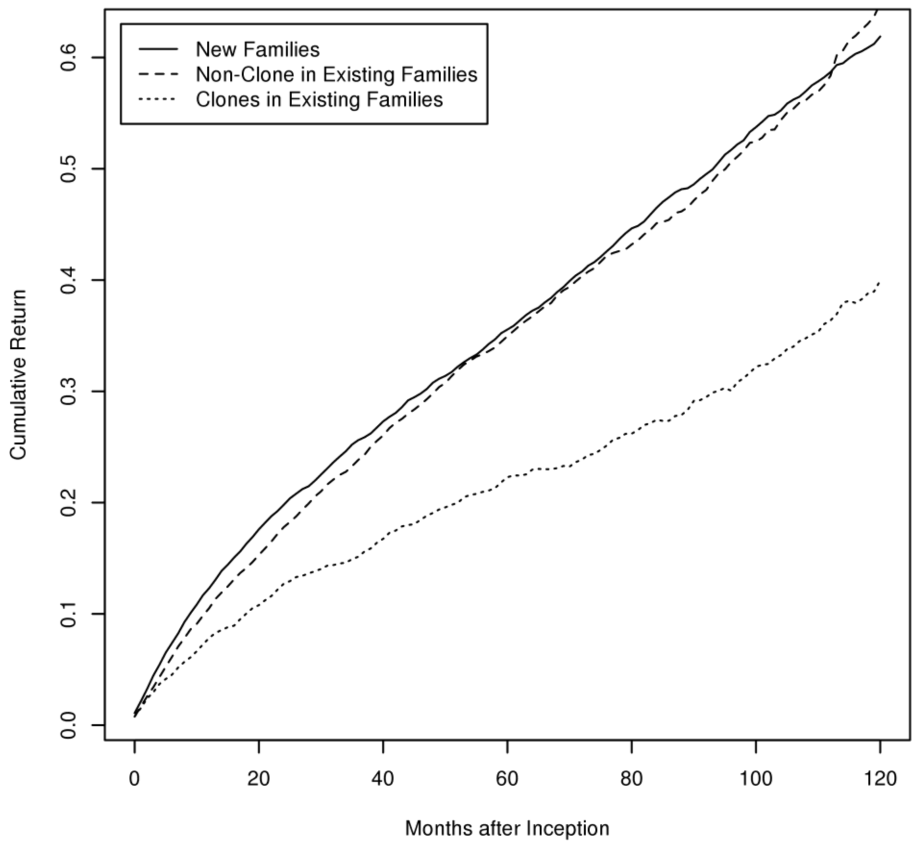

Figure 3: Cumulative Abnormal Returns after Inception by Investor Demand at the Time of Inception

Cumulative abnormal returns are plotted in event time for all available inceptions, classified by whether investor demand in their strategy was high or low at the time of inception. The strength of investor strategy category demand is measured by two variables: the magnitude of the flows into that strategy category during the previous 36 months and the returns in the strategy category over the previous 36 months. Inceptions in strategy categories in the top four deciles by both measures are considered high demand, while inceptions in strategy categories in the bottom four deciles by both measures are considered low demand. Family-level demand is proxied by whether the inception represents a new fund family (high demand) or a clone in an existing family (low demand).

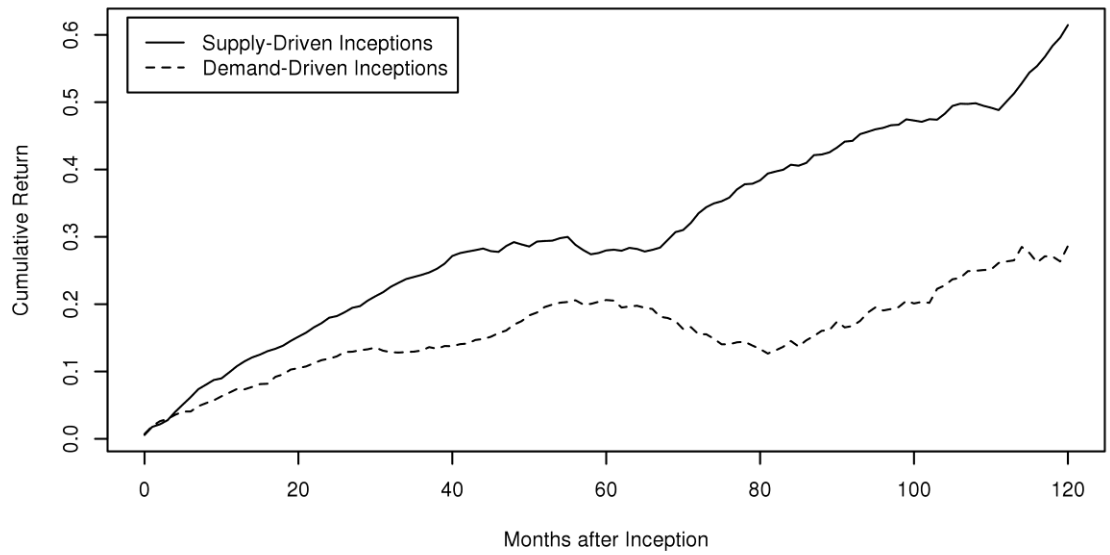

Table 1: Summary Statistics of Hedge Funds and Hedge Fund Families

This table reports the number of funds in our sample by investment objective strategy category and year. Funds are included if they report a valid AUM in December of the given year. Strategy classifications are convertible arbitrage (CA), dedicated short bias (DS), event driven (ED), emerging markets (EM), equity market neutral (EMN), fixed income arbitrage (FI), global macro (GM), long/short equity (LS), managed futures (MF), and multi-strategy (MS). We exclude are funds without a reported strategy classification in this list (e.g., funds of funds). We also report the total number of hedge funds and hedge fund families, as well as the average number of funds per family and the fraction of families that have multiple funds in each year. Data are from funds reporting a valid AUM to TASS in December of the given year. The sample extends from 1994 through 2013.

	Strategy Category Counts													
Year	CA	DS	ED	EM	EMN	FI	GM	LS	MF	MS	Number of Funds	Number of Families	Funds per Family	Fraction Multiple Funds
1994	27	7	60	47	17	22	40	176	172	16	584	423	1.38	0.24
1995	34	6	87	67	24	32	55	223	203	24	755	514	1.47	0.29
1996	38	9	110	72	30	38	48	293	180	34	852	600	1.42	0.28
1997	45	14	134	110	43	54	67	393	196	40	1,096	731	1.50	0.33
1998	53	15	157	123	69	60	76	494	208	49	1,304	853	1.53	0.34
1999	58	19	159	136	90	66	76	622	197	69	1,492	958	1.56	0.34
2000	73	23	196	134	103	68	64	760	195	82	1,698	1,066	1.59	0.34
2001	93	16	216	117	136	84	65	815	193	95	1,830	1,118	1.64	0.35
2002	110	14	239	122	155	100	91	860	187	115	1,993	1,190	1.67	0.35
2003	114	17	256	142	164	121	104	930	220	131	2,199	1,253	1.75	0.38
2004	107	12	283	175	178	135	126	987	261	155	2,419	1,314	1.84	0.39
2005	95	11	278	219	198	125	139	1,044	265	174	2,548	1,358	1.88	0.39
2006	76	9	243	237	198	106	137	980	255	226	2,467	1,301	1.90	0.39
2007	68	13	247	321	184	105	138	1,049	276	302	2,703	1,357	1.99	0.40
2008	46	13	180	328	137	91	159	1,007	274	310	2,545	1,282	1.99	0.39
2009	46	9	176	348	128	87	247	927	287	748	3,003	1,271	2.36	0.42
2010	35	4	165	317	115	105	250	807	284	863	2,945	1,195	2.46	0.41
2011	30	5	144	295	114	133	297	722	269	1,198	3,207	1,070	3.00	0.42
2012	26	3	126	218	88	110	256	635	267	1,070	2,799	939	2.98	0.42
2013	28	2	110	170	67	82	204	523	201	933	2,320	782	2.97	0.42

Table 2: Inceptions and Flows over Time

We report the flows to hedge fund inceptions and existing funds by year. The second column reports the number of fund inceptions in each year. The third column reports the number of new funds in a given year divided by the total number of funds in the universe at the beginning of the year. The fourth column shows the sum of the initial AUM of the fund inceptions in each year (all AUM and flows are in billions of US dollars). Initial AUM are defined as the first non-missing AUM reported by the fund within three months of the fund's inception. Funds with missing AUM are eliminated. The next three columns report the sum of monthly flows in that year to funds that are a year old or younger in each of the year's months, between the ages of one and five years and older than five years. Flows are computed monthly, fund by fund, using

$$\mathrm{Flow}_t = \mathrm{AUM}_t - \mathrm{AUM}_{t-1} \cdot (1 + r_{t-1,t})$$

Where $r_{t-1,t}$ is the return to the fund between time t-1 and t. The total flows column reports the sum of the previous four columns.

Year	New Funds	New /Total	New Fund AUM	Age ≤ 1 yr	1 yr < Age ≤ 5 yr	Age > 5 yr	Total Flows
1994	208	0.26	1.14	1.75	0.42	0.35	3.66
1995	224	0.22	1.46	1.11	-1.01	-0.99	0.57
1996	303	0.25	1.21	1.92	2.53	-0.73	4.93
1997	317	0.22	2.34	4.85	8.10	-0.49	14.81
1998	308	0.18	1.52	4.44	4.60	-0.97	9.58
1999	389	0.20	3.89	3.96	6.68	-9.04	5.49
2000	388	0.18	3.06	7.50	8.87	-7.82	11.61
2001	444	0.18	3.68	8.92	14.51	3.10	30.21
2002	510	0.18	3.76	9.80	9.03	-3.94	18.64
2003	616	0.18	5.93	11.15	23.41	13.81	54.30
2004	781	0.19	8.35	19.67	31.46	26.35	85.83
2005	824	0.18	7.77	19.25	13.27	-11.93	28.35
2006	771	0.15	7.32	17.56	34.51	15.05	74.44
2007	840	0.16	12.46	19.77	34.19	17.24	83.66
2008	690	0.13	8.35	8.95	-32.58	-48.99	-64.28
2009	678	0.13	8.20	4.92	-15.75	-28.43	-31.06
2010	578	0.11	8.16	8.05	6.55	-8.37	14.38
2011	430	0.08	12.29	4.97	1.48	-7.44	11.30
2012	285	0.06	7.80	3.57	-6.63	-11.25	-6.51
2013	113	0.03	1.68	2.33	-9.94	-11.26	-17.19

Table 3: Inceptions in New and Existing Families by Year

We partition the set of all inceptions into inceptions that start new families and those that add a fund to an existing family. The second and third columns report the number of inceptions in each partition by inception year. The fourth column reports the number of inceptions in existing families that are not clones of existing funds; that is, the new fund is in a different strategy category than all the existing funds in the family or has a return correlation below 90% with all the existing funds in the family. We exclude funds with fewer than 12 monthly observations. The fifth column reports the total number of inceptions in each year with no requirement of valid AUM at inception.

Year	New Families	Inceptions in Existing Families	Non-Clone Inceptions	Inceptions Subtotal
1994	157	52	32	209
1995	163	68	30	231
1996	217	84	35	301
1997	220	111	53	331
1998	230	89	34	319
1999	285	128	64	413
2000	285	127	65	412
2001	328	189	80	517
2002	368	222	107	590
2003	420	300	121	720
2004	463	415	160	878
2005	487	452	173	939
2006	474	412	196	886
2007	393	592	289	985
2008	344	452	280	796
2009	293	474	258	767
2010	217	459	266	676
2011	189	317	156	506
2012	109	197	88	306
2013	30	90	41	120

Table 4: Logistic Regression of Inception Counts on Family/Strategy Variables

This table reports the logistic regression results of the dummy variable for whether there was an inception in a given family/year/strategy on characteristics of that family, year, and strategy category. The logistic regression equation is

$$\text{Inception}_{\text{j,k,t}} = \Lambda(\beta \times X_{j,\text{t}-1} + \psi \times Y_{k,\text{t}-1}) + \varepsilon_{j,\text{k,t}}$$

where $\Lambda(\cdot)$ represents the logistic link function; $X_{j,t}$ is a vector of strategy-specific variables for strategy category j in year t - 1 and $Y_{k,t-1}$ is a vector of family-specific variables for family k in year t - 1; $\text{Inception}_{j,k,t}$ is an indicator variable that is one if there was an inception in strategy j, family k, and year t and zero otherwise. The explanatory variables are as follows: Strategy return is the average monthly return to an equal-weighted portfolio of funds for a given strategy in year t - 1. Family return is similarly defined. Strategy and family volatility are computed from equal-weighted portfolios of funds from t - 2 to t. Strategy and family AUM are the sum of reported AUM in December of year t - 1. Family Assets in Same Strategy is the sum of reported assets in strategy j and family k at the end of year t - 1. Normalized Strategy Inceptions is the number of inceptions in strategy j in year t - 1, normalized by the number of funds in strategy j at the end of year t - 2. Large Family Open is set to one if one of the largest eight hedge fund families had an inception in strategy j in year t - 1. Inceptions in Family is the count of inceptions in family k in year t - 1. In all models, year fixed effects are included as yearly dummy variables in the regression. Models (1) to (4) include only families that existed in the previous year (investigating the likelihood of inception in existing families), while Model (5) adds families that did not exist in the previous year and sets lagged family variables to zero. In specification (5), a dummy variable set to one if the family previously existed is added as well. The t-statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Families Existing in the Previous Year				Existing Plus New Families
	(1)	(2)	(3)	(4)	(5)
Strategy Return	29.203***		29.245***	28.531***	36.191***
	(6.62)		(6.59)	(6.44)	(14.67)
Strategy Inceptions	0.788***		0.792***	0.791***	0.892***
	(2.97)		(2.97)	(2.97)	(6.58)
Strategy Volatility	0.449		0.534	0.541	0.897**
	(0.57)		(0.68)	(0.68)	(2.09)
Strategy AUM	0.001***		0.001***	0.001***	0.002***
	(16.47)		(15.91)	(15.93)	(28.68)
Strategy Flow	-4.345		-4.495	-4.423	-11.065***
	(-1.36)		(-1.40)	(-1.38)	(-6.30)
Strategy Large Family Open	0.186**		0.178*	0.175*	0.250***
	(2.01)		(1.91)	(1.87)	(4.53)
Family Return		3.959**	3.864**	3.817**	3.388*
		(2.06)	(2.01)	(1.99)	(1.86)
Family Inceptions		0.175***	0.168***	0.168***	0.162***
		(12.17)	(11.62)	(11.62)	(11.32)
Family Volatility		-1.136***	-1.124***	-1.128***	-1.174***
		(-3.76)	(-3.71)	(-3.72)	(-3.99)
Family AUM		-0.188***	-0.125***	-0.124***	-0.119***
		(-3.97)	(-2.77)	(-2.77)	(-2.67)
Family Assets in Same Strategy		0.529***	0.400***	0.328***	0.326***
		(9.05)	(7.17)	(4.67)	(4.68)
Family Flow		0.321***	0.328***	0.328***	0.344***
		(6.06)	(6.15)	(6.16)	(6.52)
Strategy Return * Family Assets				12.179**	11.022*
				(2.02)	(1.86)
Family Already Existed					-2.179***
					(-37.10)
Fixed Effect: Year	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	4.90%	3.90%	7.90%	7.90%	18.40%
Obs.	132,340	132,340	132,340	132,340	166,710

Table 5: Cross-Sectional Determinants of Holding Period Performance

This table presents the results of a cross-sectional regression of five-year performance after an inception on the characteristics of funds' families and strategy categories. For each inception, excess returns are computed from the month after the inception (the month in which the inception happens is excluded) to 60 months later. These inception holding period returns are then regressed on strategy category and fund variables. The regression equation is

$$\begin{aligned} \text{Performance}_{i,j,[1,60]} = {} & \alpha + \beta_1 \text{NormFlow}_{j,[-36,-1]} + \beta_2 \text{Inceptions}_{j,[-12,-1]} \\ & + \beta_3 \text{Ret}_{j,[-36,-1]} + \beta_4 \text{Vol}_{j,[-24,-1]} + \beta_5 \text{FirstInFamily}_i \\ & + \beta_6 \text{NonClone}_i + \beta_7 \text{InceptionAUM}_i + \beta_8 \text{MissingInception}_i + \varepsilon_{i,j} \end{aligned}$$

where $\text{Performance}_{i,j}$ is the 60-month cumulative return to fund i (which reports strategy j) after its inception; NormFlow_j is the normalized flow to strategy j in the year prior to the inception; Inceptions_j represents the number of inceptions in strategy category j, which contains fund i, divided by the number of funds in this strategy at the end of the previous period; Ret_j is the lagged equal-weighted strategy excess return for strategy j; Vol_j is the volatility of strategy j, which contains fund i, computed over the previous 24 months before fund i's inception; FirstInFamily_i is an indicator variable set to one when the fund is the first reported fund in its family; NonClone_i is set to one when a fund is not the first in its family and is not considered a clone fund because it either is in a new strategy for the family or has less than 90% correlation with each previously existing fund in the family; InceptionAUM_i is the first reported AUM for a fund if the reporting month is within three months of its inception date and missing otherwise; and $\text{MissingInception}_i$ is a dummy variable set to one if there are no reported AUM for fund i within its first three months. The t-statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)
Strategy NormFlow	-9.049***			-9.094***
	(-4.92)			(-4.55)
Strategy Inceptions		-4.866		1.982
		(-1.62)		(0.57)
Strategy Return			-8.148*	-4.411
			(-1.86)	(-0.93)
Strategy Volatility	1.595***	1.567***	1.953***	1.789***
	(3.27)	(3.18)	(3.82)	(3.39)
First Fund in Family	0.267***	0.271***	0.267***	0.265***
	(6.57)	(6.64)	(6.55)	(6.52)
Non-clone Inception in Existing Family	0.289***	0.297***	0.287***	0.285***
	(5.97)	(6.10)	(5.94)	(5.85)
Inception AUM (Bil)	-0.695**	-0.693**	-0.681**	-0.689**
	(-2.03)	(-2.02)	(-1.99)	(-2.02)
Missing Inception AUM	0.016	0.025	0.019	0.014
	(0.46)	(0.71)	(0.54)	(0.38)
Fixed Effect: Inception Year	Yes	Yes	Yes	Yes
R^2	8.60%	8.20%	8.20%	8.60%
Obs.	5,102	5,102	5,102	5,102

Table 6: Cross-Sectional Determinants of Holding Period Alpha

For each inception, excess returns are computed from the month after the inception (the month in which the inception happens is excluded) to 60 months later. Alpha for these returns is then computed by regressing fund returns on the Fung–Hsieh factors. These inception alphas are then regressed on strategy and fund variables:

$$\begin{aligned}\alpha_{i,j} = \delta + \beta_1 \mathrm{NormFlow}_{j,[-36,-1]} + \beta_2 \mathrm{Inceptions}_{j,[-12,-1]} \\ + \beta_3 \mathrm{Ret}_{j,[-36,-1]} + \beta_4 \mathrm{Vol}_{j,[-24,-1]} + \beta_5 \mathrm{FirstInFamily}_i \\ + \beta_6 \mathrm{NonClone}_i + \beta_7 \mathrm{InceptionAUM}_i + \beta_8 \mathrm{MissingInception}_i + \varepsilon_{i,j}\end{aligned}$$

where $\alpha_{i,j}$ is the alpha coefficient from the Fung–Hsieh regression over the first 60 months since inception for fund i, which reports strategy category j; $\mathrm{NormFlow}_j$ is the normalized flow to strategy j over the year prior to inception i; $\mathrm{Inceptions}_j$ represents the number of inceptions in strategy category j, which contains fund i, divided by the number of funds in this strategy at the end of the previous period; Ret_j is the lagged equal-weighted strategy excess return; Vol_j is the volatility of strategy j, computed over the previous 24 months; $\mathrm{FirstInFamily}_i$ is an indicator variable set to one when the fund is the first reported fund in its family; $\mathrm{NonClone}_i$ is set to one when a fund is not the first in its family and is not considered a clone fund because it either is in a new strategy for the family or has less than 90% correlation with each previously existing fund in the family; $\mathrm{InceptionAUM}_i$ is the first reported AUM for a fund if the reporting month is within three months of its inception date and missing otherwise; and $\mathrm{MissingInception}_i$ is a dummy variable set to one if there are no reported AUM for fund i within its first three months. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)
Strategy NormFlow	-2.199**			-1.321
	(-2.07)			(-1.11)
Strategy Inceptions		-2.522		-0.782
		(-1.55)		(-0.41)
Strategy Return			-8.357***	-6.955**
			(-2.89)	(-2.24)
Strategy Volatility	-1.024***	-1.014***	-0.709**	-0.832**
	(-3.31)	(-3.25)	(-2.23)	(-2.53)
First Fund in Family	0.175***	0.175***	0.173***	0.174***
	(6.82).	(6.80)	(6.73)	(6.77)
Non-Clone Inception in Existing Family	0.251***	0.253***	0.251***	0.252***
	(8.36)	(8.42)	(8.36)	(8.38)
Inception AUM (Bil)	-0.191	-0.192	-0.190	-0.190
	(-1.43)	(-1.44)	(-1.43)	(-1.43)
Missing Inception AUM	-0.011	-0.009	-0.012	-0.011
	(-0.52)	(-0.41)	(-0.54)	(-0.50)
Fixed Effect: Inception Year	Yes	Yes	Yes	Yes
R^2	2.80%	2.70%	2.80%	2.80%
Obs.	9,738	9,748	9,748	9,738

Table 7: Performance Differences between Portfolios by Inception Type and Investor Demand

We compare the performance of portfolios of new hedge funds (inception portfolios) with the performance of portfolios comprising seasoned funds and then compare the performance of inceptions starting during periods of low and high investor demand in the strategy category (cold and hot inceptions). Strategy demand is proxied by 36-month returns and normalized flows relative to other categories. Sub-portfolios are created using a three-month formation period and then a 60-month holding period. Within Sub-portfolios, funds are equal-weighted at the beginning of each month. For each month, the overall portfolio is formed by equally weighting the sub-portfolios with holding periods in that month. We thus average over up to 60 portfolios for each monthly return. For an inception portfolio, the sub-portfolios consist of funds with inceptions during their formation period. For a non-inception portfolio, sub-portfolios consist of funds without inceptions in those formation periods and that meet the age requirement during the formation period. The alpha for each portfolio is the intercept estimate from the equal-weighted portfolio excess returns on the risk factors:

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \beta_{p,2}SMB_t + \beta_{p,3}YLDCHG_t + \beta_{p,4}BAAMTSY_t$$
$$+ \beta_{p,5}PTFSBD_t + \beta_{p,6}PTFSFX_t + \beta_{p,7}PTFSCOM_t + \varepsilon_{p,t},$$

where $r_{p,t}$ is the excess return on portfolio p in month t. The independent variables are the market excess return (MKT), a size factor (SMB), monthly change in the 10-year Treasury constant maturity yield (YLDCHG), monthly change in Moody's Baa yield less the 10-year Treasury constant maturity yield (BAAMTSY), and three trend-following factors: PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). The t-statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Inception and Non-Inception Portfolios			Inception Portfolios		
	Cold Portfolio	Hot Portfolio	Cold minus Hot	Inceptions	Non-Inceptions	Inceptions minus Non-Inceptions
Alpha	0.483***	0.188	0.295***	0.362***	0.240***	0.122***
	(5.23)	(1.57)	(2.03)	(5.73)	(3.37)	(3.76)
MKT	0.089***	0.272***	-0.182***	0.228***	0.278***	-0.050***
	(4.07)	(9.49)	(-5.28)	(15.11)	(16.36)	(-6.46)
SMB	0.095***	0.125***	-0.030	0.140***	0.156***	-0.016*
	(3.40)	(3.44)	(-0.69)	(7.31)	(7.25)	(-1.68)
YLDCHG	-1.220***	0.045	-1.265*	-0.516	-0.592*	0.077
	(-2.67)	(0.08)	(-1.77)	(-1.65)	(-1.68)	(0.48)
BAAMTSY	-3.637***	-2.600***	-1.038	-2.122***	-2.774***	0.652***
	(-6.25)	(-3.43)	(-1.14)	(-5.32)	(-6.18)	(3.19)
PTFSBD	0.009	-0.016**	0.026**	-0.002	-0.003	0.001
	(1.46)	(-2.00)	(2.59)	(-0.45)	(-0.62)	(0.48)
PTFSFX	0.009*	0.012*	-0.003	0.009**	0.014***	-0.005***
	(1.76)	(1.76)	(-0.34)	(2.51)	(3.48)	(-2.75)
PTFSCOM	0.007	0.006	0.001	0.009*	0.014**	-0.005*
	(0.99)	(0.67)	(0.07)	(1.82)	(2.51)	(-1.96)
R^2	27.90%	42.40%	17.40%	63.60%	67.00%	25.10%

Table 8: Performance Differences between Portfolios by Family Relationship and Clone/Non-Clone Status

We compare the performance of inception portfolios where the new fund is the first reported fund in the family and those that are additions to an existing hedge fund family, as well as the clone and non-clone inceptions within existing families. Clones funds are defined as inceptions in families with existing funds of the same strategy category and with 90% or higher correlation with these existing funds. Sub-portfolios are created using a three-month formation period and then a 60-month holding period. Within Sub-portfolios, funds are equal-weighted at the beginning of each month. Following Jegadeesh and Titman (1993), for each month, the overall portfolio is formed by equally weighting the sub-portfolios with holding periods in that month. Thus we average over up to 60 portfolios for each monthly return. For an inception portfolio, the sub-portfolios consist of funds with inceptions during their formation period. The alpha for each portfolio is the intercept estimate from the equal-weighted portfolio excess returns on hedge fund risk factors:

$$r_{p,t} = \alpha_p + \beta_{p,1} MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} YLDCHG_t + \beta_{p,4} BAAMTSY_t \\ + \beta_{p,5} PTFSBD_t + \beta_{p,6} PTFSFX_t + \beta_{p,7} PTFSCOM_t + \varepsilon_{p,t},$$

where $r_{p,t}$ is the excess return on each portfolio in month t. The independent variables are the market excess return (MKT), a size factor (SMB), monthly change in the 10-year Treasury constant maturity yield (YLDCHG), monthly change in Moody's Baa yield less the 10-year Treasury constant maturity yield (BAAMTSY), and three trend-following factors: PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). The t-statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	New-Family and Existing-Family Inceptions			Existing-Family Inceptions		
	New-Family Inceptions	Existing-Family Inceptions	New minus Existing	Non-Clone	Clone	Non-Clone minus Clone
Alpha	0.372***	0.338***	0.035	0.408***	0.279***	0.129***
	(6.06)	(4.55)	(0.96)	(5.36)	(3.56)	(2.61)
MKT	0.240***	0.228***	0.012	0.231***	0.233***	-0.003
	(16.36)	(12.88)	(1.38)	(12.70)	(12.46)	(-0.21)
SMB	0.144***	0.135***	0.009	0.143***	0.136***	0.006
	(7.74)	(6.01)	(0.83)	(6.20)	(5.74)	(0.43)
YLDCHG	-0.308	-0.887**	0.579***	-0.979***	-0.760*	-0.219
	(-1.01)	(-2.42)	(3.25)	(-2.60)	(-1.96)	(-0.90)
BAAMTSY	-2.107***	-2.232***	0.125	-1.854***	-2.528***	0.674**
	(-5.43)	(-4.77)	(0.55)	(-3.86)	(-5.11)	(2.16)
PTFSBD	-0.004	-0.001	-0.003	-0.001	-0.001	0.001
	(-0.93)	(-0.12)	(-1.34)	(-0.10)	(-0.21)	(0.18)
PTFSFX	0.009***	0.011***	-0.002	0.012***	0.010**	0.002
	(2.67)	(2.61)	(-0.82)	(2.78)	(2.33)	(0.59)
PTFSCOM	0.006	0.016***	-0.010***	0.013**	0.016***	-0.004
	(1.34)	(2.85)	(-3.58)	(2.21)	(2.78)	(-1.00)
R^2	67.20%	55.40%	17.20%	53.70%	54.70%	5.10%

Table 9: Strategy Demand and Inception Type Performance Matrix: Risk-Adjusted Alpha

We form inception portfolios based on the type of inception and our measure of strategy category demand at the time of inception. Investor demand (hot vs. cold) is proxied by high strategy returns and strategy flows over the previous 36 months. Inception types include non-clone inceptions, clone inceptions, and new-family funds. Sub-portfolios are created using a three-month formation period and then a 60-month holding period. Within Sub-portfolios, funds are equal-weighted at the beginning of each month. Following Jegadeesh and Titman (1993), for each month, the overall portfolio is formed by equally weighting the sub-portfolios with holding periods in that month. For an inception portfolio, the sub-portfolios consist of funds with inceptions during their formation period. The risk-adjusted alpha for each portfolio is the intercept estimate from the equal-weighted portfolio excess returns on hedge fund risk factors. The regression equation is

$$r_{p,t} = \alpha_p + \beta_{p,1} MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} YLDCHG_t + \beta_{p,4} BAAMTSY_t + \beta_{p,5} PTFSBD_t + \beta_{p,6} PTFSFX_t + \beta_{p,7} PTFSCOM_t + \varepsilon_{p,t},$$

where $r_{p,t}$ is the excess return on each portfolio in month t. The independent variables are the market excess return (MKT), a size factor (SMB), monthly change in the 10-year Treasury constant maturity yield (YLDCHG), monthly change in Moody's Baa yield less the 10-year Treasury constant maturity yield (BAAMTSY), and three trend-following factors: PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). This table reports the estimated α_p for each portfolio. The t-statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Portfolio Alphas by Strategy Demand Type			
	Non-Clone	New Family	Clone
Cold Strategy	0.489%	0.495%	0.484%
	(4.404)	(5.388)	(2.798)
Hot Strategy	0.296%	0.203%	0.114%
	(2.125)	(1.753)	(0.783)
Cold/Hot Spread Portfolio	0.193%	0.292%	0.370%
	(1.096)	(2.064)	(1.619)

Panel B: Two-Way High- and Low-Demand Portfolio Alphas	
Cold Strategy Non-Clone minus Hot Strategy Clone Portfolio	0.375%
	(2.115)
Cold Strategy New Family minus Hot Strategy Clone Portfolio	0.380%
	(2.401)

Table 10: Performance Differences between Demand-Driven and Supply-Driven inceptions: Regressions

We form inception portfolios based on the type of inception and our measure of strategy category demand at the time of inception. Investor demand is proxied by relatively high strategy returns and flows during the previous 36 months. Inception types include non-clone inceptions, clone-inceptions, inceptions in hot environments (investor demand driven), and inceptions in cold environment (managerial supply driven). Sub-portfolios are created using a three-month formation period and then a 60-month holding period. Within Sub-portfolios, funds are equal-weighted at the beginning of each month. Following Jegadeesh and Titman (1993), for each month, the overall portfolio is formed by equally weighting the sub-portfolios with holding periods in that month. For an inception portfolio, the sub-portfolios consist of funds with inceptions during their formation period. The regression equation is

$$r_{p,t} = \alpha_p + \beta_{p,1} MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} YLDCHG_t + \beta_{p,4} BAAMTSY_t \\ + \beta_{p,5} PTFSBD_t + \beta_{p,6} PTFSFX_t + \beta_{p,7} PTFSCOM_t + \varepsilon_{p,t},$$

where $r_{p,t}$ is the excess return on each portfolio in month t. The independent variables are the market excess return (MKT), a size factor (SMB), monthly change in the 10-year Treasury constant maturity yield (YLDCHG), monthly change in Moody's Baa yield less the 10-year Treasury constant maturity yield (BAAMTSY), and three trend-following factors: PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). This table reports the regression coefficients for each portfolio. The t-statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Cold Non-Clone minus Hot Non-Clone	Cold New minus Hot New	Cold Clone minus Hot Clone	Cold Non-Clone minus Hot Clone	Cold New minus Hot Clone
Alpha	0.193	0.292**	0.370	0.375**	0.380**
	(1.10)	(2.06)	(1.62)	(2.12)	(2.40)
MKT	-0.136***	-0.204***	-0.134**	-0.086**	-0.169***
	(-3.25)	(-6.06)	(-2.46)	(-2.04)	(-4.48)
SMB	-0.081	-0.021	-0.176**	-0.142***	-0.069
	(-1.52)	(-0.50)	(-2.55)	(-2.64)	(-1.45)
YLDCHG	-3.110***	-0.594	-2.692**	-2.827***	-0.560
	(-3.57)	(-0.85)	(-2.38)	(-3.22)	(-0.71)
BAAMTSY	-2.213**	-0.091	-2.529*	-2.291**	-0.648
	(-1.99)	(-0.10)	(-1.75)	(-2.05)	(-0.65)
PTFSBD	0.039***	0.023**	0.044***	0.049***	0.026**
	(3.22)	(2.32)	(2.79)	(4.03)	(2.40)
PTFSFX	-0.002	-0.002	0.016	0.012	0.006
	(-0.20)	(-0.30)	(1.20)	(1.21)	(0.61)
PTFSCOM	0.013	0.001	0.017	-0.003	-0.014
	(0.95)	(0.06)	(0.98)	(-0.19)	(-1.19)
R^2	17.50%	20.00%	15.40%	18.70%	14.20%

Table 11: performance Difference between Portfolios by Investor Demand (No Backfill)

In this table, we exclude all inceptions and returns occurring before the first date at which a fund began reporting returns to TASS. We form inception portfolios based on the type of inception and our measure of strategy category demand at the time of inception. Investor demand (hot vs. cold) is proxied by high strategy returns and strategy flows over the previous 36 months. Sub-portfolios are created using a three-month formation period and then a 60-month holding period. Within Sub-portfolios, funds are equal-weighted at the beginning of each month. Following Jegadeesh and Titman (1993), for each month, the overall portfolio is formed by equally weighting the sub-portfolios with holding periods in that month. For an inception portfolio, the sub-portfolios consist of funds with inceptions during their formation period. The risk-adjusted alpha for each portfolio is the intercept estimate from the equal-weighted portfolio excess returns on hedge fund risk factors:

$$r_{p,t} = \alpha_p + \beta_{p,1} MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} YLDCHG_t + \beta_{p,4} BAAMTSY_t + \beta_{p,5} PTFSBD_t + \beta_{p,6} PTFSFX_t + \beta_{p,7} PTFSCOM_t + \varepsilon_{p,t},$$

where $r_{p,t}$ is the excess return on each portfolio in month t. The independent variables are the market excess return (MKT), a size factor (SMB), monthly change in the 10-year Treasury constant maturity yield (YLDCHG), monthly change in Moody's Baa yield less the 10-year Treasury constant maturity yield (BAAMTSY), and three trend-following factors: PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). The t-statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Cold Portfolio (Manager Supply-Driven)	Hot Portfolio (Investor Demand-Driven)	Spread Portfolio
Alpha	0.489***	0.196	0.293**
	(5.26)	(1.63)	(2.00)
MKT	0.087***	0.274***	-0.187***
	(3.91)	(9.53)	(-5.37)
SMB	0.096***	0.126***	-0.030
	(3.40)	(3.46)	(-0.69)
YLDCHG	-1.248***	0.024	-1.273*
	(-2.72)	(0.04)	(-1.76)
BAAMTSY	-3.654***	-2.608***	-1.046
	(-6.24)	(-3.43)	(-1.13)
PTFSBD	0.011*	-0.016**	0.027***
	(1.66)	(-1.99)	(2.69)
PTFSFX	0.010*	0.012*	-0.002
	(1.82)	(1.68)	(-0.23)
PTFSCOM	0.007	0.007	0.000
	(0.94)	(0.72)	(0.00)
R^2	27.50%	42.60%	18.00%

Table 12: Performance Difference between Portfolio by Investor Demand (Alternate Formation)

We compare the performance of inception portfolios for funds that occurred during times of low investor demand (cold) and those that occurred during a time of high investor demand (hot). Investor demand at the strategy category level is proxied by two variables: relatively high strategy-normalized flows (relative to other strategies) over the previous 36 months and relatively low strategy returns over the previous 36 months. We say that an inception in the bottom four deciles of strategies in both respects happened during a cold period. A fund in the top four deciles of strategies in both respects came into being during a hot period. Sub-portfolios are created using a three-month formation period and then a 60-month holding period. Within Sub-portfolios, funds are equal-weighted at the beginning of each month. Following Jegadeesh and Titman (1993), for each month, the overall portfolio is formed by equally weighting the sub-portfolios with holding periods in that month. Thus we average over up to 60 portfolios for each monthly return. For an inception portfolio, the sub-portfolios consist of funds with inceptions during their formation period. The alpha for each portfolio is the intercept estimate from the equal-weighted portfolio excess returns on hedge fund risk factors:

$$r_{p,t} = \alpha_p + \beta_{p,1} MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} YLDCHG_t + \beta_{p,4} BAAMTSY_t \\ + \beta_{p,5} PTFSBD_t + \beta_{p,6} PTFSFX_t + \beta_{p,7} PTFSCOM_t + \varepsilon_{p,t},$$

where $r_{p,t}$ is the excess return on each portfolio in month t. The independent variables are the market excess return (MKT), a size factor (SMB), monthly change in the 10-year Treasury constant maturity yield (YLDCHG), monthly change in Moody's Baa yield less the 10-year Treasury constant maturity yield (BAAMTSY), and three trend-following factors: PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). The t-statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Cold Portfolio (Manager Supply-Driven)	Hot Portfolio (Investor Demand-Driven)	Spread Portfolio
Alpha	0.453***	0.300***	0.154**
	(7.08)	(3.71)	(2.03)
MKT	0.159***	0.233***	-0.074***
	(10.39)	(12.11)	(-4.11)
SMB	0.089***	0.155***	-0.066***
	(4.58)	(6.35)	(-2.88)
YLDCHG	-0.852***	-0.117	-0.735*
	(-2.69)	(-0.29)	(-1.96)
BAAMTSY	-2.898***	-1.929***	-0.969**
	(-7.17)	(-3.79)	(-2.02)
PTFSBD	-0.004	-0.007	0.003
	(-0.86)	(-1.19)	(0.53)
PTFSFX	0.012***	0.007	0.006
	(3.38)	(1.41)	(1.35)
PTFSCOM	0.006	0.006	0.000
	(1.28)	(1.03)	(-0.01)
R^2	52.20%	54.40%	13.30%

Table 13: Performance Differences between Portfolios by Clone/Non-Clone Status (Alternate Formation)

We compare the performance of inception portfolios of clones and non-clone funds in existing families. Clone funds are defined as inceptions in families with existing funds of the same strategy category and with 85% or higher correlation with those existing funds. Sub-portfolios are created using a three-month formation period and then a 60-month holding period. Within Sub-portfolios, funds are equal-weighted at the beginning of each month. Following Jegadeesh and Titman (1993), for each month, the overall portfolio is formed by equally weighting the sub-portfolios with holding periods in that month. Thus we average over up to 60 portfolios for each monthly return. For an inception portfolio, the sub-portfolios consist of funds with inceptions during their formation period. The alpha for each portfolio is the intercept estimate from the equal-weighted portfolio excess returns on hedge fund risk factors:

$$r_{p,t} = \alpha_p + \beta_{p,1} MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} YLDCHG_t + \beta_{p,4} BAAMTSY_t$$
$$+ \beta_{p,5} PTFSBD_t + \beta_{p,6} PTFSFX_t + \beta_{p,7} PTFSCOM_t + \varepsilon_{p,t},$$

where $r_{p,t}$ is the excess return on each portfolio in month t. The independent variables are the market excess return (MKT), a size factor (SMB), monthly change in the 10-year Treasury constant maturity yield (YLDCHG), monthly change in Moody's Baa yield less the 10-year Treasury constant maturity yield (BAAMTSY), and three trend-following factors: PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). The t-statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Non-Clone	Clone	Non-Clone minus Clone
Alpha	0.407***	0.302***	0.106*
	(5.23)	(3.72)	(1.97)
MKT	0.227***	0.236***	-0.009
	(12.26)	(12.23)	(-0.68)
SMB	0.131***	0.139***	-0.007
	(5.61)	(5.69)	(-0.46)
YLDCHG	-0.962**	-0.814**	-0.148
	(-2.51)	(-2.04)	(-0.56)
BAAMTSY	-1.834***	-2.537***	0.703**
	(-3.76)	(-4.99)	(2.09)
PTFSBD	-0.002	-0.001	-0.001
	(-0.37)	(-0.15)	(-0.30)
PTFSFX	0.012***	0.012**	0.001
	(2.75)	(2.49)	(0.23)
PTFSCOM	0.013**	0.018***	-0.005
	(2.21)	(2.92)	(-1.20)
R^2	52.30%	54.50%	4.60%