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The Economics of Hedge Fund Startups: Theory and Empirical Evidence

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ABSTRACT

This paper examines how market frictions influence the managerial incentives and organizational structure of new hedge funds. We develop a stylized model in which new managers search for accredited investors and have stronger incentives to acquire managerial skill when encountering low investor demand. Fund families endogenously arise to mitigate frictions and weaken the performance incentives of affiliated new funds. Empirically, based on a TASS-HFR-BarclayHedge merged database, we find that ex ante identified cold inceptions facing low investor demand outperform existing hedge funds and hot inceptions facing high demand and that cold stand-alone inceptions outperform all types of family-affiliated inceptions.

THE HEDGE FUND INDUSTRY HAS EXPERIENCED dramatic growth over the last few decades. For example, worth less than \$100 billion prior to the 1990s, it ballooned to \$3 trillion in assets under management (AUM) by 2019. Although capital flows to both existing and new funds are important in explaining the rapid growth of the hedge fund industry, the literature has focused primarily on the former. The pioneering work of Aggarwal and Jorion (2010) on hedge fund inceptions presents evidence of outperformance during the first two or three years of existence. They also find strong evidence that early performance by individual hedge funds is persistent. Since a competitive, frictionless market allows capital to flow freely across fund types and receive

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comparable risk-adjusted returns (see Berk and Green (2004), Berk and van Binsbergen (2015, 2017)), these findings raise important questions: do market frictions hinder the flow of capital in the hedge fund industry and, if so, do these frictions shape the managerial incentives and organizational structures of the hedge fund industry.

In this paper, we address these questions by analyzing one of the most important types of market frictions faced by new hedge fund managers, namely, the need to search for accredited investors. Prior work shows that search frictions are important for mutual funds (see Sirri and Tufano (1998), Choi, Laibson, and Madrian (2010) for empirical evidence and Hortaçsu and Syverson (2004), Gârleanu and Pedersen (2018) for theoretical treatments). Because hedge funds face many marketing restrictions, search frictions may play an even more important role for these funds. However, the burden of search for hedge funds differs from that of mutual funds: instead of investors using public information to search, as discussed in mutual fund studies, new hedge fund managers often must find accredited investors and persuade them to invest.

We develop a stylized model in which we incorporate into the model of Berk and Green (2004) the need for a new manager to raise capital. In the spirit of Rubinstein and Wolinsky (1985) and Duffie, Gârleanu, and Pedersen (2005, 2007), we model fund-raising as a two-step search-and-bargaining process. This framework delivers several novel predictions and sheds light on the critical role played by search frictions in the hedge fund industry. The need to search for investors not only influences managerial incentives of new funds but also drives the formation of fund families.

To see how search frictions influence managerial incentives, we note that the total capital raised is determined by two margins: the *extensive margin*, which refers to the investors and initial capital that the manager identifies via search, and the *intensive margin*, the fraction of capital that the manager retains after bargaining with the investors. While the extensive margin is related primarily to investor demand, the intensive margin can be influenced by the merit of the fund: by investing in costly credible skills necessary to deliver superior (expected) performance, the manager can persuade a larger fraction of matched investors to contribute.

Importantly, the two margins act as substitutes, which impacts managerial incentives. A high extensive margin reduces a manager's incentive to use superior performance to persuade investors in the bargaining step. A novel and testable implication arises. If we refer to new funds launched using a "hot" strategy (i.e., a hedge fund strategy that is popular among investors at the time) as *hot inceptions* and those launched using a "cold" strategy (an unpopular strategy) as *cold inceptions*, our model predicts that cold inceptions should outperform hot inceptions.

Search frictions also provide an economic rationale for a key organizational feature of the industry: hedge fund families. Two types of family-affiliated inceptions arise in our model. First, family structures emerge to allow affiliated new funds to benefit from existing funds' investor pool. These investors may invest in the new fund or may introduce other accredited investors to the fund.

The latter networking effect reduces new funds' search costs and is consistent with the effects of social networks (e.g., Jackson and Rogers (2007)). However, the search advantage provided by family structures reduces the performance incentive of affiliated new managers. Our model therefore predicts that family-affiliated inceptions deliver poorer performance than stand-alone inceptions.

The second channel giving rise to family-affiliated inceptions is diseconomies of scale, a widely observed feature of hedge funds. In our model, search frictions amplify diseconomies of scale. Thus, when investor demand for existing funds experiences a positive shock, fund families have incentives to launch *clone inceptions* that closely mimic existing funds to absorb the excess demand. Clone inceptions are de facto hot and unlikely to contribute new skills and deliver superior performance.

We test these model predictions using a comprehensive sample of hedge funds that we obtain by merging three leading commercial hedge fund databases—Lipper TASS, HFR, and BarclayHedge—over the period 1994 to 2016. Specifically, we conduct three tests to investigate the performance difference between cold and hot inceptions.

First, we exploit variation in the popularity of hedge fund strategies among investors. Since investors chase past performance, we use recent strategy returns and flows to capture strategy popularity. Empirically, we find that cold inceptions deliver better performance than both existing funds and hot inceptions. Over the 60-month holding period after initial inception, cold inceptions outperform hot inceptions by 0.24% per month (or 3% annually) on a risk-adjusted basis.

Second, we explore the role of hedge fund families. We find that stand-alone inceptions outperform family-affiliated inceptions by 0.23% per month (or 2.8% per year) on a risk-adjusted basis. For family-affiliated nonclone funds, cold inceptions outperform hot ones by 4.3% annually. In contrast, we do not find a performance difference between cold and hot clone inceptions.

The above results suggest that an empirical strategy combining cold stand-alone and hot clone inceptions will have the most power to identify the effects of extensive-margin advantages because this strategy incorporates the influences of both strategy demand and family structure. The performance gap between cold stand-alone inceptions and hot clone inceptions is as high as 0.55% per month (or 6.8% annually), which is statistically and economically significant. Due to its appealing economic interpretation, we adopt this empirical strategy in several tests below. The results provide strong support to the prediction that superior-performing new hedge funds can be identified ex ante based on an understanding of the effects of investor demand and family structures.

Since our model applies best to new fund managers (experienced managers may have access to more investors), we also conduct a test focusing on the inceptions of new managers. To do so, we exclude inceptions run by managers who have previously managed other funds. The results using this sample are similar to those of our main tests but have larger economic magnitudes.

We next examine the economic source of cold inceptions' outperformance. In our model, superior performance is driven by investment in managerial skills.

However, a leading concern about hedge fund performance is that greater exposure to illiquidity or deliberate return-smoothing may allow some funds to inflate performance (e.g., Getmansky, Lo, and Makarov (2004)). We conduct a battery of tests to investigate the source of the performance difference between cold and hot inceptions and the extent to which it reflects genuine skill.

We first examine the security-selection and market-timing skills (e.g., Treynor and Mazuy (1966)) of cold and hot inceptions. We find that managers of cold inceptions exhibit significant skill in security-selection but no skill in market-timing. In contrast, managers of hot inceptions demonstrate negative (incorrect) market-timing ability and weaker selection skill, with the net effect that they do not deliver alpha.

Next, since persistence analysis provides a powerful test for managerial skill (e.g., Carhart (1997)), we examine whether there is any difference in performance persistence between cold and hot inceptions. We find that the performance of cold inceptions is highly and significantly persistent over time, while hot inceptions exhibit *negative* or insignificant persistence.

Finally, we show that the performance gap between hot and cold inceptions cannot be attributed to illiquidity or return-smoothing. Additionally, it cannot be explained by risk factors beyond the Fung and Hsieh (2004) seven factors, by fund characteristics, or by fund policy choices. Rather, our subsample analysis of convertible arbitrage (CA) funds suggests that cold inceptions exploit more sophisticated economic sources than market-wide risk or well-known arbitrage opportunities.

Backfill bias is an important concern in hedge fund research. It arises when managers joining a database have the option of reporting performance between inception and the initial report date. Because funds may not report if early performance is poor, reported returns from the backfill period exhibit an upward bias. To account for this bias, in all tests we use the approach of Jorion and Schwarz (2019) to identify the add dates and we delete all observations before this date.

This study builds on and extends the work of Aggarwal and Jorion (2010), who use a novel event-time approach and careful controls for backfill bias to show that new funds deliver alpha and performance persistence during the first two to three years. Their findings highlight the importance of new talent entering the industry but also strongly suggest that market frictions exist that hinder the efficiency of capital flows to new funds. Sun, Sun, and Zheng (2020) study whether investor sentiment affects the decision to start new funds and document a significant positive impact. We develop a model to explore these issues and show that search frictions affect portfolio management through family structure and negative demand-performance incentives. Both mechanisms are novel to the literature and play an important role in determining the cross-section of new hedge fund performance. Unlike in Aggarwal and Jorion (2010), these mechanisms lead us to explore and document significant performance heterogeneity across various types of hot and cold inceptions.

An emerging literature examines the influence of market frictions, particularly search frictions, on delegated portfolio management. Theoretical treatments of search frictions concentrate on the costs that investors bear in searching for funds (e.g., Hortaçsu and Syverson (2004), Gârleanu and Pedersen (2018)).[1] We complement these studies by examining the influence of new hedge fund managers' need to search for accredited investors. Building on the work of Berk and Green (2004) and the search framework of Rubinstein and Wolinsky (1985) and Duffie, Gârleanu, and Pedersen (2005, 2007), we show that this friction critically influences the incentives of new managers and the organizational structure of the industry. Our model is tractable and its predictions are consistent with the data.

Finally, this study extends the literature on hedge fund and mutual fund families. Although family structures are widely observed in both hedge fund and mutual fund industries, the underlying economic rationales differ between these industries. Our model suggests that hedge fund families can arise to mitigate search frictions or to address search-enhanced diseconomies of scale. The predictions of the model are supported in our empirical findings.

The remainder of the paper proceeds as follows. Section I presents a model of hedge fund inceptions and its testable hypotheses. Section II describes the hedge fund data that we use in our analysis. Section III examines the determinants of hedge fund inception probability. Section IV studies the influence of strategy demand and family structure on the performance of inceptions. Section V explores alternative explanations for our findings. Finally, Section VI concludes.

I. Theoretical Framework for Hedge Fund Inceptions

In this section, we develop a stylized model of hedge fund startups. We extend the model of Berk and Green (2004; hereafter, BG) by incorporating a key feature that affects hedge fund inceptions, namely, managers' need to search for accredited investors.[2]

A. The BG Benchmark of Existing Funds in the Same Strategy Category

Before we examine the launch of a new fund in a given strategy, we describe existing funds in the same strategy category. For tractability, existing funds in the strategy are represented by a *benchmark fund* whose operation and

[1] Hortaçsu and Syverson (2004) show that investors' search costs help explain the puzzling fee dispersion among S&P 500 index funds. Gârleanu and Pedersen (2018) examine the asset pricing implications of an extended Grossman-Stiglitz (1980) model in which investors search for mutual funds. In addition to search frictions, Jylhä and Suominen (2011) show that, in a two-country model, hedge funds arise endogenously to mitigate market segmentation, while Glode and Green (2011) model the bargaining process between hedge fund managers and investors.

[2] Indeed, raising money is widely regarded as one of the most difficult tasks of a new hedge fund (see, e.g., the discussion on how to start a hedge fund at https://www.lifeonthebuyside.com/start-a-hedge-fund/). In practice, new managers often need to actively search for potential investors, for instance, through networking. Even when potential accredited investors are found, it is not an easy task to raise capital, as many such investors have professional teams to aid investment (e.g., the family office of wealthy families).

dynamics follow BG, except for an additional search term that we specify below. Although the BG model was originally designed for mutual funds, its two key features—diseconomies of scale in fund operation and the equilibrium of the industry achieved through fund size—apply well to the hedge fund industry. In particular, as Berk and van Binsbergen (2015, 2017) point out, the market for mutual funds equilibrates in quantity as the price for funds is fixed by the market value of the funds' underlying assets. In that context, fund size proxies for managerial skill. In our model, the hedge fund industry achieves a similar equilibrium with an additional key influence—search frictions.

Following the notation of BG, we assume that in a given investment period t, a benchmark hedge fund is endowed with the skill to generate a risk-adjusted strategy benchmark return of R_t, with expected value ϕ_{t-1}, which is observable to investors.[3] Further, we assume that the fund distributes a cost-adjusted return of $r_t = R_t - c(q_t^E) - s(q_t^E)$, where q_t^E denotes fund size of existing funds, E. The variable $c(q_t^E) = b \times q_t^E + f$ is the fund-size-normalized cost function following Berk and van Binsbergen (2015, 2017), where b and f denote operational costs (with diseconomies of scale) and management fees.[4] The last term, $s(q_t^E)$, we introduce in the model to describe the size-normalized *search cost* that the fund incurs to raise capital q_t^E. The search cost can be thought of as a networking and marketing cost that can be deducted from the payoff of the fund (we specify the cost below).

When investors receive zero net-of-fee returns, we have the following search-enhanced BG equilibrium condition (hereafter, the BG condition):

$$E\left(r_{t+1}\right) = \phi_t - c\left(q_t^E\right) - s\left(q_t^E\right) = 0. \tag{1}$$

This condition says that the fund industry equilibrates in fund size and that the fund manager earns the economic rents that she creates. We assume this split of the benchmark fund's economic rents to highlight new funds' incentive problem. Adjusting the split will not affect the incentive *difference* across different types of funds.

To model managerial incentives, we follow BG and assume that a fund manager benefits from more capital: she derives a utility gain of $g(q_t) = f \times q(t)$ by managing a fund of size $q(t)$. Here, we remove the superscript E because the utility applies to both new and existing funds. At the same time, the manager can enhance a fund's expected risk-adjusted return by δ if she pays a linear

[3] More explicitly, the fund can generate a risk-adjusted return of $R_t = \alpha + \epsilon_t$, where $\alpha \sim N(\phi_0, \eta^2)$, based on known information, denotes the performance of the strategy (i.e., risk-adjusted return funds in this strategy category deliver) and $\epsilon_t \sim N(0, \sigma^2)$ is noise. Investors do not observe the true distribution of managerial skill. Rather, they use the realized return to update their prior, and expect that the benchmark fund will deliver an expected return of $\phi_{t-1} \equiv E(R_t|R_{t-1}, \ldots, R_1)$ in period t.

[4] BG assumes that the dollar cost of operation exhibits diseconomies of scale; $c(q_t^E)$ is the dollar cost scaled by fund size.

private learning cost, $L(\delta) = L_0 \times \delta$, where L_0 is a positive coefficient.[5] The manager can then deliver δ to investors to attract more capital.[6]

The trade-off between the marginal benefits and marginal costs determines the optimal level of performance that the manager wants to deliver. Although this trade-off resembles BG, the critical difference is that fund managers also face search frictions, which we examine next.[7]

B. Capital-Raising as a Search-and-Bargaining Process

Search can go in two directions: investors can search for managers, and managers can search for investors. A close look at an investor-search BG model and its comparison to the data (see Section II of the Internet Appendix) suggests that new hedge funds may benefit from actively reaching out to investors, giving rise to manager-initiated search. We therefore adopt the search framework of Rubinstein and Wolinsky (1985) and Duffie, Gârleanu, and Pedersen (2005, 2007) to examine how manager-initiated search affects the incentives of new funds.[8] To do so, we introduce three sets of assumptions that help extend BG under these frictions: investor heterogeneity in supplying capital to hedge funds, capital-raising as a search-and-bargaining process, and family affiliation as a source of capital.

We first describe investor heterogeneity and capital. For a given category, its full set of existing and potential investors can be classified into four types, denoted by $\Gamma = \{ho, hn, lo, ln\}$, based on two sets of characteristics: "h" (high) and "l" (low) refer to an investor's intrinsic preference for the hedge fund strategy (i.e., investors with a high (low) preference are willing (unwilling) to invest in hedge funds in that strategy), while "o" and "n" refer to "old" investors of the existing fund and noninvestors who have not invested. For instance, "hn" refers to investors who have not invested in the existing fund of the strategy but are willing to do so if a fund in that strategy solicits capital from them.

We normalize the total mass of all investors to one (there is a continuum of investors) and assume that investors carry with them an amount of capital to invest in period t, $z(t)$. The variable $z(t)$ describes investors' aggregate demand for the strategy, which is exogenous to the new fund by assumption. Hence, if we denote the fraction of type-σ investors ($\sigma \in \Gamma$) by $\mu_\sigma(t)$, such that

[5] Although learning costs are often assumed to be convex, this assumption is not necessary in our model because the benefit of learning is concave in alpha. Having convex learning costs does not affect our main conclusions, as we will see below.

[6] The fund can of course distribute only a fraction of alpha to investors and use the remaining alpha either to enlarge fund size as in the BG condition or it can retain the remaining alpha as incentive fees. The Internet Appendix shows that our main predictions remain valid in these cases. The Internet Appendix is available in the online version of this article on *The Journal of Finance* website.

[7] Another difference is that hedge funds can use leverage, which we do not explicitly examine in this paper. Hence, we can interpret q_t as leverage-adjusted fund size when hedge funds have already taken the maximum amount of leverage. We thank the Associate Editor for this intuition.

[8] Duffie (2010) provides more discussions on the mechanisms of imperfect move of capital.

$\mu_{ho}(t) + \mu_{hn}(t) + \mu_{lo}(t) + \mu_{ln}(t) = 1$, we can interpret $\mu_\sigma(t)$ as the mass of type σ investors, who carry with them $\mu_\sigma(t) \times z(t)$ of capital.

Next, we assume that capital-raising occurs at the beginning of period t, during which the existing fund and a new fund sequentially raise capital. The existing fund moves first. Once its steady state (characterized by stabilized $\mu_\sigma(t)$) is achieved, the fund collects capital from its investors (i.e., of type $\sigma \in \{ho, lo\}$).[9] The new manager then seeks to raise capital from the remaining investors in the market (i.e., of type $\sigma \in \{hn, ln\}$). Both funds invest the capital raised during the period and deliver cost-adjusted payoffs to investors at the end of the period.

We explicitly model capital-raising as a search-and-bargaining procedure. Take the new fund as an example. In the search step, the new manager tries to find investors in the market. We assume that by paying a total search cost of TS, a new fund can be matched with investors with an intensity of ρ^N, where the superscript N denotes new funds, and paying a higher search cost allows the manager to be matched with a higher intensity of investors, that is, $\rho^N = a \times TS$, where a is a positive constant. The extensive margin of capital-raising is then the total amount of matched capital in the search step, $\rho^N(\mu_{hn}(t) + \mu_{ln}(t))z(t)$.

Next the new manager bargains with investors, trying to persuade them to invest. Of matched investors, the hn-type will immediately invest due to their high intrinsic preference, but ln-type investors are unwilling to do so. However, the manager can use her fund-specific performance, δ, to bargain. Since ln-investors receive an expected abnormal return of δ, traditional financial theories (e.g., the CAPM) suggest that their optimal asset allocation in the new fund would be in proportion to δ. Hence, without loss of generality, we assume that ln-investors can be persuaded with probability $\xi(\delta) = \xi_0 \times \delta, \xi_0 > 0$, which allows the manager to raise capital in the amount of $\rho^N \mu_{ln}(t)\xi(\delta)z(t)$ from ln-investors.[10] Superior performance, therefore, increases the fraction of capital that the manager can retain under the intensive margin of the capital-raising process.

[9] Note that the value of $\mu_\sigma(t)$ is determined in the steady-state by the expected performance ϕ_t of the existing fund, the search cost it pays, and the probabilities of h- and l-type investors switching preferences—we provide details on the search process and the steady-state of the old fund in Lemma IA.2 in the Internet Appendix. For now, we note that investors remain in the market from whom the new fund can raise capital.

[10] There is no information asymmetry about δ in our model. It is worth noting that the second step in our model is equivalent to the bargaining process of a typical search-based asset pricing model in determining the equilibrium conditions. The difference is that in asset pricing models investors typically bargain for price (e.g., Duffie, Gârleanu, and Pedersen (2005, 2007)), while in our model the manager bargains for the *quantity* of capital to be invested when the price is fixed. This notion of bargaining (for capital) is consistent with both the BG equilibrium concept and the take-it-or-leave-it Nash bargaining models widely used in the search literature (see, e.g., McMillan and Rothschild (1994) for a survey on such models). The Internet Appendix (at the end of the proof of Lemma 3) sketches a general search framework that generates the assumption of having two types of investors with heterogeneous intrinsic preferences and the assumption of increasing bargaining power based on superior performance.

In economic terms, the search and bargaining steps capture the extensive and intensive margins of the capital-raising process, during which a total of $\rho^N(\mu_{hn}(t) + \mu_{ln}(t)\xi(\delta))z(t)$ can be raised. When the amount of capital is greater than or equal to the optimal fund size, $q(t)$, the manager stops searching and locks in the capital for investment:

$$\rho^N (\mu_{hn}(t) + \mu_{ln}(t)\xi(\delta))z(t) \geq q(t). \tag{2}$$

The capital-raising process above applies to both new and existing funds. Notably, the existing fund has an advantage of existing investors for which its search cost is zero. Thus, it searches for new investors as a replacement for withdrawals by existing investors. In contrast, the burden of new funds is to find all new investors. When the search process is costly, this difference gives rise to performance heterogeneity across funds.

If the existing fund benefits from its existing investors, a family structure can endogenously arise to allow some new funds to benefit from these investors as well. To capture this effect, we assume that new hedge funds can be either stand-alone or affiliated with the existing fund through a family structure, and we separately examine the incentives and performance of these two types of new funds. We assume that a family structure enhances the mass of high-type investors available to its affiliated new managers, that is, $\mu_{hn}^{N'}(t) = \mu_{hn}(t) + \gamma_h\mu_{ho}^E(t)$, where $\mu_{ho}^E(t)$ is the high-type investors of the existing fund and $\gamma_h(>0)$ describes the networking effect of the existing investors in supplying capital, referring new investors, and providing relevant information.[11]

Conditioning on the additional assumptions above, a fund manager maximizes her utility by optimizing search cost and fund-specific performance as follows:

$$\max_{s(t),\ \delta} U(s(t),\ \delta) = g(q_t) - L(\delta) \tag{3}$$

s.t. (1) and (2).

C. The Incentives of Stand-Alone New Funds in Generating Fund-Specific Alpha

We first derive a closed-form solution to the managerial problem of stand-alone inception. Easy access to capital during the search step of the fund-raising process (a high extensive margin) influences the incentive to generate extra performance. The extensive margin is associated with investor demand, $z(t)$, which is exogenous to the new fund. The impact of demand on managerial incentives is as follows.

[11] Existing investors may also help managers reduce the intensity of low-type investors, that is, $\mu_{ln}^{N'}(t) = \mu_{ln}^N(t) - \gamma_l\mu_{lo}^E(t)$, where γ_l is a positive parameter. Adding this effect does not affect our main conclusions.

PROPOSITION 1: *When a new manager solves the general problem (3) subject to the conditions specified in (1) and (2), the following properties hold:*

(i) The optimal level of fund-specific alpha is $\delta^* = \text{Max}\{0, f^{\frac{1}{2}}(L_0 b \mu_{ln}(t)\xi_0 a z_t)^{-\frac{1}{2}} - \frac{\mu_{hn}(t)}{\mu_{ln}(t)\xi_0}\}$.

(ii) When the new manager encounters high investor demand, that is, a larger value of $z(t)$*, the level of fund-specific alpha* δ^* *decreases as a first-order effect.*

(iii) Having a convex learning cost does not affect property (ii).

The extensive margin has a profound effect on the incentive of new managers to generate additional performance. When new managers encounter high investor demand in the search phase (i.e., when $z(t)$ is high), the incentive for managers to generate additional performance to retain matched investor capital (the intensive margin) declines.[12] The interplay between the extensive and intensive margins is one of the most fundamental tradeoffs that new managers face in an economy with search frictions.

This trade-off highlights an important difference between mutual fund and hedge fund startups. In the original BG equilibrium, capital supplied to the mutual fund industry is competitive, leading a more skillful fund to enjoy a larger size in realizing its economic rents. In the Internet Appendix, we show that this positive capital-skill relationship holds even when investors bear search costs (and thus compete) for managerial skill—investors still get zero economic rents after search costs. For hedge fund startups, however, managers search (and thus compete) for accredited investors. In this case, investors can obtain economic rents, and a negative capital-skill relationship can arise, reflecting the substitution between the extensive and intensive margins.

We now discuss two concerns related to the generality of Proposition 1. The first is that the new fund may not distribute all fund-specific alpha (δ^*) to investors. The retained part can be used to pay for the operation and search costs of the fund or can be kept as incentive fees. Lemma IA.1 in the Internet Appendix demonstrates that neither case will change property ii of Proposition 1. The intuition is that while both cases change the division of rents between the manager and investors, neither eliminates the interplay between the two margins during the search-and-bargaining process.

The second concern is how the search-and-bargaining process shapes the incentives of the existing fund. Lemma IA.2 in the Internet Appendix shows that, under reasonable conditions, the existing fund optimally chooses not to deliver any additional performance. The result is intuitive: as old funds have a much smaller search burden due to existing investors, they have less incentive

[12] The fraction of optimistic investors of the hn type, $\mu_{hn,}$ can also achieve a similar effect as $z(t)$. However, unlike $z(t)$, μ_{hn} is determined by the steady-state of the existing fund and can be further influenced by an endogenous family structure. Hence, in this proposition we focus on $z(t)$; we examine μ_{hn} in later sections. Thus, in Proposition 1 we assume that new funds are independent (i.e., stand-alone).

to resort to performance as a bargaining tool to attract new capital even when new funds have the necessity of doing so.

D. Hedge Fund Families and Implications

We now examine the inception of new funds affiliated with the existing fund. The following proposition shows that family structure has a profound effect on the incentives and performance of new managers in the presence of search frictions.

PROPOSITION 2: *When an affiliated new manager solves the optimization problem in equation (3), the following properties hold:*

- *(i) A family-affiliated inception pays a lower search cost than a stand-alone inception.*
- *(ii) The optimal level of fund-specific alpha chosen by the family-affiliated inception is lower than that of a stand-alone inception.*
- *(iii) Property (ii) of Proposition 1 remains valid for family-affiliated inceptions: high investor demand reduces the level of optimal alpha.*

The first property suggests that a positive networking effect reduces the search cost of a new fund affiliated with a family, which provides the rationale for the endogenous emergence of family structure. The next two properties describe the influence of the family structure on the incentives of a new fund manager. Since the family structure makes it easier for its affiliated new funds to find capital in the extensive margin, the incentive to generate performance to improve the intensive margin is reduced. However, this does not eliminate the interplay between the extensive and intensive margins. High investor demand still reduces performance incentives for an affiliated fund. In the Internet Appendix, we further prove that convex learning costs and the retention of a fraction of rents will not change this demand-performance trade-off.

Note that the proposition above applies to a new fund that has a different investment strategy than its affiliated existing fund—hence investors of the latter are interested in supplying capital to the new fund as a networking effect. In practice, however, new clone funds are often launched with the same strategy as the affiliated existing fund(s). The existence of clone funds is puzzling because a fund family could have asked its existing funds to absorb the capital instead. What prevents fund families from doing so—and what can we say about the performance of clone funds?

Lemma IA.3 in the Internet Appendix sheds light on the underlining economics by examining a second channel through which search frictions give rise to family-affiliated inceptions, namely diseconomies of scale. This channel is widely regarded as a binding constraint for hedge funds (e.g., Goetzmann, Ingersoll, and Ross (2003), Getmansky, Lo, and Makarov (2004), Fung et al. (2008)). In particular, Lemma IA.3 in the Internet Appendix shows that the optimal search cost paid by an existing fund exhibits a diminishing benefit as fund size increases. The intuition is that funds need to search for new investors when old investors withdraw. A larger fund size (more search costs spent) reduces the mass of high-type noninvestors remaining in the market because they are converted to high-type investors. This decreases the marginal benefit of spending on search. Since search costs reduce the capital that can otherwise be used to relax the diminishing returns to scale (the BG condition), they amplify the fund's diseconomies of scale.

This amplification of diseconomies-of-scale offers one rationale for the inception of clone funds: when an existing fund encounters enthusiastic investors, the launch of a clone fund provides a cost-effective way to retain the capital for future periods. Since the goal of the clone fund is to provide an investment opportunity identical to the existing fund, its performance will not exceed that of the existing fund. For a clone fund created due to diseconomies of scale considerations, its inception reveals the excess demand the fund family faced, regardless of whether the clone fund is launched using a hot or cold strategy. Hence, as a first-order effect, we expect clone funds to deliver poorer performance than nonclones, regardless of whether they arise in hot or cold strategy categories.

E. A Numerical Example and Empirical Hypothesis on Hedge Fund Startups

The predictions of our model about the incentives of new fund managers can be demonstrated in a numerical example. We set parameters to match the observed size and performance of existing and new funds. Specifically, we calibrate the steady-state distribution of investor types (i.e., μ_σ for $\sigma \in \{ho, lo, hn, ln\}$) for the existing fund according to Lemma IA.2 in the Internet Appendix, and then apply the corresponding intensity of noninvestors (i.e., μ_{hn} and μ_{ln}) to inceptions according to Proposition 1. Table IA.I in the Internet Appendix tabulates the parameter values, which provide a baseline case to describe the existing and new funds. As can be seen, the baseline case closely matches the observed size and performance of existing and new funds.

In Figure 1, we show how the incentives of a new hedge fund change when its extensive margin deviates from the baseline case. Incentives are captured by the model-implied optimal fund-specific performance that the new fund manager is willing to deliver. Variation in the extensive margin is quantified by the ratio $z(t)/z$, where z is the value of $z(t)$ used in the baseline case. We refer to this ratio as the investor demand index. A high (low) $z(t)/z$ ratio indicates cases in which investors provide more (less) capital to the hedge fund industry. Note that variation in $z(t)/z$ is exogenous to new managers. This figure plots the optimal performance, δ^*, of stand-alone inceptions, family-affiliated nonclone inceptions, and family-affiliated clone inceptions according to Proposition 1, Proposition 2, and Lemma IA.3 in the Internet Appendix.

Figure 1 demonstrates the negative relation between investor demand along the extensive margin and performance incentives along the intensive margin. This negative relation applies to both stand-alone and family-affiliated inceptions. Family-affiliated inceptions have less incentive to deliver performance than stand-alone inceptions. As discussed in the Internet Appendix, the

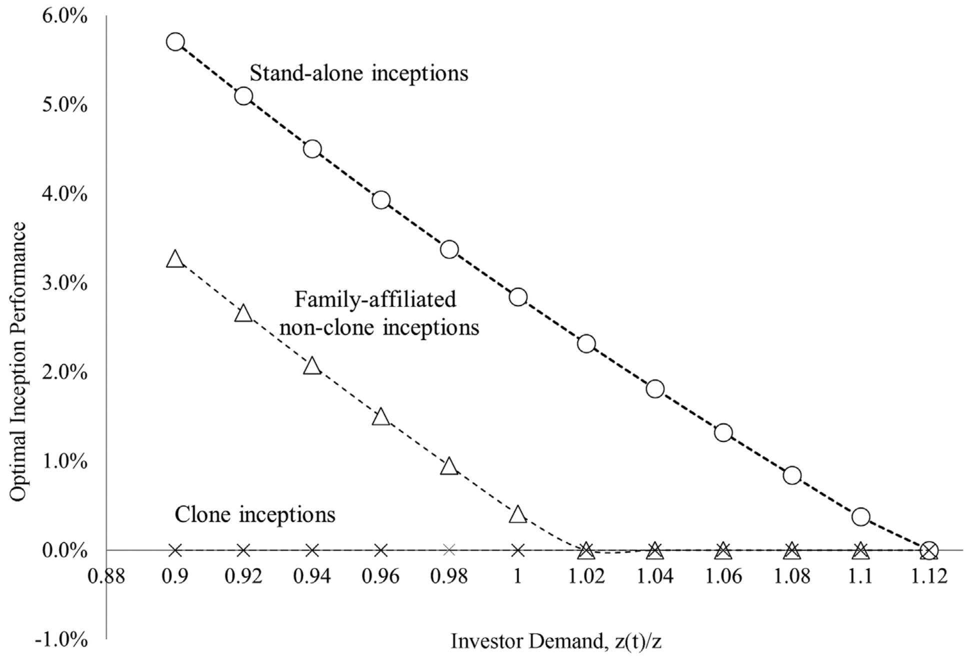

Figure 1. Optimal alpha of stand-alone and family-affiliated inceptions. This figure plots the relationship between investor demand during the search step and inception performance that the new fund manager delivers. Variation in investor demand is given by the ratio of $z(t)/z$, where z is the value of $z(t)$ used in the baseline case of the numerical example provided in the Internet Appendix. The optimal performance of stand-alone inceptions, family-affiliated nonclone inceptions, and family-affiliated clone inceptions is calculated according to Proposition 1, Proposition 2, and Lemma IA.3, respectively, in the Internet Appendix.

performance of cold and hot hedge fund inceptions in our empirical analyses can be generated from reasonable ranges of demand changes.

To better describe the empirical implications of the model visualized above, we develop hypotheses that can be tested in the data. According to Proposition 1, our first hypothesis is that the incentive for new managers to deliver performance differs according to variation in the extensive margin related to investor demand. Our model predicts that hot inceptions deliver poorer performance than cold inceptions in the cross-section. To test this empirically, we notice that hot strategies can be proxied by recent high flows and high performance (since hedge fund investors chase past performance) in a strategy category. Accordingly, we have the following hypothesis.

HYPOTHESIS 1 (Two types of inceptions): Hot inceptions (following high category performance and flows) differ from cold inceptions in their incentive to deliver performance. On a risk-adjusted basis, cold inceptions deliver superior performance in general and outperform hot inceptions in particular.

The null hypothesis is that all hedge fund inceptions are ex ante identical and, as a result, deliver similar performance ex post. We can also compare the performance of new funds to that of existing funds. The two propositions above and Lemma IA.2 in the Internet Appendix imply that only managers of cold inceptions have the incentive to deliver performance above and beyond the benchmark performance of old funds. This novel heterogeneity is summarized in the following hypothesis.

HYPOTHESIS 2 (Value-creating inceptions): Inceptions are value-creating and associated with better performance than existing funds. However, this value-creation effect concentrates in cold inceptions only.

Our model suggests that family structure arises endogenously in a market with search frictions, and influences the performance of inceptions. Proposition 2 predicts that family structure affects the performance incentives of affiliated nonclone inceptions compared to stand-alone inceptions. Lemma IA.3 in the Internet Appendix suggests that search-friction-amplified diseconomies of scale give rise to the inception of clone funds. These predictions can be summarized in the following hypotheses.

HYPOTHESIS 3 (The impact of family structure on inception performance): Hedge fund inceptions within existing families deliver poorer performance than stand-alone inceptions.

HYPOTHESIS 4 (Two types of inceptions within family-affiliated funds): Within family-affiliated nonclone funds, cold inceptions outperform hot inceptions. Clone inceptions, by contrast, deliver poor performance regardless of being launched in cold or hot categories.

The two hypotheses above propose that search-friction-motivated family structures critically influence inception performance. In the mutual fund literature, researchers have identified several important mechanisms for family structure, including the convenience of reduced within-family switching fees (Massa (2003)), the efficiency of within-family resource allocation (Fang, Kempf, and Trapp (2014), Berk, van Binsbergen, and Liu (2017)), the flexibility of cross-subsidization (e.g., Bhattacharya, Lee, and Pool (2013), among others), and the star-creation strategy of attracting flows (Nanda, Wang, and Zheng (2004)). Our model suggests that the hedge fund industry is instead dominated by search frictions and associated with a different rationale for the creation of fund families.

II. Data Description

We use monthly hedge fund data formed by merging fund and return information from three sources: Lipper TASS, HFR, and BarclayHedge. Fund counts for our merged database, the constituent databases, and the degree of overlap are reported in Table IA.II in the Internet Appendix. After the merge, we have a total of 31,402 funds. Our sample includes both live and defunct funds to mitigate survivorship bias and spans the 1994 to 2016 period. We restrict attention to funds reporting at least 12 monthly return observations and therefore retrieve inception information from the merged database up to the end of 2015. Funds reporting the same management company are considered to be from the same fund family. Because funds may come from different databases, we cross-reference family affiliations across databases.

Because funds have the option of reporting backfilled returns at the time they start reporting to a commercial database, hedge fund data are prone to backfill bias. We use the method proposed in Jorion and Schwarz (2019) to estimate the date when each fund began reporting returns based on the sequential assignment of fund IDs within databases. This is necessary for BarclayHedge, which does not provide information on which returns are backfilled. In addition, TASS has not updated the fund add-date field since 2011, so we apply this method to TASS returns where necessary. HFR reports complete and reliable information on fund add dates, so estimation is not necessary. We minimize the impact of backfill bias by excluding fund returns prior to the fund's add date. Each database also reports each fund's inception date.

Unless otherwise specified, we report returns in excess of the risk-free rate. We use the seven-factor model from Fung and Hsieh (2001, 2004) to compute the risk-adjusted return (*alpha*). The factors are constructed following the instructions from David Hsieh's Hedge Fund Data Library.[13]

The databases provide strategy classifications for each fund, but each database uses a different categorization methodology. For the purposes of this paper, we use the TASS strategy classification criteria. TASS provides 10 general hedge fund strategies—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)—which provide a reasonable cross-section to examine inception incentives.[14] To map reported strategy categories from HFR and BarclayHedge to the TASS definitions, we use fund merge information. For each fund that appears in both TASS and one of the other databases, we record the mapping from the database classification into the TASS classification. Each database classification can then be assigned to a TASS strategy based on a majority relationship. The resulting strategy mapping is reported in Table IA.III in the Internet Appendix.

Table I reports the number of funds reporting a valid AUM at the end of each year in selected hedge fund strategies. Section III in the Internet Appendix provides a more complete version of the table, which reports the number for each of the 10 hedge fund strategies. We exclude funds reporting other, minor, strategies and funds of funds. The total number of funds has steadily increased over time. We also report the number of distinct families. Over time, the average number of funds per family has increased from 1.67 at the beginning of our

[13] See https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm.

[14] The two other databases have, relatively speaking, too broad tier-one strategy categories and too detailed tier-two strategies for our testing purposes. In contrast, the TASS classification achieves a sensible balance between the number of strategies and the number of funds within each strategy.

Table I

Summary Statistics of Hedge Funds and Hedge Fund Families

This table reports the number of funds in our sample by investment strategy category and year. Funds are included if they report a return in December of the given year and have at least 12 monthly return observations. 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 report the number of funds for CA, EMN, GM, and LS, and refer the reader to Section III of the Internet Appendix for a version of the table including all strategies. We exclude funds of funds and funds without strategy information. 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 at the end of each year. Our sample is formed by merging fund/family/return information from TASS, HFR, and BarclayHedge and spans the period 1994 to 2016.

	Strategy Category Counts							
Year	CA	EMN	GM	LS	Number of Funds	Number of Families	Funds per Family	Fraction Multi-Fund
1994	77	72	297	781	2,592	1,555	1.67	0.30
1995	91	89	338	960	2,996	1,722	1.74	0.33
1996	106	98	320	1,195	3,336	1,890	1.77	0.34
1997	114	136	328	1,391	3,724	2,052	1.81	0.36
1998	135	179	339	1,599	4,032	2,215	1.82	0.36
1999	153	217	330	1,892	4,465	2,374	1.88	0.37
2000	190	238	340	2,154	4,885	2,497	1.96	0.39
2001	239	321	375	2,476	5,527	2,711	2.04	0.40
2002	289	409	456	2,706	6,259	2,883	2.17	0.41
2003	320	459	609	3,131	7,345	3,210	2.29	0.43
2004	312	513	734	3,616	8,535	3,512	2.43	0.44
2005	294	578	840	4,128	9,655	3,835	2.52	0.44
2006	280	595	936	4,558	10,612	4,042	2.63	0.44
2007	239	601	991	4,742	11,196	4,167	2.69	0.44
2008	178	544	1,015	4,451	10,765	4,070	2.64	0.43
2009	156	532	1,140	4,494	11,099	4,109	2.70	0.42
2010	180	494	1,194	4,602	11,611	4,124	2.82	0.43
2011	190	493	1,208	4,683	11,800	4,015	2.94	0.44
2012	200	464	1,186	4,631	11,554	3,877	2.98	0.43
2013	206	439	1,016	4,651	10,966	3,743	2.93	0.42
2014	196	462	924	4,485	10,410	3,526	2.95	0.42
2015	172	439	792	4,141	9,418	3,205	2.94	0.41
2016	159	379	653	3,583	8,065	2,812	2.87	0.40

sample to 2.87 by the end. The fraction of management families with multiple funds has also increased, from 30% in 1994 to 40% at the end of 2016. Both observations suggest that family structure plays an increasingly important role in the hedge fund industry.

Table II reports total inceptions per year and total funds reporting in December of the given year. The proportion of the universe represented by new funds increased from 18% in 1994 to 22% in 2003 and then decreased thereafter. We also report the total AUM of new funds raised each year (Inception AUM) and the AUM of our whole sample. We consider the inception AUM to be the first nonmissing reported AUM in the first three months of its life. Inception AUM grew from \$2.8 billion in 1994 to \$47.1 billion in 2006 and was volatile thereafter. We also report flows to existing funds each year. Flows are computed from performance and AUM according to

$$Flow_{i,t} = AUM_{i,t} - AUM_{i,t-1} \cdot (1 + r_{i,t}), \tag{4}$$

where fund flows and AUM are reported in U.S. dollars (we convert any AUM reported in another currency to U.S. dollars). The variable $r_{i,\mathrm{t}}$ represents the return to fund i in month t. Compared to flows to existing funds, inception AUM is much less volatile, suggesting that new hedge funds play a unique and important role in attracting capital to the hedge fund industry.

In the sixth column, we report the number of inceptions that are stand-alone. The difference between the first column and this column indicates the number of inceptions affiliated with an existing family. In the last column, among the family-affiliated inceptions, we report how many are clones of other funds. An inception in an existing family is categorized as a clone if it is in the same strategy category as an existing fund in the family and if the fund has a return correlation with the previously existing fund of 90% or greater. Where treated separately, a "nonclone" inception in an existing family is the first fund in a strategy within that family. Overall, 10,620 inceptions in our sample were the first in their management companies and 17,564 are inceptions in existing families. Of the inceptions in existing families, 8,950 are classified as clone funds. Overall, our sample contains 28,184 inceptions.

Using monthly returns, we construct the raw and risk-adjusted performance of funds and portfolios of funds. In each case, we measure raw performance by computing 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

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

where $r_{p,t}$ is the monthly excess 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 change in the 10-year Treasury constant-maturity yield, *BAAMTSY* is the change in Moody's Baa yield less the 10-year Treasury constant-maturity yield,

Table II

Summary Statistics of Hedge Fund Inceptions and Flows over Time

We report flows to hedge fund inceptions and existing funds by year. Variables include the number inceptions, and the ratio of inceptions to all existing funds in December, inception AUM (computed as the first AUM in the first three months for each fund), and net flows to all funds in this year (computed, fund by fund, as $Flow = AUM_t - AUM_{t-1}(1 + r_t)$). Total AUM is the AUM of all funds in December. Stand-alone inception is the number of inceptions that begin new families, and clone inceptions are inceptions in existing families in the same strategy and 90% correlated with a previously existing fund in the family. Our sample spans from 1994 to 2016 but funds are required to have 12 monthly return observations for inclusion, so our inception sample ends in December 2015.

Year	All Inceptions	Inceptions/Existing	Inception AUM (Bil)	Net Flows (Bil)	Total AUM (Bil)	Stand-Alone Inceptions	Clone Inceptions
1994	479	0.18	2.82	9.19	103.98	296	51
1995	575	0.19	4.36	–2.89	129.31	282	117
1996	653	0.20	6.65	7.01	169.46	374	104
1997	684	0.18	6.99	32.08	247.38	354	135
1998	699	0.17	8.62	17.22	277.13	390	128
1999	889	0.20	13.35	7.06	344.70	464	197
2000	891	0.18	10.94	9.79	381.70	438	181
2001	1,086	0.20	11.19	60.50	451.49	510	278
2002	1,320	0.21	14.99	39.99	480.26	596	337
2003	1,597	0.22	31.26	138.85	731.41	647	473
2004	1,815	0.21	34.00	233.53	1,034.09	675	613
2005	1,965	0.20	41.92	35.67	1,164.77	733	629
2006	2,013	0.19	47.11	234.18	1,484.61	715	667
2007	1,966	0.18	42.90	255.43	1,865.74	663	671
2008	1,613	0.15	39.12	–207.88	1,259.34	625	418
2009	1,839	0.17	58.89	–88.19	1,321.85	570	644
2010	1,825	0.16	69.44	61.04	1,522.66	535	718
2011	1,711	0.14	71.65	40.58	1,603.76	476	694
2012	1,527	0.13	97.04	–4.58	1,678.69	456	600
2013	1,309	0.12	53.09	119.88	1,877.84	370	528
2014	1,055	0.10	41.19	10.62	2,003.09	285	460
2015	673	0.07	26.70	71.72	2,216.73	166	307

and the other three variables are trend-following factors available on Hsieh's website: *PTFSBD* (bond), *PTFSFX* (currency), and *PTFSCOM* (commodity).

III. Determinants of Hedge Fund Inception Probability

Before categorizing inceptions as cold or hot, we examine how various characteristics of hedge fund strategy classifications and fund families affect the incentives of inceptions. This analysis provides intuition to help us identify different types of 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 1 when a family had an inception in a given year and strategy category and 0 otherwise. The regression equation is

$$Inception_{j,k,t} = \Lambda\left(\alpha + \beta \times X_{j,t-1} + \psi \times Y_{k,t-1}\right) + \varepsilon_{j,k,t}, \tag{6}$$

where $\Lambda(\cdot)$ represents the logistic function, $X_{j,t-1}$ is a vector of strategy explanatory variables for strategy category j and year $t-1$, $Y_{k,t-1}$ a vector of family explanatory variables for family k and year $t-1$, *Strategy return* is the average monthly return of an equal-weighted portfolio of funds in each strategy category in year $t-1$, *Strategy volatility* is computed from equal-weighted portfolios of funds over the 24 months prior to year t, *Strategy AUM* is the sum of reported AUM in December of year $t-1$, *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 $t-2$, and *Family return*, *Family volatility*, and *Family AUM* are defined following the corresponding strategy variables. In addition, *Family assets in same strategy* is the sum of assets in strategy j and family k at the end of year $t-1$, *Strategy large family open* is set to 1 if one of the largest eight hedge fund families had an inception in strategy category j in year $t-1$, *Family inceptions* 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 III reports the estimation results. Specifications (1) through (3) focus on strategy-level controls. Specifications (4) through (6) add family-level controls. In specification (7), we include an interaction term between the returns of the strategy and the assets that a family already has in that strategy. This test examines whether there is a nonlinear effect of the family already having a strong presence in a given strategy at the time that the strategy becomes popular. This would be a likely time for a family to initiate a fund to take advantage of investor demand for that strategy.

The estimation results in specifications (1) and (2) show that lagged strategy returns and lagged strategy flows are positively associated with inceptions in a family/year/strategy, with coefficients of 24.2 and 11.8, respectively (t-statistic = 14.15 and 7.44). Lagged inceptions in the strategy are also related to inceptions (t-statistic = 19.09) in specification (3). These results are highly

Table III

Logistic Regression of Inceptions within Existing Families on Family/Strategy Variables

This table reports 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 $Inception_{j,k,t} = \Lambda(\alpha + \beta \times X_{j,t-1} + \psi \times Y_{k,t-1}) + \varepsilon_{j,k,t}$, where $\Lambda(\cdot)$ represents the logistic link function, $X_{j,t-1}$ 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 $t-1$; $Inception_{j,k,t}$ is a dummy variable that is 1 if there was an inception in strategy j, family k, and year t, and 0 otherwise. In year t, the explanatory variables are as follows. *Strategy return* and *Family return* are the average monthly return to an equal-weighted portfolio of funds for a given strategy or family in year $t-1$. *Strategy volatility* and *Family volatility* are computed from monthly equal-weighted portfolios from $t-2$ to t. *Strategy AUM* and *Family AUM* are the sum of AUM in December of year $t-1$ in billions of USD. *Family assets in same strategy* is the sum of assets in strategy j and family k at the end of year $t-1$. *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 $t-2$. *Strategy large family open* is set to 1 if one of the largest eight hedge fund families had an inception in strategy j in year $t-1$. *Family inceptions* 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. t-Statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Strategy return	24.177***			24.403***			22.679***
	(14.15)			(13.63)			(12.66)
Strategy flow		11.770***			11.965***		10.587***
		(7.44)			(7.51)		(6.54)
Strategy inceptions			2.179***			2.238***	
			(19.09)			(19.29)	
Strategy volatility	2.507***	3.436***	3.615***	2.917***	3.867***	4.104***	3.346***
	(6.98)	(9.97)	(10.34)	(7.95)	(11.00)	(11.50)	(9.14)
Strategy AUM (Bn)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(25.48)	(24.26)	(27.53)	(24.16)	(23.33)	(26.55)	(24.69)
Strategy large family open	0.538***	0.575***	0.499***	0.541***	0.575***	0.497***	0.534***
	(14.14)	(15.11)	(13.01)	(14.02)	(14.89)	(12.78)	(13.79)
Family return				0.058	3.286***	2.332**	−0.083
				(0.06)	(3.54)	(2.49)	(−0.09)
Family inceptions				0.130***	0.130***	0.131***	0.129***
				(36.01)	(36.01)	(36.12)	(35.89)

(*Continued*)

Table III—*Continued*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Family volatility				−0.346**	−0.387***	−0.498***	−0.310**
				(−2.31)	(−2.58)	(−3.30)	(−2.07)
Family AUM (Bn)				−0.007**	−0.007**	−0.006**	−0.004
				(−2.29)	(−2.29)	(−2.03)	(−1.45)
Family flow				0.346***	0.337***	0.331***	0.334***
				(11.90)	(11.55)	(11.36)	(11.41)
Family assets in same strategy (Bn)				0.068***	0.067***	0.066***	0.033***
				(8.23)	(8.21)	(8.07)	(3.64)
Strategy return × family assets							9.612***
							(6.30)
Pseudo-R^2	2.70%	2.40%	2.80%	6.00%	5.60%	6.10%	6.10%

robust in specifications (4) through (7). Other strategy-level variables that are positively associated with subsequent inceptions include volatility, strategy AUM, and the strategy having a recent inception from a very large family.

The positive relations between strategy return, flow, and inceptions and subsequent inceptions are relevant to our analysis. We employ lagged strategy returns and lagged strategy flow as proxies for investor demand for that strategy. We use these proxies to identify cold and hot strategies and use lagged strategy inceptions as an alternative proxy in a robustness check.

Although family flows are related to the inception of new funds (see specification (7)), family returns are insignificant after we control for strategy returns. This difference between family and strategy returns suggests that the family structure and strategy-level demand operate on inceptions through different channels. The positive relation between family assets in a strategy and subsequent inceptions in the strategy (i.e., clone inceptions) reveals that clone funds can be launched when families are unwilling or unable to use existing funds to efficiently absorb more capital due to diseconomies of scale. Finally, specification (7) reports an interaction effect: families with high assets in the previous year in strategy categories that had good returns are particularly likely to have an inception (t-statistic = 6.30).

Taken together, both strategy-level variables related to investor demand and the presence of a family structure facilitate the inception of new hedge funds. These results motivate our identification strategies, which we use to examine the performance of the two types of inceptions.

IV. Performance Difference between Cold and Hot Inceptions

In this section, we test our hypotheses by constructing cold and hot inception portfolios and examining their performance differences.

A. Inceptions in Hot and Cold Strategy Categories

We start by analyzing inception performance in hot and cold strategy categories. To determine whether an inception is in a hot or cold strategy, we use two measures: the 36-month (prior to inception) flows into a given strategy and the 36-month (prior to inception) returns to the strategy. Each month, we rank the 10 hedge fund strategies using these two lagged variables. Strategy categories with a high rank (eight or greater) in both measures are defined as "hot," whereas strategies with a low rank (three or lower) in both measures are defined as "cold." New hedge funds employing a hot (cold) strategy are accordingly classified as hot (cold) inceptions.

In each month, portfolios are formed from new hedge fund inceptions over the prior three-month period. Among these inceptions, cold and hot inceptions are identified and included in their respective inception portfolios while existing funds alive during that period are included in the noninception portfolio. Each inception is held in its portfolio for a 60-month holding period after its inception. Holding periods follow actual fund inception dates. We exclude backfilled returns and require at least 12 monthly return observations for an inception to be included. Funds within portfolios are equally weighted. Since the inception portfolios of a given type are created in each month and held for 60 months to assess their performance, we follow Jegadeesh and Titman (1993) and equal-weight overlapped inception portfolios in each month to create the final holding portfolio for the inception type. Portfolio returns are then regressed on the seven Fung and Hsieh (2004) risk factors to obtain the risk-adjusted alpha (see equation (5) for the regression specification).

These portfolio regression results are in the first three columns of Table IV. The portfolio of cold inceptions has a significant alpha of 0.376% monthly or 4.6% per year (t-statistic = 4.95), as can be seen in the first column, whereas that of hot inceptions in the second column does not have a significant alpha (t-statistic = 1.1). Furthermore, the monthly spread between the two portfolios (labeled "Cold-Hot") is 0.242% per month, or 2.9% per year (t-statistic = 2.36). These estimates are economically sizable and support our first hypothesis, suggesting that cold inceptions deliver superior risk-adjusted performance in general and outperform hot inceptions in particular.

The next three columns report the performance of existing funds (labeled "Old funds"), as well as the spread between cold/hot inceptions and existing funds. Existing funds also deliver significant risk-adjusted performance (α = 0.224% per month, or 2.7% annually). This result is consistent with the literature documenting that hedge funds deliver abnormal performance (see, among others, 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 et al. (2013), Jiao, Massa, and Zhang (2016)).

More importantly for our purposes, the last two columns show that cold inceptions outperform existing funds by 0.152% per month or 1.8% per year (t-statistic = 2.35), whereas hot inceptions do not deliver a significant alpha over existing funds (nor do they deliver a significant alpha overall). Hence, our results support Hypothesis 2, which predicts that the value-creation effect of new funds is concentrated in cold inceptions.

B. Family-Affiliated Inceptions in Hot and Cold Strategy Categories

We now examine the effect of family structure on inception performance. We first examine the general difference between stand-alone inceptions (or new family inceptions, as each inception effectively creates a new family) and family-affiliated inceptions. For each group of inceptions, we form inception portfolios as above and regress portfolio returns (and pairwise and corner spreads) on hedge fund risk factors to obtain the risk-adjusted alpha.

The alphas of stand-alone inceptions and family-affiliated inceptions are reported in Table V. Stand-alone inceptions generate a risk-adjusted alpha of 0.458% per month (5.7% annually) with a t-statistic of 8.49. The alpha of family-affiliated inceptions is smaller, at 0.233% per month (2.8% annually),

Table IV

Performance Differences between Portfolios by Inception Type

This table presents the results of regression analysis of inceptions and existing funds. We compare the performance of inceptions in hot (popular) strategies with those in cold (unpopular) strategies as well as the long-short spread portfolio. We also examine the portfolio of all inceptions and the old-fund portfolio. A strategy is classified as hot (cold) if its past 36-month returns and flows are both among the top (bottom) 30% of all strategies. In any month, inception portfolios are formed from new hedge fund inceptions of a given family structure and strategy identification over the prior three months. Each inception will be held in its corresponding portfolio for a 60-month holding period after its inception. The holding period follows the actual inception date of each fund. Within the holding period, we exclude backfilled returns and require at least 12 monthly return observations for an inception to be included in any inception portfolio. Funds are equally weighted and rebalanced at the beginning of each month. Portfolio returns are then regressed on the Fung and Hsieh (2004) seven risk factors to obtain the risk-adjusted return (alpha). 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 portfolio p in month t. The independent variables are the market excess return (MKT), a size factor (SMB), the monthly change in the 10-year Treasury constant-maturity yield (YLDCHG), the 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). t-Statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Cold Inception Portfolio	Hot Inception Portfolio	Cold – Hot Inception Portfolio	All Inception Portfolio	Old Fund Portfolio	Cold Inception – Old Fund Portfolio	Hot Inception – Old Fund Portfolio
alpha	0.376***	0.134	0.242**	0.313***	0.224***	0.152**	−0.090
	(4.95)	(1.11)	(2.36)	(5.46)	(3.53)	(2.35)	(−0.90)
MKT	0.202***	0.320***	−0.118***	0.261***	0.269***	−0.066***	0.052**
	(10.79)	(10.75)	(−4.64)	(18.43)	(17.16)	(−4.13)	(2.08)
SMB	0.102***	0.051	0.051	0.134***	0.134***	−0.032	−0.083***
	(4.39)	(1.39)	(1.62)	(7.61)	(6.89)	(−1.59)	(−2.68)
YLDCHG	−0.876**	−0.039	−0.837	−0.487*	−0.585*	−0.291	0.546
	(−2.27)	(−0.06)	(−1.61)	(−1.68)	(−1.82)	(−0.88)	(1.07)
BAAMTSY	−3.137***	−3.149***	0.012	−2.227***	−2.672***	−0.465	−0.477
	(−6.35)	(−4.02)	(0.02)	(−5.99)	(−6.49)	(−1.11)	(−0.73)
PTFSBD	0.005	−0.014*	0.019***	−0.001	0.000	0.005	−0.014**
	(0.92)	(−1.69)	(2.66)	(−0.28)	(0.05)	(1.04)	(−2.05)
PTFSFX	0.007	0.025***	−0.018***	0.010***	0.016***	−0.009**	0.010*
	(1.60)	(3.68)	(−3.13)	(2.93)	(4.30)	(−2.32)	(1.70)
PTFSCOM	−0.001	−0.010	0.009	0.004	0.008*	−0.009*	−0.019**
	(−0.12)	(−1.14)	(1.24)	(0.93)	(1.82)	(−1.92)	(−2.51)
Adjusted R^2	46.20%	41.10%	12.70%	67.30%	64.50%	8.10%	7.70%

Table V

The Influence of Family Structure on Inception Performance

This table presents results of the analysis of the influence of family structure on inceptions. We form inception portfolios based on (1) the family structure of each inception (i.e., the stand-alone inception, or family-affiliated inception including nonclone inceptions and clone inceptions), and (2) the strategy-based identification of each inception (i.e., cold or hot inception). In any month, inception portfolios are formed from new hedge fund inceptions of a given family structure and strategy identification over the prior three months. Each inception is held in its corresponding portfolio for a 60-month holding period after its inception. The holding period follows the actual inception date of each fund. Within the holding period, we exclude backfilled returns and require at least 12 monthly return observations for an inception to be included in any inception portfolio. Funds are equally weighted and rebalanced at the beginning of each month. Portfolio returns are then regressed on the Fung and Hsieh (2004) seven factors to obtain the risk-adjusted alpha. The regression equation is presented in Table IV. t-Statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Stand-Alone (New Family) Inceptions	Family Affiliated Inceptions	Stand-Alone minus Family-Affiliated Inceptions	Cold Stand-Alone Minus Hot Stand-Alone Inceptions	Cold Nonclone Minus Hot Nonclone Inceptions	Cold Clone Minus Hot Clone Inceptions	Cold Nonclone Minus Hot Clone Inceptions	Cold Stand-Alone Minus Hot Clone Inceptions
alpha	0.458***	0.233***	0.225***	0.307**	0.350**	0.172	0.413***	0.551***
	(8.49)	(3.77)	(9.51)	(2.34)	(2.59)	(1.26)	(3.56)	(4.77)
MKT	0.261***	0.265***	−0.004	−0.114***	−0.089***	−0.082**	−0.062**	−0.033
	(19.65)	(17.42)	(−0.71)	(−3.54)	(−2.68)	(−2.45)	(−2.17)	(−1.16)
SMB	0.150***	0.129***	0.022***	0.048	0.031	0.009	0.011	0.097***
	(9.06)	(6.78)	(2.96)	(1.19)	(0.76)	(0.21)	(0.31)	(2.74)
YLDCHG	−0.111	−0.569*	0.458***	−0.317	−0.762	−1.050	−0.667	0.299
	(−0.40)	(−1.81)	(3.80)	(−0.48)	(−1.11)	(−1.51)	(−1.13)	(0.51)
BAAMTSY	−1.779***	−2.467***	0.688***	1.048	−2.083**	−0.544	−1.363*	1.014
	(−5.11)	(−6.18)	(4.51)	(1.24)	(−2.39)	(−0.62)	(−1.82)	(1.36)
PTFSBD	0.001	−0.001	0.002	0.003	0.034***	0.039***	0.030***	0.025***
	(0.22)	(−0.29)	(1.27)	(0.34)	(3.61)	(4.07)	(3.68)	(3.09)
PTFSFX	0.011***	0.012***	−0.002	−0.010	−0.021***	−0.019**	−0.012*	−0.015**
	(3.51)	(3.49)	(−1.11)	(−1.39)	(−2.73)	(−2.37)	(−1.88)	(−2.22)
PTFSCOM	0.004	0.004	0.000	0.016*	0.002	−0.004	−0.009	−0.001
	(1.05)	(0.97)	(−0.13)	(1.71)	(0.19)	(−0.38)	(−1.00)	(−0.08)
Adjusted R^2	69.10%	64.30%	9.30%	8.60%	8.40%	6.50%	6.40%	5.30%

although it is still significant (t-statistic = 3.77). Stand-alone inceptions outperform family-affiliated inceptions by as much as 0.225% per month or 2.8% per year (t-statistic = 9.51), supporting the prediction in Hypothesis 3 that stand-alone inceptions outperform family-affiliated inceptions.

To further understand the impact of inception conditions, we combine family structure with strategy-based cold and hot inception measures. We create three groups of inceptions based on their family affiliation: new family inceptions, family-affiliated nonclone inceptions, and family-affiliated clone inceptions. Within each group, we further differentiate between cold and hot inceptions. For each of these six types of inceptions, we form portfolios and regress portfolio returns (as well as pairwise and corner spreads) on hedge fund risk factors to obtain alpha.

Columns (4) to (6) report the spread between cold and hot inceptions within each type of family inceptions. Cold inceptions significantly outperform hot inceptions when the inceptions are stand-alone (by 0.31% per month) or nonclone (by 0.35% per month). These results support Hypotheses 1 and 4. In contrast, the performance difference between cold and hot clones is insignificant, which also supports the prediction in Hypothesis 4, that clone funds are de facto hot and deliver poor performance irrespective of whether they arise in hot or cold conditions.

In the last two columns ((7) and (8)), we examine two groups that synchronize the influence of family structure (Hypotheses 3 and 4) and hot/cold inception conditions (Hypothesis 1). Column (7) reports the performance difference between family-affiliated nonclone inceptions in cold strategies and clone inceptions in hot strategies. The performance spread, 0.41% per month, is positive and significant at the 1% level. The last column reports the difference between cold stand-alone inceptions and hot clone inceptions. The performance difference is 0.55% per month (6.8% annually), which is not only economically and statistically significant, with a t-statistic of 4.77, but also the largest portfolio spread of all those that we report in Table V. Since the corner spread portfolio (cold stand-alone minus hot clone inceptions) best captures the impact of family and demand conditions on inception performance, below we use this specification to examine the economic source of the performance difference between cold and hot inceptions. Figure 2 illustrates the performance difference between cold stand-alone funds and hot clones in event time. The cold-hot spread lasts for at least 10 years, suggesting that strategy demand conditions and family structure have long-term effects on the performance of new funds.

Panel A of Table VI summarizes the matrix of alpha coefficients for these six types of inceptions. The first and second rows report the alphas of inceptions launched in cold and hot strategies, respectively. The alpha of the spread portfolio is reported in the third row. Focusing on cold inceptions, we see an interesting pattern: stand-alone (new family) inceptions deliver the highest alpha, followed by family-affiliated nonclone inceptions and then family-affiliated clone inceptions. A similar pattern emerges for hot inceptions. This

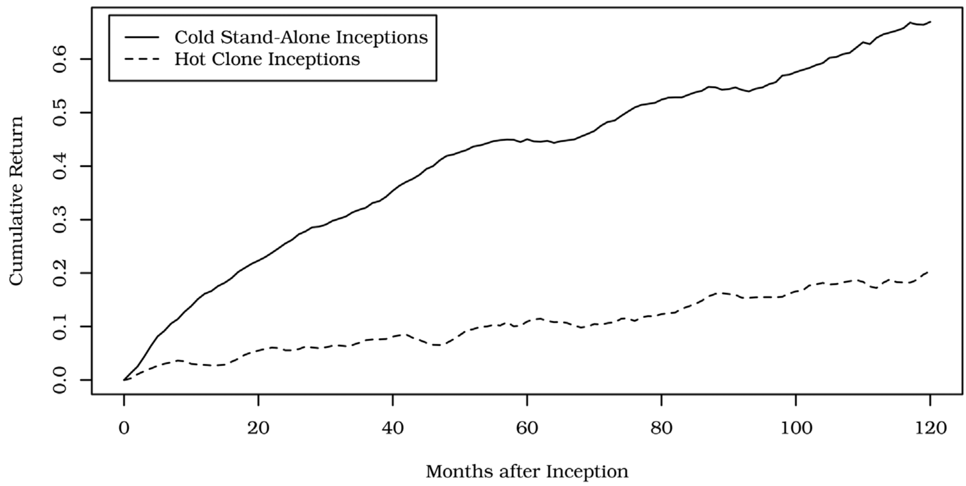

Figure 2. Cumulative abnormal returns after inception by inception type. This figure plots cumulative abnormal returns in event time for cold and hot inception portfolios. We classify a strategy as hot (cold) if its past 36-month returns and flows are among the top (bottom) 30% of all strategies, and focus on the average postinception returns that can be generated by new stand-alone funds incepted in cold strategies (cold inceptions) and by new clone funds incepted in hot strategies (hot inceptions).

result further supports our previous conclusion on the performance gap between stand-alone and family-affiliated inceptions.

Tabulated alphas provide additional evidence to support the view that clone inceptions are de facto hot: clone inceptions in cold strategies generate an alpha (0.22% per month) that is on par with the alpha of the new family hot inceptions (0.29% per month), suggesting that even clone funds launched in cold strategies are likely to encounter an extensive margin that is as high as stand-alone funds launched in hot strategies. To further investigate whether clone funds are launched to absorb the extra demand for the preceding fund, we compare policies of clone funds and affiliated preceding funds related to fees (both incentive and fixed), redemption notice, and lockup periods. We do not find any significant difference between the policies of clone funds and preceding funds. The average incentive fee for the preceding nonclone funds is 15.6%, compared to 15.5% for the follow-up clone funds; the difference is insignificant (t-statistic = 0.896). Thus, clone inceptions do not deviate much from their preceding funds' policies.

In Panel B, we see that for the corner portfolios (cold nonclone minus hot clone inceptions and cold stand-alone minus hot clone inceptions), the alphas are 0.41% and 0.55% per month (or 5% and 6.8% annually), respectively. Both alphas are economically large and statistically significant, suggesting that both stand-alone and family-affiliated cold inceptions outperform hot clone inceptions. If cold inceptions are not affiliated with existing families, they

Table VI

Strategy Demand and Family Structure: Risk-Adjusted Performance

This table presents a two-way summary of the risk-adjusted returns (alphas) of different types of inception portfolios. Each portfolio's alpha is estimated by using the Fung-Hsieh (2004) seven-factor model. We form inception portfolios based on (i) the family structure of each inception (i.e., the stand-alone inception, or family-affiliated inception including nonclone inceptions and clone inceptions), and (ii) the strategy-based identification of each inception (i.e., cold or hot inception). In any month, inception portfolios are formed from new hedge fund inceptions of a given family structure and strategy identification over the prior three months. Each inception is held in its corresponding portfolio for a 60-month holding period after its inception. The holding period follows the actual inception date of each fund. Within the holding period, we exclude backfilled returns and require at least 12 monthly return observations for an inception to be included in any inception portfolio. Funds are equally weighted and rebalanced at the beginning of each month. The regression equation is presented in Table IV. *t*-Statistics are in parentheses.

Panel A: Portfolio Alphas by Family Structure and Hot/Cold Strategy Identification

	Stand-Alone (New Family)	Family-Affiliated Inceptions	
	Inceptions	Nonclone	Clone
Cold inceptions	0.600%	0.463%	0.221%
	(7.446)	(4.638)	(1.903)
Hot inceptions	0.293%	0.113%	0.050%
	(2.059)	(0.952)	(0.504)
Cold minus hot spread	0.307%	0.350%	0.172%
	(2.344)	(2.593)	(1.255)

Panel B: Cold-Hot Corner Portfolio Spreads

Cold nonclone minus hot clone spread	0.413%
	(3.557)
Cold stand-alone minus hot clone spread	0.551%
	(4.767)

outperform hot clone inceptions by a larger margin than family-affiliated cold inceptions.

Overall, the predictions of our hypotheses are well supported by the data. In later tests, we focus on estimated alphas, and we use the two-way display of Table VI as a template to analyze performance differences between various types of inceptions.

C. Managerial Experience

A manager with previous experience running a hedge fund may have a preexisting network of investors from whom to raise capital and has an advantage in the persuading/bargaining step. Since we have identified hot inceptions using only strategy information and family structure, differences in manager experience may confound our measurement. To eliminate effects that managerial experience may have on our results, we identify and exclude experienced managers.

The TASS, HFR, and BarclayHedge databases report the fund managers or principals for each fund. After cleaning these names by removing honorifics and similar features ("Ph.D.," "Doctor," "Jr.," etc.), we identify the funds associated with each manager. Inceptions with a manager associated with a prior fund are marked as having an "experienced" manager. For stand-alone, family-affiliated nonclone, and clone funds, the proportions of funds with experienced managers are 4%, 13%, and 17%, respectively. We remove funds managed by experienced managers and replicate Table VI using the sample of inexperienced managers only.

Table VII presents the results. Overall, the results are similar to those reported in Table VI: hot inception portfolios underperform their cold inception peers, particularly among stand-alone inceptions (the spread portfolio's alpha is 0.434% monthly with a t-statistic of 2.83) and nonclone inceptions (alpha = 0.336% monthly, t-statistic = 2.39). As reported in the last line of Panel B, the performance spread between cold stand-alone inceptions and hot clone inceptions is economically large: 0.723% per month (or 9.0% per year) compared to 0.551% per month (or 6.8% per year) in the unrestricted sample (see Table VI). Thus, our results are slightly stronger when using this restricted sample. By removing experienced managers who might start a new fund for reasons beyond our stylized model, such as reputation, the remaining pool of inceptions managed by new managers better fit the setting—and therefore predictions—of our model.

One caveat of this test is that there could be matching errors in our identification of experienced managers. For instance, since funds only report a snapshot of fund managers to the databases, some managers may be missed from the list of names that we can empirically identify. This could lead to the failure to exclude some experienced managers. For this reason, we include this analysis as an additional test, rather than the main specification. Since the removal of experienced managers sharpens our results, if our exclusion methodology is improved (e.g., due to the availability of more precise data) we expect our primary results to be even stronger.

D. Market-Timing and Security-Selection Ability

Thus far, our results are consistent with our model predictions on the impact of investor strategy demand and family structure on inception performance. But what is the nature of the performance difference between cold and hot inceptions? That is, what kind of managerial skills or strategies deliver outperformance? Superior performance could come from genuine managerial skills, such as security-selection or market-timing ability. Alternatively, it may be driven by nonstandard risk exposure or it may be an artifact of return-smoothing (e.g., Getmansky, Lo, and Makarov (2004), Cao et al. (2013) (2016)). In this and subsequent sections, we address these questions by examining: (i) what skills managers of cold inceptions

Table VII

Strategy Demand and Family Structure: Risk-Adjusted Performance using the Sample of Inexperienced Managers

This table presents two-way summary of the risk-adjusted returns (alphas) of different types of inception portfolios after excluding funds with experienced managers. Each portfolio's alpha is estimated by using the Fung-Hsieh (2004) seven-factor model. For each fund, we identify the set of principal managers for the fund. If a fund has at least one manager that is associated with a fund with an earlier inception date, we mark the fund as having an "experienced" manager. We exclude these funds from this analysis. Using only funds with "inexperienced" managers, we form inception portfolios based on (1) the family structure of each inception (i.e., the stand-alone inception, or family-affiliated inception including nonclone inceptions and clone inceptions); and (2) the strategy-based identification of each inception (i.e., cold or hot inception). In any month, inception portfolios are formed from new hedge fund inceptions of a given family structure and strategy identification over the prior three months. Each inception is held in its corresponding portfolio for a 60-month holding period after its inception. The holding period follows the actual inception date of each fund. Within the holding period, we exclude backfilled returns and require at least 12 monthly return observations for an inception to be included in any inception portfolio. Funds are equally weighted and rebalanced at the beginning of each month. The regression equation is presented in Table IV. t-Statistics are in parentheses.

Panel A: Portfolio Alphas by Family Structure and Hot/Cold Strategy Identification

	Stand-Alone (New Family)	Family-Affiliated Inceptions	
	Inceptions	Nonclone	Clone
Cold inceptions	0.638%	0.407%	0.177%
	(7.675)	(3.971)	(1.427)
Hot inceptions	0.204%	0.071%	−0.085%
	(1.253)	(0.571)	(−0.771)
Cold minus hot spread	0.434%	0.336%	0.263%
	(2.825)	(2.387)	(1.708)

Panel B: Cold-Hot Corner Portfolio Spreads

Cold nonclone minus hot clone spread	0.492%
	(3.889)
Cold stand-alone minus hot clone spread	0.723%
	(6.029)

possess, (ii) whether there is any difference in performance persistence between cold and hot inceptions, and (iii) how illiquidity and return-smoothing are related to the performance of cold and hot inceptions.

We first examine the security-selection and market-timing skills of cold and hot inceptions. In the literature, the Treynor and Mazuy (1966) model has been used to evaluate market-timing skills while the Fung and Hsieh (2004) seven-factor model has been used to assess security-selection ability. Here, we use the Treynor and Mazuy (1966) model augmented with Fung and Hsieh's seven risk factors. Specifically, we estimate the following model separately for the portfolios of cold stand-alone and hot clone inceptions:

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p MKT_t^2 + \beta_{p,2}SMB_t + \beta_{p,3}YLDCHG_t + \beta_{p,4}BAAMTSY_t + \beta_{p,5}PTFSBD_t + \beta_{p,6}PTFSFX_t + \beta_{p,7}PTFSCOM_t + \epsilon_{p,t}, \quad (7)$$

where for portfolio p the parameters of interest are α_p, the selection ability, and γ_p, the market-timing ability of the fund manager. The coefficient γ_p measures market-timing skill, that is, how market beta changes, with market condition forecasts. If a hedge fund manager possesses market-timing ability, she will increase (decrease) her market exposure before the market goes up (down) and the timing coefficient γ_p will be positive.

The abnormal return of portfolio p includes two components: α_p and $\gamma_p M$, where M is the long-term mean of MKT_t^2. To assess the statistical significance of the selection coefficient (α_p), the timing coefficient (γ_p), and the abnormal return in the presence of both selection and timing skill ($\alpha_p + \gamma_p \times M$), we appeal to the bootstrap procedure proposed by Kosowski et al. (2006) and Fama and French (2010). Details on our bootstrap procedure are outlined in Section III of the Internet Appendix. In Table VIII, we present the bootstrapped results to evaluate the significance of α_p, γ_p, and ($\alpha_p + \gamma_p \times M$). Figure 3 graphically illustrates the distribution of bootstrapped α_p, γ_p, and ($\alpha_p + \gamma_p \times M$) and the estimates from our data.

We find that cold inceptions exhibit positive and significant skill in security-selection, but not in market-timing. The selection skill performance (alpha) is 0.54% monthly (6.7% annually) and its bootstrapped p-value is 0, but the market timing coefficient is insignificant (the bootstrapped p-value is 0.28). By contrast, hot inceptions exhibit weaker selection skill (alpha = 0.26% monthly, 3.1% annually), and negative (incorrect) and significant market-timing ability, leading to overall insignificant skill-based performance (p-value = 0.54). Cold inceptions significantly outperform hot ones along all three dimensions—selection skill (α_p), timing ability (γ_p), and combined skill ($\alpha_p + \gamma_p \times M$)—with bootstrapped p-values less than 5%. Hence, it is the superior security-selection skills possessed by cold-inception managers and incorrect market-timing of hot-inception managers that drive the performance difference.

An alternative market-timing model is proposed by Henriksson and Merton (1981). To cross-validate our findings, we use the Henriksson and Merton model, augmented with the Fung and Hsieh seven factors, to assess the security-selection and market-timing skills of cold and hot inceptions. We find qualitatively similar results.

E. Performance Persistence

Since performance persistence provides a powerful test of managerial skill, we perform three tests to estimate the degree of performance persistence in hot clone inceptions and cold stand-alone inceptions. A higher degree of performance persistence among cold stand-alone inceptions over annual horizons

Table VIII

Bootstrapped Security-Selection and Market-Timing Regression Coefficients

This table presents the bootstrapped results of security-selection and market-timing analysis for cold stand-alone inceptions and hot clone inceptions. The following security-selection and market-timing regression is applied to each portfolio:

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

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), the monthly change in the 10-year Treasury constant maturity yield (YLDCHG), the 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). We also compute the time-series average of MKT_t^2, which we denote by M. Bootstrapped p-values corresponding to a two-sided test against the null hypothesis of (i) no security-selection skill (e.g., $\alpha = 0$), (ii) no market-timing skill (e.g., $\gamma = 0$), and (iii) no security-selection and market-timing skills (e.g., $\alpha = 0$ and $\gamma = 0$ jointly) are reported in square brackets.

	α	γ	$\gamma * M$	$\alpha + \gamma * M$
Cold stand-alone inceptions	0.541%	0.300	0.056%	0.598%
[p-value]	[0.000]	[0.278]	[0.278]	[0.000]
Hot clone inceptions	0.258%	−1.062	−0.199%	0.058%
[p-value]	[0.023]	[0.002]	[0.002]	[0.541]
Cold stand-alone minus hot clone spread	0.284%	1.362	0.256%	0.540%
[p-value]	[0.034]	[0.001]	[0.001]	[0.000]

would suggest that the outperformance in these funds is attributable to managerial skill.

We start by dividing the 60-month holding period for each fund into an early period (1–30 months) and late period (months 31–60). Within each period, we compute the alpha of each fund using the Fung and Hsieh seven-factor model and rank funds into quintiles based on their alpha for cold stand-alone and hot clone inceptions. Table IX reports the transition matrix of quintile-based ranks. For instance, Panel A reports that the first-period top-quintile cold and hot inceptions receive a second-period rank of 3.71 and 3.09, respectively,. If managers have persistent skill, funds ranked high in the first period should receive higher ranks in the second period as well, leading to a positive (cross-period) rank correlation. We can see that cold inceptions exhibit this persistence. For cold inceptions, the second-period ranks of funds monotonically increase in their first-period ranks with a significant Spearman rank of 30.95% with a p-value of virtually 0. By contrast, hot inceptions exhibit a negative rank correlation (significant at the 10% level). We obtain the same conclusion using the Spearman test on the ranks directly (without sorting into quintiles). These

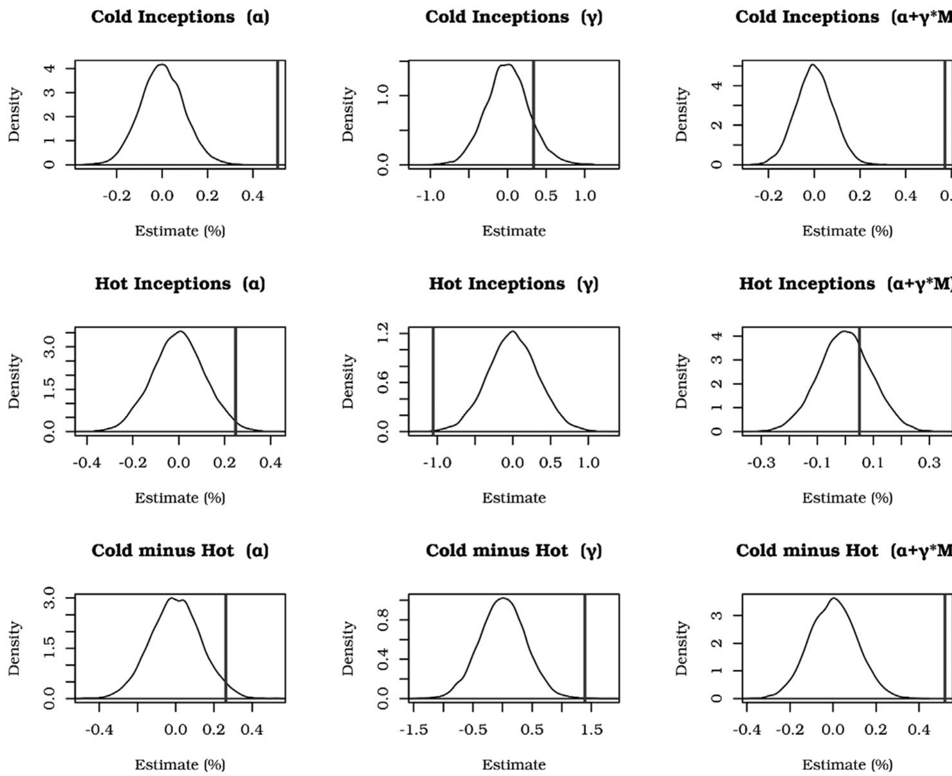

Figure 3. Estimated alphas (gammas) versus bootstrapped alpha (gamma) distributions. We plot kernel density estimates of (1) the bootstrapped (α), security skill, distribution, (2) the bootstrapped gamma (γ), market-timing skill, distribution, and (3) the bootstrapped distribution of ($\alpha + \gamma * M$), the combined skill. We present the bootstrapped distribution for three inception portfolios: the cold stand-alone portfolio, the hot clone portfolio, and the spread portfolio. The vertical lines indicate the parameter estimates from the data.

results suggest that high-performing cold inceptions are likely to continue to have high performance, while the same cannot be said of high-performing hot inceptions.

Panel B reports results of the performance persistence test proposed by Brown and Goetzmann (1995), which is a nonparametric test based on contingency tables. Annual fund returns for cold and hot inceptions are classified as winners (W) or losers (L) based on being above or below the median for that group. Consecutive years for each fund are then classified as Winner-Winner, Winner-Loser, Loser-Winner, or Loser-Loser. Performance persistence for the group is characterized by more WW and LL than WL and LW. The cross-product ratio (CPR) is the odds ratio of the number of repeat performers to the number of those that do not repeat, that is, $CPR = (WW \times LL)/(WL \times LW)$. Under the null of no performance persistence, the standardized log(CRP) follows a normal distribution with mean 0 and variance 1. Our sample of cold

Table IX

Tests of Performance Persistence: Cold versus Hot Inceptions

This table presents results of three performance persistence analyses for hot and cold inceptions. In Panel A, we report the rank persistence over the first 60 months of funds' lives. For each cold stand-alone and hot clone inceptions, we divide fund performance over the first 60 months into the early period (months 1 to 30) and the late period (months 31 to 60). Within each period, we compute the Fung and Hsieh (2004) alpha of each fund. We then rank funds into quintiles based on their alpha within the period (inceptions with larger alpha values receive high ranks). Panel A reports the average late-period rank for each early-period quintile. For each group, we also report the Spearman rank coefficient of the funds' early- and late-period ranks (calculated as $1-(6\sum d_i^2)/(n^3-n)$, where d_i is the difference in quintiles between the early- and late-period for fund i). Panel B reports annual performance persistence using the test from Brown and Goetzmann (1995), who classify annual fund returns as winners or losers and calculate the average logarithm of the odds ratio for cold stand-alone inceptions and hot clone inceptions. Under the null of no performance persistence, the log of the odds ratio would be 0. The standard error of the log odds ratio is given by $\sigma_{CPR}=\sqrt{\frac{1}{WW}+\frac{1}{LL}+\frac{1}{LW}+\frac{1}{WL}}$ and the Z-statistic is $\frac{\ln(CPR)}{\sigma_{CPR}}$. Panel C reports results of the persistence test from Aggarwal and Jorion (2010), who use a one-factor model to compute annual risk-adjusted returns $r^*_{i,t}=r_{i,t}-\beta * MKT^b_t$, where MKT^b_t is the excess return on the market portfolio in year t and β is estimated from the first-year monthly returns of each fund. Risk-adjusted returns for either cold stand-alone inceptions or hot clone inceptions over their five-year inception period are then pooled to estimate the $AR1$ coefficient. The regression equation is $r^*_{\{i,t\}}=\alpha+AR1\times r^*_{\{i,t-1\}}+\epsilon_{i,t}$.

Panel A: Spearman Test of Early/Late Alpha Persistence

Early-period rank	Cold Inceptions Late-Period Rank	Hot Inceptions Late-Period Rank
1	2.21	3.33
2	2.65	2.97
3	2.81	2.37
4	2.95	2.47
5	3.71	3.09
Rank correlation	30.95%	−13.88%
[p-value]	[0.000]	[0.055]

Panel B: Brown-Goetzmann Annual Persistence Test

	Cold Inceptions	Hot Inceptions
Log odds ratio	0.30	−0.10
Z-statistic	5.75	−1.67
[p-value]	[0.000]	[0.090]

Panel C: Aggarwal-Jorion Annual Persistence Test

	Cold Inceptions	Hot Inceptions
AR1	0.167	−0.003
[p-value]	[0.000]	[0.891]

Table X

Additional Evidence from Convertible Arbitrage Funds

This table presents results on how market conditions of convertible bond issuance influence the performance of inceptions in the convertible arbitrage strategy category. For each inception i in the convertible arbitrage strategy category, we perform the Fung and Hsieh (2004) seven-factor regression to obtain fund specific alpha, denoted by α_i. We then use two variables to describe convertible bond market conditions: *AveNewIssue* and *AveTotAssets*, calculated as the average market cap of newly issued convertible bonds and the average total market cap of outstanding convertible bonds in the same 60-month period that we measure the performance of a fund. We then regress fund alpha on three dummy variables, $D_{\text{cold},i}$, $D_{\text{hot},i}$, and $D_{\text{others},i}$. The dummy variable $D_{\text{cold},i}$ takes the value of 1 if inception i is a cold inception. The other two dummy variables are defined similarly. The regression equation is

$$\alpha_i = b_1 \times D_{\text{cold},i} + b_2 \times D_{\text{hot},i} + b_3 \times D_{\text{others},i} + b_4 \times AvgNewIssue_i + b_5 \times AvgTotAssets_i + \nu_i.$$

Since the coefficients on the market condition variables are very small, we scale *AvgNewIssue* and *AvgTotAssets* by 10^3. This scaling does not affect the significance of our results. t-Statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)
D_{Cold}	0.638***	0.534***	0.899***	0.774***
	(6.067)	(4.46)	(7.31)	(6.05)
D_{Hot}	−0.277	−0.348	0.032	−0.018
	(−0.92)	(−1.15)	(0.10)	(−0.06)
D_{Others}	0.216***	0.115*	0.446***	0.319***
	(9.30)	(1.89)	(7.16)	(4.36)
AvgNewIssue (Bn)		14.093*		26.236***
		(1.81)		(3.25)
AvgTotAssets (Bn)			−0.337***	−0.427***
			(−3.98)	(−4.82)
Adjusted R^2	14.50%	14.80%	16.20%	17.30%
Observations	715	715	715	715

stand-alone inceptions has an odds ratio of 0.30 that is positive and significant (p-value = 0.00), in line with performance persistence among these funds. Hot clone funds, in contrast, have a log odds ratio of −0.10, with an associated p-value of 0.09. Robustness tests that repeat this experiment using 24-month returns yield the same inference, so we relegate these results to the Internet Appendix.

Panel C of Table IX reports results of our third persistence test, based on the methodology proposed by Aggarwal and Jorion (2010). In this test, we examine inception returns in event time over the first 60 months of the fund's life (e.g., year 1 runs from the inception month to 12 months later). In each fund-year, we compute the risk-adjusted annual return for that fund from a one-factor model by subtracting the factor return times the fund's beta from the fund's return. We then estimate a pooled AR(1) model as follows:

$$r^*_{i,t} = \alpha + AR1 \times r^*_{i,t-1} + \epsilon_{i,t}, \tag{8}$$

where $r^*_{i,t}$ is the risk-adjusted return for fund i in year t, and the estimation pools all fund-year risk-adjusted returns for cold stand-alone inceptions or hot clone inceptions in their five-year inception period. A positive *AR1* coefficient indicates performance persistence at the annual frequency. For cold stand-alone funds, the AR1 coefficient is 0.167, which is statistically significant with a p-value of essentially 0. Conversely, there is no significant evidence of performance persistence among our hot clone sample.

In summary, the results of the three tests above indicate that the performance of cold stand-alone inceptions is persistent over time and that these inceptions deliver skill-based performance. In contrast, we do not find evidence of performance persistence among hot clone inceptions. Taken together, the tests on the managerial skills related to security-selection and market-timing and the test on performance persistence point to the same conclusion: cold inceptions deliver outperformance based on genuine managerial skill.

V. Additional Analysis and Alternative Explanations

In this section, we conduct additional analysis to shed light on the nature of managerial skill and to evaluate the robustness of our main findings to alternative risk factors, fund policies, and empirical specifications.

A. Evidence from CA Funds

We first provide additional evidence on the level of sophistication associated with managerial skill using the subsample of CA funds. Convertible bonds tend to be underpriced at issue, which provides an arbitrage opportunity for hedge fund managers (see Chan and Chen (2007), Choi et al. (2010, hereafter CGHT)). Thus, the convertible bond market provides an ideal laboratory in which to evaluate whether cold CA inceptions benefit mostly from the well-known arbitrage opportunity of bond issuance or whether they derive alpha from plausibly more sophisticated managerial skills.

We collect convertible bond data from Mergent FISD and SDC from 1989 to 2016 and calculate the market cap of newly issued convertible bonds by summing the dollar value of proceeds in each month. This variable quantifies the market-wide arbitrage opportunities associated with new bond issuance. In periods overlapping with CGHT, our variable is very similar to what CGHT plot. We also calculate the total market cap of outstanding convertible bonds to examine whether the total market size influences hedge fund performance.[15]

[15] One empirical issue in constructing this variable is that we do not observe the conversion decisions of all bondholders. Both Chan and Chen (2007) and Choi et al (2010) argue that hedge funds typically hold convertible bonds for a long period of time because the convergence of underpriced bonds to fundamental value takes a long time. We follow the literature to obtain a reasonable proxy for the total market cap by assuming that all bonds are held until maturity.

Our sample includes 715 CA inceptions. Of these inceptions, 33 are classified as cold and four as hot in our previous analysis.[16] Due to this distribution, we focus our analysis on whether cold CA inceptions outperform all other (i.e., neither hot nor cold) CA inceptions and whether the outperformance originates from the issuance of convertible bonds. For each inception, i, in the CA strategy, we use the Fung and Hsieh (2004) seven-factor regression to obtain the fund's alpha, denoted by α_i. We use two variables to describe convertible bond market conditions: *AveNewIssue* and *AveTotAssets*, the average market cap of newly issued convertible bonds and the average total market cap of outstanding convertible bonds over the fund's 60-month performance period. We then regress alpha on three dummy variables, $D_{\text{cold},i}$, $D_{\text{hot},i}$, and $D_{\text{others},i}$. Each dummy takes the value of 1 if i belongs to the corresponding inception group. The regression equation is

$$\begin{aligned} \alpha_i = & b_1 \times D_{\text{cold},i} + b_2 \times D_{\text{hot},i} + b_3 \times D_{\text{others},i} \\ & + b_4 \times \ \mathit{AvgNewIssue}_i + b_5 \times \mathit{AvgTotAssets}_i + \nu_i. \end{aligned} \tag{9}$$

Table X presents the results of these cross-sectional regressions. In specification (1) we observe a cold-others spread of 0.42% per month (or, 5.1% annually), inferred from the difference between the coefficients on "Cold" and "Others," with an F-test p-value of 0.00), confirming that cold convertible bond inceptions deliver better performance than other types of inceptions. In specification (2), we include the market cap of newly issued convertible bonds. Convertible bond issuance is positively related to fund alpha, indicating that CA funds benefit from this well-known arbitrage opportunity. Importantly, the cold-others spread remains largely unchanged (about 0.42%) after controlling for bond issuance, suggesting that bond issuance conditions do not drive the outperformance of cold inceptions.[17] Specification (3) replaces new issuance with total market size, which leaves the magnitude of the cold-others spread almost unchanged (i.e., about 0.45%). Finally, in specification (4) we control for both issuance and total market conditions and find that the *cold-others* spread remains economically larger and significant, 0.46% monthly (5.7% annually) with an F-test p-value of 0.00.

Although these results focus on a subsector of the hedge fund industry, they provide evidence that cold CA inceptions generate outperformance from sources other than simple reliance on well-known arbitrage opportunities.

[16] The paucity of hot CA inceptions may appear surprising but is reasonable because cold and hot inceptions are defined across strategy categories over time. The performance of the CA strategy has been relatively smooth during our sample period, and hence the likelihood has been small that CA would become a category that encounters high investor demand. By contrast, there are periods in which CA was relatively cold and other categories attracted more capital.

[17] Summary statistics further show that cold inceptions on average encounter *less* issuance of convertible bonds than other funds during their performance generating period: the difference in proceeds is about \$15.4 billion, with a significant t-statistic of 3.57. If anything, therefore, cold inceptions encounter *fewer* arbitrage opportunities than other inceptions.

B. Alternative Explanations: Return-Smoothing, Risk Factors, and Fund Policies

To test the robustness of our results, we first examine a leading alternative explanation for the performance difference between cold and hot inceptions: exposure to illiquidity or return-smoothing. To address this concern, we follow Getmansky, Lo, and Makarov (2004) and Cao et al. (2017) to assess the serial correlation associated with illiquidity and return-smoothing. We then compare the degree of return-smoothing for hot and cold inceptions.

In the interest of space, we summarize our findings here, reporting the formal tests in Table IA.IV in the Internet Appendix. We find that both types of inceptions exhibit return-smoothing. However, hot inceptions have a significantly *higher* degree of return-smoothing than cold inceptions do, suggesting that the returns of hot inceptions benefit more from illiquidity and smoothing. The difference holds not only in summary statistics but also in cross-sectional analysis detailed in the Internet Appendix. Hence, the superior performance of cold over hot inceptions is unlikely to be due to return-smoothing.

Next, although the seven-factor model of Fung and Hsieh (1997) is widely used in the hedge fund literature to evaluate risk-adjusted returns, funds can nonetheless be exposed to additional risk factors related to liquidity (Pástor and Stambaugh (2003), Sadka (2010)), correlation risk (Buraschi, Kosowski, and Trojani (2014)), economic uncertainty (Bali, Brown, and Caglayan (2014)), and volatility-of-volatility (Agarwal, Arisoy, and Naik (2017)). A study of the influence of these factors is important because they can be exploited by hedge fund managers seeking risk-based returns, and we thank the respective authors for providing the data. In addition, since nonsynchronous trading of illiquid assets can lead to biased estimates of fund beta (see Scholes and Williams (1977)), we include lagged market returns as an additional factor.

In Table IA.V in the Internet Appendix, we start from the seven-factor model explaining the alpha of the spread portfolio between cold stand-alone and hot clone inceptions and add additional factors one at a time. Most factors—except for the liquidity factor of Sadka (2010)—do not have significant power in explaining the inception portfolio return spread. Sadka's liquidity factor is likely relevant because it is constructed from variables related to informed trading. We also find that, after the inclusion of the Sadka liquidity factor, our conclusions from Tables V and VI do not change. The coefficient estimate of risk-adjusted spread (alpha) is close to that reported in column (8) of Table V. We conclude that our results are not explained by alternative risk factors.

In Table IA.VI in the Internet Appendix, we further examine whether our results can be explained by fund characteristics. We control for fund return characteristics, including two measures of risk (market beta, return volatility), two measures on how distinctive a fund's strategy is with respect to other hedge funds in the same strategy category or with respect to common risk factors in the market (the Strategy Distinctiveness Index [SDI] of Sun, Wang, and Zheng (2012) and the R^2 of Amihud and Goyenko (2013)), as well as operational policy choices related to incentive fees, management fees, the redemption notice period, and redemption frequency (we express redemption frequency in days—a larger value indicates a more restrictive redemption policy).

To achieve this goal, we conduct a cross-sectional analysis by linking fund-specific alpha to a dummy variable indicating the type of an inception (i.e., whether is it a cold stand-alone inception) as well as fund characteristics. The Internet Appendix provides more details of the analysis. Our main finding is that the cold stand-alone dummy is associated with a significant and positive coefficient in this cross-sectional regression, and that fund characteristics do not absorb this significance. For instance, although SDI is positively related to fund alpha, our main result remains unchanged (cold stand-alone inceptions are associated with higher alphas). Controlling for other characteristics and policies yields a very similar result.

Taken together, our findings suggest that the outperformance of cold inceptions cannot be attributed to exposure to return-smoothing, additional risk factors, characteristics of fund returns, fund policy choices, or flows. These results lend further support to our conclusion that cold inceptions deliver performance because managers of these inceptions possess genuine skill.

C. Alternative Holding Periods and Definitions of Cold and Hot inceptions

Next, we use alternative holding periods and alternative definitions of cold and hot inceptions to investigate their impact on our main findings. Since there is a trade-off between the length of a holding period and the number of funds available, our baseline analysis adopts a holding period of 60 months, which is often used in the literature to estimate portfolios' dynamic risk exposure. We re-do Table VI using a shorter holding period of 48 months (Panels A1 and B1 of Table IA.VII in the Internet Appendix) and a longer period of 72 months (Panels A2 and B2 of Table IA.VII in the Internet Appendix). We see that the main features of Table VI remain unchanged. It is perhaps not surprising to see the robustness of our results over different testing horizons considering our previous finding that cold inceptions are associated with persistent managerial skills that are superior to hot inceptions.

We also examine the impact of alternative definitions of cold and hot inceptions. In our main analysis, inceptions are classified as hot when they invest in strategies with high investor demand as proxied by high strategy category return and flows. Since (past) category inceptions provide another observable signal of investor demand, we can also define hot inceptions as those invested in strategies with high recent strategy category inceptions. A strategy is classified as hot (cold) if its normalized inceptions are among the top (bottom) 30% of all strategies over the 36 months prior to inception. Inceptions are normalized by dividing by the number of funds in that strategy at the beginning of the given period. We form inception portfolios based on both family structure and this alternative strategy identification. The results are reported in Table IA.VIII in the Internet Appendix. Our main conclusions from Table VI remain largely unchanged.

D. The Impact of Data Biases

The seminal papers of Fung and Hsieh (1997, 2000) and Jorion and Schwarz (2019) document biases (e.g., survivorship bias, backfill bias, and selection bias) in hedge fund data and their impact on hedge fund performance. Here, we address concerns related to these biases. The Internet Appendix provides additional discussion regarding the bias related to voluntary reporting to databases.

To mitigate survivorship bias, we include both live and defunct funds from each of the three databases. To minimize measurement errors caused by funds reporting after they have been alive for some time, we measure inception periods from the true inception date (not the date at which the fund starts reporting to the database nor the date of the first available return for the fund). As mentioned in Sections II and IV, we address the backfill bias (caused by funds choosing to backfill their returns only if they are proud of their early performance) using the method developed in Jorion and Schwarz (2019). This involves estimating the date at which each fund is added to the database using information from the cross-section of fund IDs for each database, then marking returns before the add date for each fund as missing. Jorion and Schwarz (2019) show that this is a more effective method of eliminating the backfill bias than deleting early performance (12 or 24 months) from all funds, as is frequently done in the literature.

VI. Conclusion

In this paper, we explore the economics of hedge fund inceptions in the presence of search frictions. To do so, we incorporate into the Berk and Green (2004) model one of the most important types of frictions in the hedge fund industry, namely, new managers' need to search for accredited investors. The novel intuition from our stylized model is that investor demand and performance influence the search-and-bargaining process associated with raising capital for new funds. The substitution effect between the extensive and intensive margins of capital-raising gives rise to two different types of inceptions: *hot inceptions* that replicate the strategy of existing funds and *cold inceptions* that deliver new skills and superior performance. Moreover, family structure arises endogenously to reduce the search frictions, but negatively affects the performance incentives of affiliated nonclone inceptions. Since search frictions amplify diseconomies of scale, they also motivate the inception of clone funds.

Empirically, we develop proxies for strategy popularity among investors and for family structure. We find that funds arising in strategies with high investor demand (i.e., hot inceptions) subsequently underperform those facing demand headwind at inception (i.e., cold inceptions) on a risk-adjusted basis. We further find that cold inceptions, but not hot inceptions, outperform existing funds and that family-affiliated inceptions underperform stand-alone inceptions. Using an identification involving both strategy popularity and family structure, we sharpen our results by identifying cold stand-alone inceptions and hot clone inceptions that exhibit a risk-adjusted performance spread as high as

6.8% per year. We further show that the performance difference is attributable to genuine managerial skills that managers of cold inceptions bring into the hedge fund industry, as opposed to loading on alternative sources of risk such as illiquidity or return-smoothing. Cold inceptions also exhibit significant performance persistence, suggesting that their performance is skill-based. Finally, tests excluding experienced managers lead to stronger results with larger economic performance differences between cold stand-alone and hot clone inceptions.

Overall, our findings suggest that market frictions are an important economic mechanism that drives cross-sectional variation in the risk-adjusted performance of hedge fund inceptions and leads to the formation of family structure in the industry. Importantly, we show that it is possible to distinguish ex ante new funds that provide genuine innovations to the industry. Our model, methodology, and empirical analysis have important normative implications that may also apply to other fast-growing markets in which managers need to actively search for capital. Private equity funds and private pension funds are two examples. Although our analysis focuses on the cross-section of hedge fund strategies, the search mechanism may also impact time-series patterns of fund returns. Our results call for more attention to market frictions that new funds face as we seek to better understand the incentives and overall value of the hedge fund industry.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.