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

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

$\mu_{ho}(t) + \mu_{hn}(t) + \mu_{lo}(t) + \mu_{ln}(t) = 1$, 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 μ

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 $\delta^* = \mathrm{Max}\{0, f^{\frac{1}{2}}(L_0 b\mu_{ln}(t)\xi_0 a z_t)^{-\frac{1}{2}} - \frac{\mu_{hn}(t)}{\mu_{ln}(t)\xi_0}\}$.

(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, μ_{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).

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.

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.