The Effect of Investment Constraints on Hedge Fund Investor Returns

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ABSTRACT

This paper examines the effect of investor-level real-world investment constraints, including several which had not been studied before, on hedge fund performance and its persistence. Using a large consolidated database, we demonstrate that hedge fund performance persistence is significantly reduced when rebalancing rules reflect fund size restrictions and liquidity constraints, but remains statistically significant at higher rebalancing frequencies. Hypothetical investor portfolios that incorporate additional minimum diversification constraints and minimum investment requirements suggest that the performance and its persistence documented in earlier studies of hedge funds is not easily exploitable, especially by large investors.

Keywords: Hedge Fund Performance, Persistence, Frictions, Managerial Skill

JEL Classification: G11, G12, G23

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This paper examines the effect of investor-level real-world investment constraints, including several which had not been studied before, on hedge fund performance and its persistence. Using a large consolidated database, we demonstrate that hedge fund performance persistence is significantly reduced when rebalancing rules reflect fund size restrictions and liquidity constraints, but remains statistically significant at higher rebalancing frequencies. Hypothetical investor portfolios that incorporate additional minimum diversification constraints and minimum investment requirements suggest that the performance and its persistence documented in earlier studies of hedge funds is not easily exploitable, especially by large investors.

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1. Introduction

THE HEDGE FUND INDUSTRY has experienced a transformation and significant growth since the financial crisis. Hedge funds' assets under management (AuM)[1] have recovered from the lows in 2008 to reach $2.3 trillion in 2013. However, as reported in a recent *Financial Times* article:

> There are far fewer marginal hedge funds out there because we have gone through a period of really culling the herd. . . . The result is a calmer, if less lucrative life, both for hedge fund managers and their investors.[2]

The main beneficiaries of recent investor flows have been the largest hedge fund management companies and funds. Although only around 30% of the 9,861 funds in our sample at the end of 2012 have more than $100 million assets under management (AuM), for example, these 30% of funds account for more than 90% of the whole industry AuM. Is this skewed distribution of AuM across funds driven by the investment restrictions that hedge fund investors face? More fundamentally, what is the effect of these constraints on hedge fund performance persistence?

In practice, one can distinguish constraints that hedge fund managers face from those that their investors face. The aim of this paper is to examine the effect of the investment constraints that hedge fund investors face on these investors' returns. Although the effect of investment constraints on portfolio performance has been studied in the empirical and theoretical asset pricing literature (Figlewski 1981; Diamond and Verrecchia 1987; Luttmer 1996; Pastor and Stambaugh 2012; Ang, Papanikolaou and Westerfield 2014), empirical and theoretical research on hedge funds seldom accounts for such restrictions or examines their effect on the performance persistence of hedge fund portfolios. Recent studies document that investment fund *managers* face capacity constraints (Ramodarai 2013) and investment constraints (Almazan, Brown, Carlson, and Chapman 2004), but it is

[1] See Preqin (2013). According to our aggregate database, hedge fund AuM was $2.2 trillion in February 2013.
[2] James Mackintosh, "Transformed hedge funds in calmer waters," *Financial Times,* 7 June 2013.

not clear how *investor* level constraints impact on hedge fund performance persistence. Our aim is to fill this research gap by documenting the effects of a combined set of investment constraints faced by real-world hedge fund investors on their opportunity set as indicated by historical hedge fund data over the period 1994–2012.

Institutional hedge fund investors face multiple constraints. Some are related to the liquidity and rebalancing needs of the investor. Others are related to the size of the investor's portfolio. We distinguish five different types of constraints and use stylized examples to illustrate them.

The return of an investor's portfolio will depend on how often the investor monitors portfolio constituents and rebalances the portfolio. Therefore, the first investment constraint – labelled C1 – that we examine is related to the *rebalancing frequency* that the investor adopts. Some investors may evaluate funds on an annual basis and make asset allocation decisions at the end of the year, for example. Other investors may, for example, evaluate performance every 6 months and rebalance the portfolio mid-year and at the end of the year. Using a survey and fund of hedge fund holdings data we are able to document how often certain types of hedge fund investors monitor and rebalance their portfolio. These investment rules have an important effect on the evaluation of the hedge fund portfolio performance and its persistence, as we show.

A second investment constraint is related to investors' liquidity needs. An investor such as a high net worth individual, for example, may require that she be able to liquidate her hedge fund investment and receive her money back in less than three months. This would preclude the investor from allocating to hedge funds with tight share restrictions and lockups. Although share restrictions such as notice, redemption and lockup periods are under the control of the fund, it is the liquidity needs of the investor that will determine which of them are binding for the investor's hedge fund portfolio. We use lockup, redemption and notice periods to proxy for the effect of *liquidity constraints* (C2) on performance persistence. This is related to the issue of the *rebalancing frequency* (C1) needs but represents a separate investment constraint.

A third constraint facing hedge fund investors is related to the fact that, both large and small investors typically operate under minimum and maximum *diversification constraints* (C3) which implies that there is typically a target number of funds that the investor holds in her portfolio. To confirm that our minimum and maximum diversification requirements as well as the baseline assumption of a diversified hypothetical investor portfolio consisting of 30 funds are realistic, we report summary statistics on real-world fund of hedge fund portfolios provided by EurekaHedge and a sample of FoHFs that register with the US Securities and Exchange Commission (SEC).

Two further constraints that a hedge fund investor is subject to depend on the size of the investor's portfolio. We label the fourth one the *percentage of AuM constraint* (C4). The largest investors, such as the Norwegian sovereign wealth fund, for example, with hundreds of billions of dollars under management are more likely to be constrained by a requirement that any allocation to a hedge fund not exceed, say, 10% of that hedge fund's AuM. Such a requirement might be motivated by a desire to reduce potential adverse effects resulting from other investors' redemptions (Liu and Mello 2011) or financial losses due to the lack of funding liquidity and limits to arbitrage (Hombert and Thesmar 2014). However, such a constraint might reduce the sovereign wealth fund's ability to allocate to small funds. According to Ganshaw (2010), for example, few institutional investors want to account for more than 10% of a given fund's assets under management. We do not have data on all hedge fund investor types, but using fund of hedge fund (FoHF) holdings we confirm that most FoHF follows a 10% AuM constraint, which is why we use it as a baseline assumption.[3]

Smaller hedge fund investors such as family offices or private banks, for example, who manage several hundred million dollars, may find their allocations to individual funds too small to meet some

[3] According to FoHF holdings, 90% of FoHF's allocations to hedge funds do not violate the 10% AuM constraint.

large hedge funds' *minimum investment requirements,* which represent the fifth constraint (C5). The Bridgewater Pure Alpha fund's minimum investment is $10 million, for example. This can be expected to reduce smaller investors' ability to invest in some of the largest funds. Although this constraint is under the control of the company managing the hedge fund, in practice, it is the size of the investor allocation to the fund that determines whether it is a binding constraint for the investor or not. To reflect the perspective of investors that have different portfolio sizes, we examine the effect of the following five constraints on hypothetical hedge fund investor portfolios of different size: *rebalancing frequency constraint* (C1), *liquidity constraint* (C2), *diversification constraint* (C3), *percentage of AuM constraint* (C4) and *minimum investment constraint* (C5).[4]

As our *first* main contribution we explore, by means of portfolio sorts, whether hedge fund performance persistence is a robust phenomenon under realistic *rebalancing constraints* (C1) and *liquidity constraints* (C2).[5] These performance persistence tests are of interest since they are very common in the extant literature and allow a comparison of our constrained and unconstrained results with earlier studies. We find that performance persistence is significantly reduced when *rebalancing constraints* (C1) are implemented. We document statistically significant performance persistence only at the quarterly and semiannual portfolio rebalancing frequencies, whereas at the annual portfolio rebalancing frequency we do not find evidence of performance persistence. Performance persistence further decreases when we implement *liquidity constraints* (C2). We show that the *liquidity constraint* (C2) has a marginally bigger economic impact than the *rebalancing constraint* (C1) on the result of persistence tests. Although the constraint C2 decreases performance persistence, the performance of the

[4] In robustness test, described below, we also add a sixth constraint in the form of discretionary liquidity restrictions (DLR) which are studied by Aiken, Clifford and Ellis (2015a).
[5] We implement a portfolio sort approach and form quintile portfolios of hedge funds based on their historical performance. As a test of persistence, we test the significance of the difference in performance between the top and bottom portfolios.

top-portfolio remains economically and statistically significant. This finding is in line with studies that document a positive association between share restrictions and hedge fund performance (Aragon 2007).

The limitation of the above standard performance persistence tests is however that their simple portfolio sorts do not allow the incorporation of more complex constraints and it is not possible to short sell hedge funds in practice.

Our *second* main contribution emerges from our simulations of hypothetical investor portfolios under further restrictions and more realistic conditions. We address concerns raised above by creating hypothetical investor portfolios that incorporate all five constraints. We also carefully document the *marginal* impact of each constraint on the proportion of funds available to the hypothetical investor and the investor's returns in this framework.

To capture the experience of different investor types, that is both large hedge fund investors such as sovereign wealth funds, pension funds as well as smaller investors such as private banks or family offices, we first assume, for illustrative purposes, that their total hedge fund allocations are $100 million, $500 million and $1 billion, respectively, as of December 2012. We construct three hypothetical portfolios that allocate to the top 30 past performing funds and then study which of the constraints have the biggest economic impact on performance persistence.

We find that a more concentrated portfolio of the top 30 hedge funds performs better than portfolios that contain hundreds of funds in each performance interval. Our simulations of the performance of a hypothetical investor suggest that redemption restrictions partly hinder investors' ability to exploit the performance persistence of top 30 hedge funds. The economic value of additionally imposing constraint C4 related to *the percentage of AuM constraint* is large and portfolio performance falls by 1 to 2 percent per year in terms of the Fung and Hsieh (2004) alpha (hereafter FH alpha). A potential explanation of this finding is that the constraint C4 filters out better performing small hedge funds from larger investors' portfolio. Therefore, since we document a strong negative relationship between future fund performance and current fund size, it is not surprising that we find that the constraint C4 has an important impact on hedge fund performance persistence. In contrast, imposing the *minimum investment constraint* (C5) does not seem to have an economically large impact on portfolio performance. After imposing all five constraints we find that the performance of the hypothetical portfolios decreases with portfolio size. The $100 million investor portfolio generates the highest FH alphas, which are statistically and economically significant ranging from 2.8% to 4.7% per year depending on the liquidity constraint assumed.

Overall, we conclude from our results that incorporating the set of investment restrictions reduces average performance dramatically, and reduces, but does not eliminate, performance persistence at shorter rebalancing frequencies. Therefore, even though our conclusion from standard performance persistence tests is that evidence of hedge fund performance persistence is weak, more realistic tests based on hypothetical constrained investor portfolios suggest that an investor can generate risk-adjusted performance by investing in the historically best performing funds. Our findings support the view that return expectations of the predominant investor type (i.e., the large institutional investor) should be significantly lower than expectations that are based on unrestricted portfolio allocations across the broader hedge fund universe. These results qualify the practicality and implementability—from the perspective of real-world hedge fund investors—of the findings reported in previous hedge fund studies. They caution against "chasing performance" of hedge funds generally and of large hedge funds in particular. The impressive performance and its persistence that the earlier literature has documented of hedge funds are not easily exploitable by investors.

Our results are closely related to recent literature that examines market efficiency, transaction costs and short sale constraints. Several papers have documented short-term performance persistence in hedge fund portfolios (e.g., Agarwal and Naik (2000), Brown, Goetzmann, and Ibbotson (1999), Liang (1999), Baquero, ter Horst, and Verbeek (2005)). Using sophisticated econometric approaches, Jagannathan, Malakhov, and Novikov (2010), and Kosowski, Naik, and Teo (2007) show that top abnormal performance of hedge funds persists even at annual horizons. Aragon (2007) shows that hedge funds with strict share restrictions may deliver superior performance on average, but does not study performance persistence. Although the recent literature shows that stock return anomalies are difficult to exploit in real time due to transaction costs (e.g., Novy-Marx and Velikov 2015) and short selling constraints (e.g., Drechsler and Drechsler 2014), the extant hedge fund literature does not explicitly account for effect of investor-level real-world investment constraints on performance persistence. Even though the evidence of performance persistence is mild, we show that a real-world investor is able to exploit performance persistence in risk-adjusted returns of hedge funds by investing in top past-performing funds.

Our paper relates to a growing set of studies on operational risk and its relation on hedge fund performance. According to Brown, Fraser, and Liang (2008), diligent due diligence is a source of alpha when forming portfolios of hedge funds. Brown, Goetzmann, Liang, and Schwarz (2008, 2009, 2012) show that hedge funds with higher operational risk deliver lower average performance and exhibit a greater likelihood of failure. Aiken, Clifford and Ellis (2015b) document that fund of hedge funds seem to provide valuable due diligence and monitoring services for investors by firing underperforming hedge fund managers. Bollen and Pool (2012) develop a set of flags based on suspicious patterns in hedge fund returns and relate these flags to misbehaviour and frauds. This paper adds to this literature by exploring explicitly the impact of real-world investment constraints on hedge fund performance and its persistence.

The rest of paper is organized as follows. Section 2 describes the data, and Section 3 provides preliminary evidence from the size–performance relationship. Section 4 examines the effect of constraints on hedge fund performance persistence, and Section 5 evaluates a hypothetical hedge fund investor performance and its persistence. Section 6 concludes.

2. Data and Methodology

2.1. Hedge Fund Database

To carry out our empirical analysis, we construct a comprehensive hedge fund database consisting of funds from the BarclayHedge, EurekaHedge, HFR (Hedge Fund Research), Morningstar, and Lipper TASS databases. We use the "merging" approach of Joenväärä, Kosowski, and Tolonen (2014) to identify unique investment programs and to exclude multiple share classes. Our final sample contains 6,453 unique management firms and 36,498 unique hedge funds. The database contains monthly fund-level AuM observations and net-of-fees return observations for the period from January 1994 through December 2012. We also obtain cross-sectional fund information such as fee structures and share restrictions. We focus on the post-1994 period because data prior to 1994 are less reliable for a variety of reasons.[6] In our baseline results, we address several concerns associated with hedge fund return data. We exclude the first 12 months of the return history of each fund to control for backfill bias. Hedge funds that report the same return observations (e.g., "stale returns") for three consecutive months or more are excluded from portfolios.[7]

2.2. Motivation of Size Limits

The effect of several of the investors' investment constraints crucially depends on the fund size. Therefore, we use economically motivated fund size categories that are relevant to real-world investors. According to Panel A of Table 1, the total AuM of single-manager hedge funds, which report net-of-

[6] Few of the data vendors keep records of defunct funds prior to 1994. Beginning our period of study in that year mitigates the effects of survivorship bias and backfill bias (see, e.g., Liang (2000), Fung and Hsieh (2000, 2009), Malkiel and Saha (2005)).

[7] We use algorithm proposed by Bollen and Pool (2012) to estimate the number of the consecutive return observations.

fees returns in USD, was approximately $1.6 trillion at the end of 2012.[8] We find that the total AuM of all single-manager hedge funds was approximately $2.6 trillion at the end of 2012 that mirrors recent surveys (e.g., HFR, PerTrac),[9]).

[[INSERT TABLE 1 ABOUT HERE]]

As mentioned previously, most of the assets under management are concentrated in the largest hedge fund firms. Therefore, instead of defining size deciles or quintiles as used in previous studies (Teo 2010 and Boyson 2008), we use in our performance persistence tests five economically motivated size interval limits – namely, *Mega*, *Large*, *Medium*, *Small* and *Micro*.

Panel A of Table 1 summarizes our five fund size intervals as of December 2012. It shows that the number of funds and the proportion of assets under management are not equally distributed between categories. Indeed, there are relatively few Mega funds, but they manage a large proportion of the whole industry's AuM. In contrast, there are a large number of funds in the Micro category, but they only manage a tiny portion of the industry's AuM. Therefore, it is important to investigate whether these Micro funds are driving performance persistence results.

We start by categorizing hedge funds managing at least $1 billion as *Mega* funds [10].[11] According to Table 1, only 4.1% of the funds as of December 2012 have AuM of at least $1 billion, but they account for 57.8% of the industry AuM. In contrast, using the equal-weighted top-quintile, we compute that the respective limit is only $198 million. This indicates that the equal-weighted top-quintile contains funds that institutional investors do not consider as large.

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[8] We exclude all "funds of funds" in order to prevent double counting.
[9] The PerTrac 2012 survey shows that the AuM of hedge funds totaled approximately $1.89 trillion at the end of that year's fourth quarter; HFR reports total AuM of $2.01 trillion at the end of 2011Q4.
[10] Edelman, Fung, and Hsieh (2013) offer a comprehensive analysis of the capital formation process of Mega hedge fund firms.
[11] According to the Preqin 2013 survey, which covers 176 investors that invest more than $1 billion in hedge funds, the average AuM of those funds is $818 million. These investors represent over $550 billion in combined capital allocated to hedge funds.

Given rising regulatory, compliance, and other costs, the break-even size for a fund has increased over the years and is often placed at several hundred million dollars. The 2012 Citi report finds that a hedge fund needs between \$250 million and \$375 million in AuM in order to sustain itself on management fees alone.[12] We therefore choose \$500 million as a conservative lower limit for the second interval (our *Large* funds category). According to a recent article in *The Economist*, a new hedge fund typically opens with \$50–100 million in assets under management. Hence we choose \$100 million as the lower limit for the third interval (our *Medium* funds category).[13]

We define two additional categories: *Small* and *Micro* funds, which manage (respectively) \$10–100 million and less than \$10 million. *The Economist* quotes Kent Clark, of Goldman Sachs Asset Management, as follows: "Gone are the days when two traders with a Bloomberg terminal and some banking contacts could brand themselves as a hedge fund and attract outside money." Table 1 also shows that 70.5% of the hedge funds have AuM of less than \$100 million and that less than 10% of hedge funds have AuM of at least \$500 million. These values are consistent with the recent trend in this industry for Mega hedge funds to receive the majority of assets under management.

Tracking the performance of the largest funds over time requires that we adjust for the effect of fund growth. Toward this end, we sort hedge funds into the above nominal groups at the end of the sample (2012Q4) and then calculate the corresponding percentiles of the number of funds that belong to each size group. We apply these percentile limits and sort hedge funds into five size groups every December from 1994 through 2012.[14]

Given our rebalancing frequency constraint (C1) and liquidity constraints (C2), Panel B of Table 1 reports the summary statistics of share restrictions in the form of lockup, redemption and notice

[12] See http://icg.citi.com/transactionservices/home/demo/tutorials8/Hedge_Fund_Dec2012/
[13] "Launch bad," *The Economist*, 20 April 2013.
[14] At the end of 1995, for example, the average (respectively, median) AuM of all Mega funds was \$655 million (respectively, \$375 million).

periods as well as the fund's minimum investment amount. We find that a typical hedge fund provides monthly redemptions with a 30 day notice period. 27% of funds impose a lockup period, which is typically 12 months long. Panel B shows significant variation in funds' share restrictions. This implies that some of the funds will not be investable when we impose liquidity constraints (C2) in the empirical analysis.

2.3. Hedge Fund Investor Data

There are many different types of investors that invest in hedge funds including pension funds, endowments, sovereign wealth funds, high net worth individuals and funds of funds. Although we do not have information on the hedge fund holdings of each of these investor types, we are able to obtain information on fund of hedge fund holdings from data provided by EurekaHedge, SEC filings, and Preqin Hedge Fund Investor Profiles Services. This data enables us to relate our assumed investor constraints to real-world FoFHs holdings.

Panel A of Table 2 reports that the majority of EurekaHedge's FoHFs manages less than $100 million. However, around 12.7% of FoHFs manage more than half a billion US dollars. Panel B reports the minimum individual fund's AuM that the EurekaHedge's FoHFs require. 76.2% of their FoHFs' invest in small funds below $100 million AuM, while 9.7% of FoHFs consider only larger funds with above $100 million of AuM.

Panel C shows that our assumed diversification constraint (C3) is realistic, since the majority of FoHFs hold between 16 and 30 hedge funds in their portfolios. This is confirmed by using the data from registered FoHFs holdings. Following Aiken, Clifford and Ellis (2013), we gather the underlying hedge fund holdings of our sample FoHFs from SEC forms N-Q, N-CSRS, and N-CRS. These registered FoFs are often run by the most prominent hedge fund management firms that are rarely available for researchers (Edelman, Fung and Hsieh 2013).[15] We estimate that a typical registered FoHF holds 28 underlying hedge funds. In addition, the Preqin 2013 survey, which covers 176 investors that invest more than $1 billion in hedge funds, report that surveyed investors typically have from 28 to 35 investments. Therefore, our baseline *diversification* constraint (C3) is that a typical FoHF holds 30 hedge funds.

Confirming the anecdotal evidence from Ganshaw (2010), Panel D shows that 33.1% of EurekaHedge's FoHFs impose a requirement that any single hedge fund allocation not represent more than 10% of the AuM of the hedge fund. We verify this fact using a panel of quarterly hedge fund holdings of registered FoHFs that 90% of FoHF's allocations to hedge funds do not represent more than 10% of the AuM of hedge funds. Hence, this evidence motivates our *percentage of AuM constraint (C4)*, which we set to equal 10%. However, the panel shows that there is variation in this constraint across investors; therefore in our robustness section we quantify the impact of the constraint on hypothetical portfolio performance.

[[INSERT TABLE 2 ABOUT HERE]]

The rebalancing constraint (C1) that we impose can be partly motivated by how often hedge fund investors rebalance or monitor their portfolio. Panel E reports that 61.5% of FoHFs monitor their investments every 6 months or more frequently.

2.4. Benchmark data

We use the Fung and Hsieh (2004) model to evaluate and predict hedge fund performance. We regress $r_{i,t}$, hedge fund portfolio *i* excess returns against *k* factors as follows:

[15] Agarwal, Lu and Ray (2013) find that only 8 of registered FoFs report voluntarily to the Lipper TASS database.

$$r_{i,t} = \alpha_i + \sum_{k=1}^{K} \beta_{i,k} f_{k,t} + \varepsilon_{i,t} \ .$$

(1)

These k factors are defined as the excess return of the S&P 500 index (SP); the return spread between the Russell 2000 index and the S&P 500 index (SIZE); the excess return of 10-year U.S. Treasuries (TY); the return of Moody's BAA corporate bonds minus 10-year Treasuries (BAA − TY); and the excess returns of look-back straddles on bonds (PTFSBD), currencies (PTFSFX), and commodities (PTFSCOM).[16] The model's intercept, α_i, the FH alpha, measures the average abnormal return of a portfolio *i*.

We use this alpha's *t*-statistic to predict each fund's future performance because doing so corrects for outliers by normalizing a fund's alpha in terms of its estimated precision (Kosowski, Timmermann, Wermers, and White 2006). Of the 384 FoHFs that report a preferred minimum track record length, 62.5% require a track record of two years or less, while 21% of these FoFHs require a 3-year track record. When constructing our hypothetical investor portfolios in Section 5, we require hedge funds to have a 3-year track record to be included; we exclude the first year of returns of each fund to control for backfill bias.

3. Economically Motivated Size–Performance Relationship

The effect of investors' investment constraints depends on the underlying fund size–performance relationship. The reason is that several of the investment constraints such as the *percentage of AuM constraint* (C4) and *minimum investment constraint* (C5) have an implication for the size of hedge fund that an investor is able to allocate to. Therefore, as a preliminary step, we investigate the relationship

[16] We obtain the data for equity- and bond-oriented factors from Datastream. We thank David Hsieh for making the trend-following factors available on his website.

between a hedge fund's size and its performance. This relationship has been studied in earlier studies, but it is important to document it for economically motivated size intervals to fully understand the effect of different constraints on investor returns.

3.1. Size–Performance Relationship

We start by showing that it is crucial to distinguish between the forward-looking and the backward looking relation, as the former is what matters to hedge fund investors. Using economically motivated size intervals, we find that larger funds tend to have performed better than smaller funds *in the past* but tend to perform worse *in the future*.

Using alphas, Figure 1 clearly illustrates this result: the backward-looking size–performance relationship is upward sloping whereas the forward-looking relationship is downward sloping. To compute forward-looking alphas, we use nominal fund size categories described in Section 2. The forward-looking alphas clearly indicate that smaller funds outperform larger ones and that there is a substantial spread in their respective alphas. To obtain the backward-looking alphas, hedge funds are first sorted into nominal size groups based on each fund's last observed available monthly AuM. This sorting is performed only once, but all the available return observations are used to estimate the alphas for each of the size category portfolios. The pattern evidenced by backward-looking alphas is that larger funds outperform smaller funds; the reason is that only the most successful large funds survive whereas poorly performing hedge funds are simply liquidated. Consequently, some hedge funds that perform well grow rapidly over time yet do not deliver superior future performance. This result is consistent with predictions of the Berk and Green (2004) model.

[[INSERT FIGURE 1 ABOUT HERE]]

Panel A of Table 3 shows that the forward-looking size–performance relationship is monotonic, and it holds in terms of alphas and when adjusted for risk. For the period 1994–2012, the difference in the FH alpha between Micro and Mega funds (3.26%) remains statistically significant at 5% level.[17]

One of the strengths of our analysis is the use of economically motivated size intervals. Our results regarding the negative size–performance relationship are not sensitive to this choice, but we find that the performance of the largest funds is lower compared to Teo (2010). To prove this, instead of using economically motivated size limits, we create conventional quintile portfolios based on fund size. Following Teo (2010), the two smallest quintiles comprise the portfolio of the smallest funds and the two largest size quintiles comprise the portfolio of the largest funds. The forward-looking alphas of the quintile portfolios confirm the negative size–performance relationship.[18] Since our more realistic definition of the size interval for Mega funds excludes funds below $1 billion in AuM, one interesting result is that in contrast to conventional quintile portfolios, which would include funds as small as $200m in the largest quintile, we do not find statistically significant FH alphas for Mega funds. In Section 4.1, we investigate the performance persistence conditional on economically motivated size categories, to realistically gauge the investors' expected returns from hedge fund allocations.

[[INSERT TABLE 3 ABOUT HERE]]

Panel B of Table 3 shows that the conclusions regarding the size–performance relationship are reversed when we examine the *backward-looking* size performance relationship. The portfolio consisting of the 471 largest Mega funds at the end of our study period (i.e. in 2012) generated a FH alpha of 7.31% in the past, whereas the corresponding portfolio the 7,697 Micro funds generated a FH alpha of 1.15%.

[17] Backfill bias does not significantly change the performance of the biggest funds, but as Figure A1 in the Appendix highlights, such bias leads to important differences in the performance of Micro funds.
[18] We leave these findings untabulated due to reasons of space. The findings are available from authors upon request.

3.2. Robustness of Size–Performance Relationship

One natural question that arises in this context is whether the positive backward-looking size–performance relationship is driven by flows or returns. Are funds large now because they grew the asset base by generating large returns or attracting large flows in the past? To answer this question, we construct backward-looking portfolios and sort hedge funds into nominal size groups based on the last available AuM observation. Second, we divide hedge funds into two groups based on the cross-sectional median of flow-based AuM observations. We find that the positive size–performance relationship is present both for high and low inflow funds within each size interval. This implies that the result is not driven by flows or artificially by return-based AuM growth.[19]

4. Investor Investment Constraints and Performance Persistence

In this section we evaluate the effect of the *rebalancing frequency* (C1) and *liquidity constraint* (C2) on hedge fund performance persistence. Our performance persistence tests focus on the FH alpha spread between top and bottom quantile portfolios and on the monotonicity patterns in quantile portfolios. Importantly from a general economic perspective, this allows us to test whether performance persistence is an industry wide phenomenon or limited only to illiquid and small funds that represent a small proportion of the hedge fund industry's total assets.

4.1. Rebalancing Frequency and Performance Persistence

To investigate the effect of the *rebalancing frequency* (C1) on performance persistence, we rank funds quarterly, semiannually, or annually into quintile portfolios. We divide funds into quintiles based on

[19] The findings of robustness checks regarding the backward-looking size–performance relationship are available from authors upon request.

the t-statistic of ranking-period alpha estimated from the prior 24-month data. We then calculate equal-weight returns for each of the quintile portfolios and evaluate the resulting performance persistence.

Table 4 reports that hedge funds deliver significant performance persistence at the quarterly and semiannual portfolio rebalancing frequencies, but not at annual portfolio rebalancing frequency. As captured by the spread between the top and bottom quintile portfolio performance, we find a statistically significant Fung and Hsieh (2004) alpha spread of 3.24% (3.12%) at the quarterly (semiannual) rebalancing frequency. In contrast, at the annual rebalancing frequency, the alpha spread is insignificant and considerable lower, that is only 0.64% per annum. As additional evidence on performance persistence, we test whether the estimated post-rank alphas are monotonically increasing across the portfolios. We run the monotonic relation (MR) test of Patton and Timmermann (2010) for each portfolio. The estimated p-values of the MR test in Table 4 confirm that the pattern is monotonically increasing at the quarterly rebalancing frequency. The null of no relation is rejected at the 5% level of significance in favor of a monotonically increasing relation. The monotonic pattern in post-rank alphas is not evident at longer rebalancing frequencies. This also indicates that the performance of hedge funds only persists at short rebalancing horizons.[20]

To indirectly analyze the effect of the *percentage of AuM constraint (C4)*, we conduct performance persistence test conditional on fund size. We divide hedge funds into nominal size groups as described in Section 2.[21] We expect that too low an AuM percentage constraint may filter out better performing small hedge funds from larger investors' portfolio and thereby significantly impact on the performance persistence. The table confirms that when persistence is evident, it decreases almost monotonically with fund size groups. Even for the smallest funds, which exhibit the strongest

[20] The hypothesis testing of the difference in the t-statistic of the FH alpha using the Ledoit and Wolf (2008) approach is equivalent to the hypothesis testing of information ratios (IR) since the IR can be approximated as follows: $IR \approx t_\alpha/\sqrt{T}$, where t_α is the t-statistic of the alpha and T is the number of observations used in the estimation.

[21] To ensure that each portfolio has a reasonable number of funds, we form three size groups: (1) the Micro and Small funds; (2) the Medium funds; and (3) the Large and Mega.

persistence, the alpha spread between top and bottom quintiles is only positive and significant at the quarterly and semiannual portfolio rebalancing horizons. In contrast, at the annual rebalancing horizon, we cannot find any evidence of performance persistence even for the smallest funds. This suggests that performance persistence is not pervasive, but is rather limited to a small proportion of total assets of hedge fund universe. Therefore, it is important to investigate in Section 5 explicitly how the percentage of AuM constraint effects on performance persistence.

[[INSERT TABLE 4 ABOUT HERE]]

4.2. Liquidity Restrictions and Performance Persistence

So far, our out-of-sample persistence tests did not take into account constraint C2 related to liquidity restrictions such as notice periods and lockup provisions. To understand better the effect of liquidity constraints on investors' opportunity set, we plot in Figure 2 the proportions of hedge funds that are investable after imposing liquidity constraints one by one. More specifically, we first remove from the persistence tests funds that have lockup period or redemption period longer than the imposed rebalancing frequency. We then vary the funds' maximum acceptable notice period, which specifies investors' information set that is used to rank hedge funds in persistence tests. We implement 1-month, 3-month or 6-month maximum acceptable notice period constraint to account realistically for the effect of notice period on persistence tests. For instance, in the case of annual portfolio sorts with a 1-month maximum acceptable notice period, the investor can rank funds' using information available at the end of November (instead of December) and cannot invest in funds that impose a notice period longer than one month.

We apply these liquidity requirements across different rebalancing frequencies. We find that over 98% of hedge funds allow quarterly redemptions and specify a lockup period and redemption period of one year or less. In addition, over 99% of hedge funds set the notice period equal to 6 months or less. Therefore, when evaluating performance persistence, we set the maximum constraints for the lockup and redemption periods (notice period) equal to one year (6 months).

According to Figure 2, the maximum acceptable notice period constraint has a stronger impact on the proportion of investable funds than the lockup and redemption restrictions. If an investor accepts a 6 month notice period, it implies that almost every hedge fund is investable. In contrast, if an investor only accepts a 1 (3) month notice period, then the percentage of investable funds ranges from 46% to 65% (92% and 98%) funds. Because of typical 1-year lockup provisions, the number of investable funds is lower at the quarterly and semiannual portfolio rebalancing frequency compared to the annual portfolio rebalancing frequency. Even if investors choose the most demanding liquidity terms they invest in more than 40% of the funds.

[[INSERT FIGURE 2 ABOUT HERE]]

So far we have documented how many funds in our sample would fulfill certain fund-level liquidity restrictions. Next, we examine how these restrictions affect our earlier conclusions about performance persistence. We do so by imposing constraints reflecting lockup, redemption and notice periods one by one; and thereafter we gauge the economic value of each constraint using a performance persistence test procedure similar to the one above.

[[INSERT TABLE 5 ABOUT HERE]]

Table 5 shows that performance persistence decreases after we impose the lockup provision, redemption period constraints and especially the maximum acceptable notice period constraint. We start our performance persistence tests by adding first lockup and redemption period constraints. Based on the spread alphas and the Patton and Timmermann (2010) monotonicity tests, we conclude that performance persists at quarterly and semiannual portfolio rebalancing frequencies. These constraints are more important at the quarterly portfolio rebalancing frequency than at the annual frequency. The lockup provision constraint seems to be more binding than the redemption restriction constraint. Clearly, a large number of hedge funds that have a 1-year lockup provision are not included into the quarterly persistence tests, but these funds can be exploited in annual performance tests. Also, there are very few funds that allow redemptions less frequently than at quarterly frequency. This explains why the lockup provision constraint reduces performance persistence more than does the redemption restriction constraint.

We next vary the maximum acceptable notice period constraints in the performance persistence tests. In contrast to the effect of previously considered constraints, we now find very little evidence of performance persistence. At the quarterly portfolio rebalancing frequency, there is performance persistence only when the maximum acceptable notice period constraint is solely taken into account. After imposing a 1-month or 3-month maximum notice period constraint, we find monotonicity in *t*-statistics of alphas, but the alpha spreads between top and quintile portfolios are not consistently positively significant. At the semiannual and annual portfolio rebalancing frequencies, we cannot document any evidence of performance persistence once the maximum acceptable notice period rules are imposed. The performance persistence vanishes when we simultaneously impose lockup provision and redemption period constraints in addition to the maximum notice period constraint. Hence, constraints related to notice period seem to be more important than the constraints related to lockup provision and redemption restriction are. To conclude, when performance persistence is measured using the alpha spreads between quintile portfolios as well as Patton and Timmermann (2010) monotonicity tests, the imposition of liquidity constraints (C2) leads to an absence of performance persistence.[22]

[22] In untabulated robustness tests, we find that after adjusting for additional liquidity risk factors (e.g., Pastor and Stambaugh 2003) our conclusions remain qualitatively unchanged.

4.3. The Marginal Effect of Rebalancing Frequency and Liquidity Constraints

So far we have assessed the economic value of the effect of imposing investment constraints related to *rebalancing frequency* and *liquidity constraints* (C1 and C2) on performance persistence. What remains to be shown is which of the effects is the most important. Therefore, in Table 6, we compare the differences in the top-quintile alphas between the constrained portfolios specified in Table 4 (*rebalancing frequency*) and Table 5 (*liquidity constraints*). Given difficulties to short sell hedge funds, we investigate the marginal impact of both constraints using the top-quintile portfolio alphas.

[[INSERT TABLE 6 ABOUT HERE]]

We begin the analysis by first evaluating portfolios, which incorporate the rebalancing frequency constraint (C1) and liquidity constraints for lockup and redemption periods (C2). Results in Table 6 show that at the quarterly rebalancing frequency the implementation of a lockup provision significantly reduces performance and that portfolios formed without lockup constraints would lead to unrealistically high top-quintile alphas. At quarterly rebalancing horizon, we document a slightly lower top-quintile alpha of 0.5% when the lockup provision is imposed, while at the annual portfolio rebalancing horizon the respective alpha difference is insignificant. This highlights the importance of accounting for lockup provision in persistence test at higher portfolio rebalancing frequencies.

We next incorporate the redemption frequency constraint and the liquidity constraint for the maximum acceptable notice period. To compare performance of top-quintile alphas, we use the same information set to rank funds. For instance, in the case of annual holding periods, if the constrained portfolios impose a 1-month maximum acceptable notice period, we form the constrained portfolios every November (instead of December); in this case we also form portfolios, which impose only constraint C1 (rebalancing frequency), every November in order to make them comparable with the liquidity-constrained portfolio. Across rebalancing frequencies, we find significantly lower top-quintile alphas after imposing a 1-month maximum acceptable notice period restriction, while 3- and 6-month notice period restrictions do not consistently lower the performance of top-quintile portfolio alphas.

We finally simultaneously incorporate lockup, redemption and notice period constraints. We find that the lockup and redemption period constraints only marginally lower the top-quintile alphas when notice period constraints are imposed. Hence, notice period constraints seem to be more important than constraints related to lockups and redemption restrictions.[23]

Note that although the difference in performance between the top- and bottom quintiles is not strongly significant, the strong performance of the top-quintile of funds generates economically and statistically significant risk-adjusted returns across size groups and rebalancing horizons. Therefore, in the next section we examine whether the impressive performance of the top-quintile of funds is exploitable by a real-world investor when we carefully incorporate other investment constraints.

5. Effects of Investment Constraints on Performance of Hypothetical Investors

In the preceding section, we saw that the alphas of the top-quintile of hedge funds are statistically significant and economically large. Such a portfolio may, however, not be implementable in practice since hedge fund investors face additional constraints beyond rebalancing frequency constraints (C1) and liquidity needs (C2). Instead of hundreds or thousands of funds, as implicitly assumed in the preceding section, a typical hedge fund portfolio will contain only a few dozen funds, as our diversification constraint (C3) suggests. There are other constraints as well. On the one hand, large investors may not be able to invest in smaller funds if the investor's guidelines prevent a capital allocation that would represent more than ten percent of a fund's AuM, for example, as captured by constraint C4 introduced earlier. On the other hand, small investors may not meet minimum investment

[23] This conclusion is robust to the inclusion of additional liquidity risk factors (e.g., Pastor and Stambaugh 2003) as results available upon request show.

constraints (C5). Hence, from a practical point of view, it is important to examine whether hedge fund investors can exploit top-past performing funds.

5.1. Constructing Hypothetical Investor Portfolios

How does the imposition of different constraints affect the investment opportunity set for our hypothetical investor? To capture the experience of both large hedge fund investors such as sovereign wealth funds, pension funds as well as smaller investors such as private banks or family offices, we first assume, for illustrative purposes, that their respective hedge fund portfolio sizes are $100 million, $500 million or $1 billion as of December 2012.[24] Since one needs to make an assumption how these size limits evolve over time until 2012, we use the monthly HFRI fund-of-fund aggregate index return to simulate the growth of the three hypothetical investor portfolios' AuM from December 1997 to December 2012. Each portfolio satisfies the constraint for rebalancing frequency (C1) such that each portfolio is formed at the end of the year depending on the constraint for the maximum acceptable notice period (C2). Given that the holding period of each portfolio is one year, we impose liquidity constraints for the lockup and redemption periods and require that they not exceed one year. Following the *diversification constraint* (C3), each hypothetical portfolio is assumed to contain 30 funds. We calculate the allocation to each fund as a ratio of the portfolio size to the number of funds held.

In an attempt to capture the investment constraints C1 to C5, we construct hypothetical investor portfolios containing 30 funds with the highest alpha *t*-statistic estimated using 24 return observations. We next impose the restriction that the investment per fund is *10% of the fund's AuM* (C4) and the underlying fund's minimum investment amount does not exceed the hypothetical investor's fund-level

[24] A recent WSJ article documents that the size of a family office should be at least $100 million to cover required expenses, while Preqin's Hedge Fund Investor Profile service currently contains 176 investors with more than $1 billion invested in hedge funds (excluding fund of hedge funds managers). Based on this evidence, it seems that our three investor portfolios provide realistic upper and lower size limits for typical portfolios of hedge funds.

allocation (C5). We rebalance portfolios only at annual frequency. Those funds that do not meet these assumptions are excluded from the hypothetical portfolio.

Table 7 shows that these additional constraints have a significant impact on the proportion of hedge funds in the hypothetical investors' investment opportunity set. Panel A reports the average number of funds in the investor's opportunity set after the rebalancing frequency (C1) and the liquidity constraints (C2) are imposed. On average, there are 1,630 funds in the investor's opportunity set after imposing only the liquidity constraints for the lockup and redemption periods and requiring that they not exceed 12 months. If the constraint for the maximum accepted notice period is also added to the liquidity constraints, the number of funds available for the investor is lower. For instance, if the investor accepts a short notice period equaling to one year, the number of funds available for investors decreases 34%, on average.

According to Panel B of Table 7, which reports the effect of the diversification constraint (C3) on the proportions of available funds, only around 7% of hedge funds are not in the \$100 million investor's opportunity set, whereas the \$1 billion investor cannot invest in around 40% of hedge funds. Hence, the diversification constraint on its own significantly reduces the hypothetical investor's opportunity set. Panel C implements the percentage of AuM constraint (C4) with a 10% limit. We find that the proportion of investable funds is reduced dramatically. Even for the \$100 million investor, only around 60% of funds are investable. The \$1 billion investor can only invest in around 15% of funds. Panel D shows that the minimum investment constraint (C5) is not strongly binding. The findings of Panel D support our hypothesis, which suggests that the C5 constraint has the strongest effect on the small investors' portfolio. The results show that the \$100 million investor that allocates to 30 funds can still invest in around 86% of the funds and the \$500 million investor can invest in 60% of funds. Hence, it seems that funds such as the Bridgewater Pure Alpha with high minimum investment requirements (of $10 million or more) are rare.[25] Although we have shown that constraint C5 does not significantly affect the number of investable funds, it is still unclear whether the constraint impacts on the hypothetical investor's performance. We finally add all constraints simultaneously in Panel E. We find that the $100 million investor's opportunity set contains slightly more than half of the available funds. The $500 million investor's investment universe contains a quarter of funds. The largest hypothetical investor with the $1 billion portfolio can only invest in 15% of funds.

[[INSERT TABLE 7 ABOUT HERE]]

5.2. Performance of Hypothetical Investor Portfolios

We next turn to assess how these constraints affect the hypothetical investor performance. We distinguish several scenarios which differ depending on the size of the hypothetical investor's portfolio and which of the liquidity constraints (C2) are accounted for. Each portfolio satisfies the constraint for rebalancing frequency (C1) such that each portfolio is formed at the end of the year depending on the constraint for the maximum acceptable notice period (C2). We use a one year holding period to calculate returns for each of the portfolios.

Table 8 reports the performance for hypothetical portfolios consisting of the top 30 funds that differ depending on the portfolio size and rebalancing rules. We find that realistic portfolio construction rules have a significant economic impact.

Panel A shows the effect of the diversification constraint (C3) on the hypothetical investor's portfolio performance. After imposing only the liquidity constraints for the lockup and redemption periods and requiring that they not exceed 12 months, we find that the performance of the top 30 funds is extremely high ranging from an annual alpha of 6.2% (t = 8.21) for the $100 million investor to an

[25] The numbers of unique funds excluded from the investor's opportunity set due to the constraint C5 is 379, 55, and 35 for the $100mn, $500mn. and $1bn. portfolio, respectively. Constraint C5 has the largest impact on the $100 mn. portfolio.

alpha of 4.8% (t = 6.21) for the $1 billion investor. This performance decreases when we add constraints for the maximum acceptable notice period. However, across specifications, we still find that the alphas of portfolios consisting of the top 30 funds are economically large and at least marginally significant.

[[INSERT TABLE 8 ABOUT HERE]]

Panel B shows the effect of the percentage of AuM constraint (C4) on the hypothetical investor's portfolio performance. The hypothetical investor's performance decreases significantly once we include this constraint in addition to constraints C1–C3. Alphas remain statistically significant only for the smallest ($100 million) hypothetical investor. For the larger investors ($500 million and $1 billion), alphas are significant when the maximum acceptable notice period is 3 months.

Panel C shows the effect of the minimum investment amount constraint (C5) on the hypothetical investor portfolio performance. This constraint does not significantly reduce the hypothetical investor's performance when imposed together with constraints C1–C3. Alphas are now almost identical to those in Panel A. Hence, the exclusion of funds with extremely large minimum investment amounts does not significantly reduce the performance of our hypothetical investor portfolios.

Panel D shows the simultaneous effect of all constraints on the hypothetical investor's portfolio performance. The smallest $100 million investor portfolio is able to deliver significant alpha even after all of the constraints are imposed. The $500 million and $1 billion hypothetical investor portfolios generate significant alphas of 2.6% (t = 2.88) and 2.5% (t = 2.49), respectively, when the 3-month maximum acceptable notice period constraint is imposed. This is, however, not the case for other maximum acceptable notice periods (1-month or 6-months).

Although we set out to test the effect of realistic investment constraints on hedge fund performance persistence including diversification requirements (C3) and the percentage of AuM constraint (C4), our analysis also raises normative questions. Investors and policy makers may, for example, ask what the optimal number of hedge funds in a portfolio is if the objective is to maximize out-of-sample performance. To test the sensitivity of the hypothetical investor performance persistence to these two constraints, we vary the number of hedge funds held in the portfolios from 10 to 100. We also separately allow for different percentage of AuM limits ranging from 2% to 30%. The choice of the ranges for both constraints is motivated by investors' actual holdings documented in Table 2.

[[INSERT FIGURE 3 ABOUT HERE]]

Overall, the results documented in Figure 3 show that the hypothetical portfolio performance is decreasing with the number of hedge funds held in hypothetical investor portfolios. According to Panel A of Figure 3, there is an almost negative monotonic relationship between alphas and the number of funds held in the hypothetical portfolios. Given that we do not incorporate constraints for liquidity needs or the diversification constraint (C4), alphas are economically large and statistically significant for all three hypothetical investor portfolios.[26] To measure the marginal importance of the diversification constraint (C3), we estimate the performance difference between our baseline 30 fund portfolio and other specifications. Panel B of Figure 3 shows that the performance of portfolios having *less* than 30 funds is not statistically significantly higher than the performance of the baseline portfolio with 30 funds. In contrast, for the hypothetical \$100 million investor, portfolios with *more* than 30 funds underperform the baseline top 30 portfolio. For the hypothetical \$500 million investor, we find that the top 30 fund portfolio starts to outperform when the number of funds held in the portfolio exceed 55. The effect of the diversification constraint is not significant for the \$1 billion portfolio.

[26] For reasons of space, the statistical significance of the alphas in Figure 3 is reported in Table A1 in the Appendix.

Although there is a monotonically decreasing relationship between alphas and number of fund held, it is not statistically significant when we compare the baseline top 30 fund's performance with other specifications that vary the number of funds held.

Panel C of Figure 3 complements this analysis and shows that the performance of the hypothetical portfolios increases with the percentage of AuM constraint (C4). This can be explained by the fact that the larger percentage of AuM limit allows the inclusion of smaller funds to the hypothetical portfolios than smaller percentage of AuM limits would allow. Again, we observe that alphas are large and statistically significant across specifications, because we do not impose tight liquidity needs but rather focus on the percentage of AuM limit. The tighter percentage of AuM constraint has the most significant effect on the hypothetical $1 billion portfolio, but it only marginally reduces the performance of the $100 investor portfolio. Panel D confirms the finding that the increase in the percentage of AuM constraint has the strongest effect on the performance of the $1 billion portfolio. The portfolio with the 10% of AuM constraint consistently underperforms the portfolios with larger percentage of AuM constraints; the differences in the FH alphas between the portfolio with 10% of AuM constraint and other portfolios with the percentage of AuM constraint varying between 16% and 34% are statistically significant at 5% level.

Overall our simulations of hypothetical investor portfolios reveal that incorporating realistic constraints has a significant economic impact. The effect of the liquidity constraint (C2) and the percentage of AuM constraint (C4) in particular have a large negative impact. Increasing the number of funds held in the portfolio also reduces performance. These results based on hypothetical investor portfolios confirm earlier insights from persistence tests that investor level constraints have statistically and economically significant effects on the return expectations of hedge fund investors. Policy makers should also take note of the importance of minimum diversification requirements and the percentage of AuM constraint when considering regulation since these constraints will affect the returns that hedge investors such as pension funds can expect form their portfolios.

5.3. Robustness of Hypothetical Portfolio Performance

So far, we have not addressed the impact of discretionary redemption restrictions (DLR) on our results. As a robustness test, following Aiken, Ellis and Clifford (2015a), we define a hedge fund as using a DLR when any fund-of-fund reports a position for the hedge fund that is 1) in a side pocket (either completely or partially), 2) subject to investor-level gates, 3) liquidating, 4) organized as a special purpose vehicle or special liquidating vehicle, or 5) explicitly said to be illiquid or having its liquidity restricted. We gather this data from SEC forms N-Q and N-CSR(S) to capture each fund of fund's portfolio holdings. We hand match DLR data with our aggregate databases based on 5 commercial databases. One caveat is that not all funds in our database feature in fund of fund portfolios that report to the SEC. Therefore the data only provides us with partial information about potential restrictions to redeem capital from funds in our sample. Only very few of the funds that impose DLRs belong to our top 30 hypothetical investor portfolios. Once the fund has imposed a DLR, we keep the fund in our top portfolios even after rebalancing portfolios at end of the year. The results in Table 7 are qualitatively unchanged when we incorporate DLRs. For parsimony and since only relatively few top funds impose DLRs in our sample we do not add DLRs as a sixth constraint in our baseline tests and incorporate them in unreported robustness tests instead.

6. Conclusions

This paper examines the effect of frictions and real-world investment constraints on hedge fund performance persistence. The empirical and theoretical asset pricing literature has studied the effect of frictions on asset prices, but little research has addressed the effect of investment constraints on the investment opportunity set of hedge fund investors. We contribute to the literature by accounting for five major investment constraints related to rebalancing frequency, liquidity, diversification requirements, the maximum relative size of a hedge fund allocation and minimum investment amounts, respectively —all of which are commonly faced by institutional investors, as we show. Overall, using two different methodologies we find that constraints related to rebalancing frequencies, liquidity needs, diversification requirements and percentage of AuM constraint have an economically and statistically significant impact on hedge fund performance persistence, while the effect of minimum investment constraints appears to economically less important.

Based on the performance persistence test methodology, we find that hedge fund performance persistence is significantly reduced when rebalancing rules reflect fund size restrictions and liquidity constraints such as share restrictions (e.g., notice and lockup periods). Our findings also establish that fund size is an important determinant of hedge fund performance persistence. Based on the hypothetical investor portfolios methodology, we conclude that the out-of-sample performance of the hypothetical portfolios is significantly reduced after additional restrictions related to the relative size of the hedge fund allocation as well as diversification requirements and minimum investment constraints are realistically incorporated into the rebalancing of the hypothetical portfolios. In fact, after imposing all the relevant rules, we find that the smallest \$100 million hypothetical investor portfolio is the only one able to deliver significant alpha even after all of the constraints are imposed including realistic notice periods. For the larger \$500 million and \$1 billion hypothetical investor portfolios the imposition of all constraints does not lead to consistently statistically significant performance. Our results offer important lessons for hedge fund investors. They caution against “chasing performance” of hedge funds, in particular by large investors that face multiple binding constraints. The impressive alpha that the literature has documented of hedge funds is not easily exploitable by investors. Our findings can be used to inform new theoretical models on the economics of the hedge funds that incorporate realistic investment constraints.

Finally, an interesting avenue for future research would be to investigate which fund characteristics beyond past performance are able to predict hedge fund performance once investor constraints are realistically incorporated.[27] In particular, operational risk measures developed by Brown, Goetzmann, Liang and Schwarz (2008, 2009, 2012), the R-squared (Titman and Tiu (2011)) or the Strategy Distinctiveness Index (Sun, Wang and Zheng’s (2012)) could be used as an additional filter to screen potential hedge funds. Macroeconomic information could be incorporated to forecast performance (Avramov, Kosowski, Naik and Teo 2011). However, these extensions are beyond the scope of this paper.

[27] Implicit in our analysis is that search costs associated with identifying the top 30 funds are economically small. This is plausible if search costs are based on quantitative selection criteria as applied in this paper.

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Table 1
Summary statistics

Panel A shows the number of hedge funds (# Funds), the average fund-level assets under management in millions of U.S. dollars (Avg. fund size), and the total AuM in billions of U.S. dollars (Total AuM) for five nominal size groups as of December 2012. The first column shows the range of the AuM in each size group measured in millions of U.S. dollars (AuM range). Panel B shows the summary statistics of the share restrictions, which include lockup, redemption and notice periods as well as the minimum investment amount (in thousands of U.S. dollars) for the sample period of 1994–2012. Reported values are the cross-sectional mean, median, standard deviation as well as the 25th and 75th percentiles of the share restrictions. The sample includes hedge funds that report at least two years of monthly returns in U.S. dollars. The sample is a consolidated database of hedge funds from the five databases including TASS, HFR, BarclayHedge, EurekaHedge and Morningstar.

Panel A: The number of funds and total AuM by size groups

AuM range (in \$mn.)	Size group	# Funds	# Funds%	Avg. fund size (\$mn.)	Total AuM (\$bn.)	Total AuM%
$0 < \text{AuM} < 10$	Micro	1,722	26.2%	3.6	6.2	0.4%
$10 \leq \text{AuM} < 100$	Small	2,910	44.3%	40.3	117.2	7.6%
$100 \leq \text{AuM} < 500$	Medium	1,359	20.7%	227.5	309.2	19.9%
$500 \leq \text{AuM} < 1{,}000$	Large	316	4.8%	704.7	222.7	14.4%
$\text{AuM} \geq 1{,}000$	Mega	267	4.1%	3358.1	896.6	57.8%
Total		6,574	100.0%		1551.9	100.0%

Panel B: Summary statistics of share restrictions

Variable	Mean	Median	Std	25th pct	75th pct
Lockup (months)	3	0	7	0	1
Redemption (months)	2	1	2	1	3
Notice (days)	32	30	32	5	45
Min. Investment (in \$1,000s)	907	200	3,542	10	1,000

Table 2

Summary statistics of fund-of-funds in EurekaHedge database.

This table shows the summary statistics of the cross-section of fund-of-funds (FoF), which report to the EurekaHedge database. In Panel A, the FoFs are categorized to the nominal size groups based on the FoF size at the end of 2012. Panels B and C categorize the FoFs based on the minimum individual fund size required by FoFs and the average number of hedge funds held by FoFs. In Panel D, the FoFs are grouped based on the their imposed percentage of AuM constraint (Panel D) which specifies a requirement that any allocation to an individual fund cannot exceed a certain percentage of the fund's AuM. In Panel E, the FoFs are categorized based on the monitoring frequency (in months) specifying how frequently FoFs monitor their holdings. Reported values are the number of FoFs in each category (# Funds) as well as the proportions of the number of FoFs in percentages (# Funds%).

Panel A: FoF size at the end of December 2012 (in millions of U.S. dollars)

Statistic	0 < AuM < 10	10 ≤ AuM < 100	100 ≤ AuM < 500	500 ≤ AuM < 1000	AuM ≥ 1000
# Funds	89	470	225	80	34
# Funds%	9.9%	52.3%	25.1%	8.9%	3.8%

Panel B: Minimum AuM required for underlying funds (in millions of U.S. dollars)

Statistic	< 10	10	10 < AuM < 20	20	20 < AuM < 50	50	50 < AuM < 100	100	100 < AuM ≤ 200	> 200
# Funds	371	146	13	64	112	323	34	196	90	46
# Funds%	26.6%	10.5%	0.9%	4.6%	8.0%	23.2%	2.4%	14.1%	6.5%	3.3%

Panel C: Number of individual hedge funds held by FoFs

Statistic	1–5	6–10	11–15	16–20	21–25	25–30	31–40	41–50	51–60	> 60
# Funds	102	260	390	395	244	393	226	56	24	142
# Funds%	4.6%	11.6%	17.5%	17.7%	10.9%	17.6%	10.1%	2.5%	1.1%	6.4%

Panel D: Percentage of AuM constraint

Statistic	< 5%	5%	5% < Limit < 10%	10%	10% < Limit < 15%	15%	15% < Limit < 20%	20%	20% < Limit ≤ 30%	> 30%
# Funds	10	45	122	406	30	141	4	360	43	66
# Funds%	0.8%	3.7%	9.9%	33.1%	2.4%	11.5%	0.3%	29.3%	3.5%	5.4%

Panel E: Monitoring frequency (in months)

Statistic	Monitoring ≤ 1m	1m < Monitoring ≤ 3m	3m < Monitoring ≤ 6m	6m < Monitoring ≤ 12m	Monitoring > 12m
# Funds	76	228	484	249	244
# Funds%	5.9%	17.8%	37.8%	19.4%	19.0%

Table 3
Hedge fund size–performance relationship.

This table reports the size–performance relationship of hedge funds for the 1994–2012 study period. In Panel A, for December 2012 we calculate the percentiles of funds belonging to the respective nominal fund size category. For each preceding December, we use these percentile limits to sort funds into size category portfolios and calculate equal-weighted returns for each size portfolio using one year holding period; we then estimate performance measures for each of the size category portfolios (Forward-looking). In Panel B, funds are sorted into nominal size groups based on the last available AuM observation for each fund. This size sorting is performed only once, but all the available fund return observations are used to compute equal-weighted returns for each fund size category; we then estimate performance measures for each of the size category portfolios (Backward-looking). Columns present the number of hedge funds (# Funds), annualized average excess returns (Avg. ER), annualized Sharpe ratios (Sharpe), annualized Fung–Hsieh (2004) alphas (Alpha) as well as the risk loadings as follows: excess return of the S&P 500 index (SP), return spread between the Russell 2000 index and the S&P 500 index (SIZE), excess return of 10-year Treasuries (TY), return spread between Moody's BAA corporate bonds and 10-year Treasuries (BAA − TY), excess returns of look-back straddles on currencies (PTFSFX), bonds (PTFSBD), and commodities (PTFSCOM). Reported is also the R^2 of the model. The t-statistics of the parameter estimates are reported in parentheses.

Panel A: Out-of-sample performance of fund size portfolios (Forward-looking)

Size	# Funds	Avg. ER	Sharpe	Alpha	SP	SIZE	TY	BAA –TY	PTFSFX	PTFSBD	PTFSCOM	R^2
Micro	7,228	6.85	1.00	4.71%	0.260	0.156	0.059	0.219	0.020	0.007	0.020	0.60
				(4.27)	(11.92)	(5.95)	(1.33)	(4.45)	(3.73)	(1.05)	(2.79)	
Small	11,203	6.30	0.87	3.75%	0.306	0.177	0.037	0.217	0.013	-0.002	0.008	0.73
				(3.90)	(16.08)	(7.75)	(0.97)	(5.07)	(2.74)	(-0.30)	(1.25)	
Medium	5,716	4.33	0.65	1.80%	0.251	0.144	0.035	0.255	0.008	-0.010	0.007	0.70
				(1.93)	(13.59)	(6.48)	(0.93)	(6.13)	(1.75)	(-1.77)	(1.20)	
Large	1,811	4.31	0.67	1.86%	0.235	0.119	0.072	0.243	0.008	-0.007	0.010	0.60
				(1.78)	(11.32)	(4.79)	(1.72)	(5.22)	(1.45)	(-1.17)	(1.52)	
Mega	948	4.14	0.64	1.45%	0.225	0.084	0.100	0.254	0.008	-0.017	0.010	0.58
				(1.36)	(10.64)	(3.31)	(2.32)	(5.34)	(1.43)	(-2.61)	(1.42)	
Micro–Mega		2.71		3.26%	0.036	0.072	-0.041	-0.035	0.013	0.024	0.010	0.23
				(3.56)	(1.96)	(3.31)	(-1.10)	(-0.86)	(2.83)	(4.30)	(1.71)	

Panel B: In-sample performance of size portfolios (Backward-looking)												
Size	# Funds	Avg ER	Sharpe	Alpha	SP	SIZE	TY	BAA –TY	PTFSFX	PTFSBD	PTFSCOM	R^2
Micro	7,697	3.82	0.56	1.15	0.280	0.166	0.050	0.237	0.003	0.017	0.013	0.67
				(1.18)	(14.43)	(7.12)	(1.28)	(5.41)	(0.51)	(3.75)	(2.18)	
Small	8,858	7.58	1.07	4.78	0.304	0.185	0.027	0.196	-0.003	0.013	0.006	0.72
				(5.16)	(16.48)	(8.36)	(0.71)	(4.70)	(-0.63)	(2.98)	(1.07)	
Medium	3,100	9.17	1.48	6.74	0.236	0.141	0.021	0.237	-0.004	0.010	0.008	0.67
				(7.57)	(13.29)	(6.63)	(0.59)	(5.92)	(-0.86)	(2.40)	(1.43)	
Large	585	10.46	1.67	7.73	0.238	0.119	0.073	0.230	-0.009	0.015	0.007	0.62
				(8.11)	(12.56)	(5.23)	(1.91)	(5.37)	(-1.56)	(3.49)	(1.12)	
Mega	471	9.58	1.75	7.31	0.174	0.106	0.065	0.222	-0.010	0.012	0.003	0.53
				(7.82)	(9.34)	(4.73)	(1.72)	(5.27)	(-1.74)	(2.86)	(0.45)	

Table 4

Rebalancing frequency and performance persistence.

This table reports the impact of rebalancing frequency (C1) on performance persistence. We impose the constraint for rebalancing frequency (C1) and sort hedge funds into quintiles quarterly, semiannually, or annually using the t-statistic of the alpha that are estimated from the 24 most recent return observations. To account for fund size in the formation of portfolios, for December 2012 we calculate the percentiles of funds belonging to the respective nominal fund size category. For each preceding month of portfolio formation, we use these percentile limits to sort funds into size category portfolios; we then calculate post-formation returns for each of the portfolios. In order to gauge performance persistence, we estimate the spread between top and bottom portfolios, and conduct the Patton and Timmermann (2010) monotonicity test. Reported are the alpha and its *t*-statistic (t(α)) for each of the portfolios and the *p*-value of the Patton and Timmermann (2010) test for monotonicity. Panel A, B and C report the results for the quarterly, semiannually and annually sorted portfolios, respectively. The time period covered is January 1994 through December 2012.

	All Funds		Micro and Small		Medium		Large and Mega	
Portfolio	Alpha	*t*(α)	Alpha	*t*(α)	Alpha	*t*(α)	Alpha	*t*(α)
Panel A: Quarterly								
Top	4.60%	4.64	5.14%	4.81	4.73%	5.01	2.99%	2.80
4	3.50%	2.86	4.45%	3.38	2.93%	2.32	2.11%	1.52
3	3.04%	2.50	3.29%	2.59	2.18%	1.78	0.89%	0.59
2	1.79%	1.51	2.10%	1.68	1.44%	1.23	0.06%	0.04
Bottom	1.36%	1.07	1.94%	1.35	-0.03%	-0.03	0.18%	0.13
Top–Bottom	3.24%	3.56	3.20%	3.46	4.76%	5.04	2.81%	2.67
Top–Bottom (*t*-statistic)	2.46	3.05	2.03	2.88	3.63	4.02	2.20	2.38
Monotonicity (*p*-value)	0.001	0.021	0.014	0.011	0.000	0.003	0.041	0.074
Panel B: Semiannual								
Top	4.28%	4.38	4.90%	4.69	4.29%	4.69	3.15%	2.89
4	3.85%	3.11	4.74%	3.57	3.33%	2.61	1.02%	0.67
3	2.92%	2.47	3.71%	2.89	1.61%	1.40	1.18%	0.78
2	1.85%	1.58	1.30%	1.04	1.85%	1.58	0.56%	0.44
Bottom	1.15%	0.91	1.96%	1.41	-0.29%	-0.24	1.21%	0.83
Top–Bottom	3.12%	3.47	2.94%	3.28	4.58%	4.93	1.94%	2.06
Top–Bottom (*t*-statistic)	2.52	3.30	2.01	2.94	3.51	4.08	1.50	1.81
Monotonicity (*p*-value)	0.001	0.000	0.388	0.285	0.064	0.091	0.141	0.142
Panel C: Annual								
Top	3.42%	3.43	4.09%	3.67	3.15%	3.37	2.01%	1.80
4	3.22%	2.67	4.17%	3.18	1.85%	1.58	-0.20%	-0.12
3	1.84%	1.56	2.77%	2.25	1.63%	1.45	1.13%	0.78
2	2.77%	2.33	2.95%	2.37	0.83%	0.65	0.83%	0.68
Bottom	2.78%	2.20	3.45%	2.45	1.72%	1.50	2.38%	1.81
Top–Bottom	0.64%	1.22	0.63%	1.22	1.43%	1.87	-0.36%	-0.01
Top–Bottom (*t*-statistic)	0.49	1.03	0.42	1.05	1.13	1.42	-0.28	-0.01
Monotonicity (*p*-value)	0.695	0.709	0.278	0.133	0.476	0.570	0.534	0.537

Table 5

Liquidity constraints and performance persistence.

This table shows the effects of liquidity constraints (C2) on performance persistence. We impose the constraint for rebalancing frequency (C1) and sort hedge funds into quintiles quarterly, semiannually, or annually using the t-statistic of the alpha estimated from the 24 most recent return observations. If liquidity constraints for the lockup or redemption periods are imposed we exclude hedge funds having lockup or redemption periods longer than the holding period. If the constraint for the maximum acceptable notice period is imposed we set it equalling to one (1m), three (3m) or six months (6m). The maximum acceptable notice period is assumed to determine the lag in the investor's available information set, which can be used to rank funds. If the maximum acceptable notice period is one month, the lag in the investor's available information set is one month; then, for instance, annually sorted portfolios are formed at the end of November (instead of December). We use similar logic to each constraint of notice period and each holdings period. We then calculate equal-weighted returns and estimate post-formation alphas for each portfolio. Panel A, B and C report the results for the quarterly, semiannually and annually sorted portfolios, respectively. Reported are the same performance measures as in Table 4.

Rank	All funds		Imposed liquidity constraints (C2): Only lockup period		Only lockup and redemption periods		Only notice period: Notice ≤ 1m		Notice ≤ 3m		Notice ≤ 6m		Lockup, Redemption and Notice Periods: Notice ≤ 1m		Notice ≤ 3m		Notice ≤ 6m	
	Alpha	$t(\alpha)$	Alpha	$t(\alpha)$	Alpha	$t(\alpha)$	Alpha	$t(\alpha)$	Alpha	$t(\alpha)$	Alpha	$t(\alpha)$	Alpha	$t(\alpha)$	Alpha	$t(\alpha)$	Alpha	$t(\alpha)$
Panel A: Quarterly																		
Top	4.6%	4.64	4.1%	3.85	4.2%	3.93	3.4%	3.07	4.0%	4.21			3.0%	2.56	3.9%	3.78		
4	3.5%	2.86	3.8%	3.01	3.5%	2.78	3.8%	2.89	2.9%	2.38			3.4%	2.53	2.7%	2.09		
3	3.0%	2.50	2.7%	2.11	2.4%	1.84	2.3%	1.92	2.5%	2.01			2.1%	1.75	1.9%	1.50		
2	1.8%	1.51	1.5%	1.30	1.5%	1.31	1.6%	1.31	2.3%	1.97			1.3%	1.03	2.0%	1.71		
Bottom	1.4%	1.07	1.5%	1.11	1.8%	1.29	1.8%	1.37	2.2%	1.74			1.9%	1.38	2.4%	1.73		
Top–Bottom	3.2%	3.56	2.6%	2.73	2.4%	2.64	1.6%	1.70	1.8%	2.48			1.1%	1.18	1.5%	2.05		
t-statistic	2.46	3.05	1.81	2.39	1.64	2.34	1.09	1.44	1.56	2.57			0.71	1.01	1.20	2.13		
Monot. *p*-value	0.00	0.03	0.04	0.06	0.07	0.06	0.12	0.14	0.09	0.06			0.26	0.26	0.14	0.06		
Panel B: Semiannual																		
Top	4.3%	4.38	4.1%	4.02	4.1%	3.97	2.6%	2.34	3.7%	3.85	2.6%	2.82	2.3%	2.05	3.5%	3.53	2.5%	2.49
4	3.8%	3.11	3.9%	3.05	3.8%	2.95	2.9%	2.30	2.2%	1.89	2.5%	2.15	2.4%	1.80	2.2%	1.79	1.7%	1.42
3	2.9%	2.47	2.7%	2.24	2.5%	1.98	3.4%	2.74	2.7%	2.22	1.9%	1.59	3.3%	2.63	2.5%	2.02	1.7%	1.38
2	1.9%	1.58	1.7%	1.43	1.6%	1.31	2.2%	1.75	2.8%	2.32	3.2%	2.65	2.1%	1.60	2.2%	1.76	3.2%	2.66
Bottom	1.2%	0.91	1.1%	0.80	1.3%	1.00	1.9%	1.45	2.4%	1.81	3.5%	2.71	1.8%	1.32	2.2%	1.51	3.3%	2.30
Top–Bottom	3.1%	3.47	3.0%	3.22	2.8%	2.98	0.6%	0.88	1.3%	2.04	-0.9%	0.10	0.5%	0.73	1.3%	2.02	-0.8%	0.19
t-statistic	2.52	3.30	2.41	3.14	2.15	2.90	0.44	0.78	1.00	1.79	-0.72	0.09	0.35	0.65	0.95	1.81	-0.55	0.17
Monot. *p*-value	0.01	0.02	0.01	0.02	0.02	0.03	0.40	0.33	0.21	0.10	0.77	0.56	0.44	0.41	0.24	0.12	0.74	0.55

Rank	All Funds		Only lockup period		Only lockup and redemption periods		Imposed liquidity constraints (C2)											
							Only notice period						Lockup, redemption and notice periods					
							Notice ≤ 1m		Notice ≤ 3m		Notice ≤ 6m		Notice ≤ 1m		Notice ≤ 3m		Notice ≤ 6m	
	Alpha	$t(\alpha)$	Alpha	$t(\alpha)$	Alpha	$t(\alpha)$	Alpha	$t(\alpha)$	Alpha	$t(\alpha)$	Alpha	$t(\alpha)$	Alpha	$t(\alpha)$	Alpha	$t(\alpha)$	Alpha	$t(\alpha)$
<u>Panel C: Annual</u>																		
Top	3.4%	3.43	3.4%	3.38	3.4%	3.39	2.4%	2.30	3.3%	3.50	1.9%	2.04	2.4%	2.28	3.2%	3.41	1.9%	2.00
4	3.2%	2.67	3.2%	2.70	3.3%	2.70	2.0%	1.60	1.5%	1.32	2.2%	1.86	2.0%	1.62	1.5%	1.34	2.1%	1.86
3	1.8%	1.56	1.7%	1.46	1.7%	1.45	2.9%	2.37	2.6%	2.16	2.1%	1.86	2.8%	2.37	2.6%	2.18	2.1%	1.79
2	2.8%	2.33	2.8%	2.36	2.8%	2.36	3.2%	2.44	3.1%	2.74	3.9%	3.18	3.2%	2.46	3.0%	2.68	3.8%	3.19
Bottom	2.8%	2.20	2.6%	2.13	2.6%	2.13	2.8%	2.10	3.3%	2.13	3.7%	2.52	2.6%	2.00	3.2%	2.06	3.7%	2.46
Top–Bottom	0.6%	1.22	0.7%	1.25	0.7%	1.26	-0.3%	0.20	-0.1%	1.37	-1.8%	-0.48	-0.2%	0.28	0.0%	1.36	-1.8%	-0.47
t-statistic	0.49	1.03	0.56	1.06	0.58	1.07	-0.25	0.18	-0.05	0.99	-1.20	-0.36	-0.16	0.25	-0.01	0.99	-1.19	-0.35
Monot. *p*-value	0.42	0.34	0.39	0.35	0.40	0.32	0.66	0.52	0.56	0.31	0.86	0.68	0.65	0.52	0.55	0.31	0.88	0.70

Table 6

Marginal effects of rebalancing frequency and liquidity constraints on performance persistence.

This table shows the economic impact of liquidity restrictions (C2) on the alphas of the top-quintiles of the alpha *t*-statistic-sorted portfolios. We compare the alphas of the portfolios subject only to the rebalancing frequency constraint (C1) to alphas of the portfolios which simultaneously impose both the constraints for rebalancing frequency (C1) and liquidity restrictions (C2). We form the portfolios subject to constraints C1 and C2 as in Table 5. If the portfolio with the constraints C1 and C2 imposes the constraint for the maximum acceptable notice period, the same lag in the investor's available information set is imposed to the portfolio which only imposes the constraint C1. In Panel A, we report the alpha and its *t*-statistic for each of the portfolios. To gauge the economic impact of the liquidity restrictions on the performance of the top-quintile portfolios, we estimate the spread in the alphas between the portfolio with the constraint C1 and the portfolio, which impose both the constraints C1 and C2 simultaneously. In Panel B we measure the economic impact of the constraint C1 on the alphas of the top-quintile portfolios and estimate the spread in the alphas between the (B1) quarterly and annually sorted portfolios; (B2) quarterly and semiannually sorted portfolios; and (B3) semiannually and annually sorted portfolios.

Panel A: Marginal effects of liquidity constraints (C2) on performance persistence

	Imposed Liquidity Constraints (C2)															
	Only lockup period		Only lockup and redemption periods		Only notice period						Lockup, redemption and notice periods					
					Notice ≤ 1m		Notice ≤ 3m		Notice ≤ 6m		Notice ≤ 1m		Notice ≤ 3m		Notice ≤ 6m	
Constraint / Statistic	Alpha	*t*(α)	Alpha	*t*(α)	Alpha	*t*(α)	Alpha	*t*(α)	Alpha	*t*(α)	Alpha	*t*(α)	Alpha	*t*(α)	Alpha	*t*(α)
Panel A1: Quarterly																
Rebalancing frequency (C1)	4.6%	4.64	3.9%	4.24	4.0%	4.09	4.6%	4.64			4.0%	4.09	4.6%	4.64		
Liquidity restrictions (C1,C2)	4.1%	3.85	4.2%	3.93	3.4%	3.07	4.0%	4.21			3.0%	2.56	3.9%	3.78		
Rebalancing–Liquidity	0.5%	0.79	-0.3%	0.31	0.6%	1.03	0.6%	0.42			1.0%	1.53	0.7%	0.86		
t-statistic	2.55	3.64	-0.46	0.55	1.99	3.36	1.22	0.83			2.71	4.46	1.39	1.69		
Panel A2: Semiannual																
Rebalancing frequency (C1)	4.3%	4.38	4.3%	4.38	3.2%	3.26	3.7%	3.96	4.3%	4.38	3.2%	3.26	2.5%	2.81	4.3%	4.38
Liquidity restrictions (C1,C2)	4.1%	4.02	4.1%	3.97	2.6%	2.34	3.7%	3.85	2.6%	2.82	2.3%	2.05	3.5%	3.53	2.5%	2.49
Rebalancing–Liquidity	0.2%	0.36	0.1%	0.41	0.7%	0.92	0.0%	0.11	1.7%	1.57	0.9%	1.21	-1.0%	-0.72	1.8%	1.89
t-statistic	0.98	1.84	0.67	2.00	2.28	3.25	0.73	2.25	3.48	3.16	2.34	3.42	-1.70	-1.14	3.45	3.65
Panel A3: Annual																
Rebalancing frequency (C1)	3.4%	3.43	3.4%	3.43	2.9%	2.98	3.3%	3.56	1.9%	2.03	2.9%	2.98	3.3%	3.56	1.9%	2.03
Liquidity restrictions (C1,C2)	3.4%	3.38	3.4%	3.39	2.4%	2.30	3.3%	3.50	1.9%	2.04	2.4%	2.28	3.2%	3.41	1.9%	2.00
Rebalancing–Liquidity	0.1%	0.05	0.0%	0.04	0.5%	0.68	0.0%	0.07	0.0%	-0.01	0.5%	0.71	0.1%	0.15	0.0%	0.03
t-statistic	1.21	0.96	1.00	0.87	1.66	1.93	0.32	1.04	-0.81	-1.07	1.63	1.93	0.92	1.56	0.70	0.41

Panel B: Marginal effects of the rebalancing frequency (C1) on performance persistence

	Imposed liquidity constraints (C2)															
	Only lockup period		Only lockup and redemption periods		Only notice period						Lockup, redemption and notice periods					
					Notice ≤ 1m		Notice ≤ 3m		Notice ≤ 6m		Notice ≤ 1m		Notice ≤ 3m		Notice ≤ 6m	
	Alpha	*t*(α)	Alpha	*t*(α)	Alpha	*t*(α)	Alpha	*t*(α)	Alpha	*t*(α)	Alpha	*t*(α)	Alpha	*t*(α)	Alpha	*t*(α)
<u>Panel B1: Quarterly – annual</u>																
Rebalancing frequency																
Alpha	1.2%	1.21	5.1%	0.81	1.1%	1.11	1.3%	1.07			1.1%	1.11	1.3%	1.07		
t-statistic	3.03	2.57	1.25	2.01	2.77	2.16	2.13	1.46			2.77	2.16	2.13	1.46		
Liquidity restrictions																
Alpha	0.7%	0.47	8.1%	0.54	1.0%	0.76	0.7%	0.72			0.6%	0.29	0.7%	0.36		
t-statistic	1.57	0.90	1.77	1.03	2.09	1.61	1.53	1.14			1.17	0.62	1.16	0.53		
<u>Panel B2: Quarterly – semiannual</u>																
Rebalancing frequency																
Alpha	0.3%	0.25	-3.5%	-0.15	0.8%	0.84	0.9%	0.68			0.8%	0.84	2.1%	1.83		
t-statistic	1.19	0.79	-0.87	-0.37	2.28	1.90	1.41	0.91			2.28	1.90	3.55	2.65		
Liquidity restrictions																
Alpha	0.0%	-0.17	0.4%	-0.04	0.9%	0.73	0.3%	0.36			0.6%	0.51	0.3%	0.24		
t-statistic	-0.08	-0.57	0.13	-0.14	2.07	1.68	0.94	0.86			1.57	1.38	0.88	0.55		
<u>Panel B3: Semiannual – annual</u>																
Rebalancing frequency																
Alpha	0.9%	0.95	8.6%	0.95	0.4%	0.28	0.5%	0.39	2.4%	2.35	0.4%	0.28	-0.8%	-0.76	2.4%	2.35
t-statistic	3.10	3.15	3.10	3.15	1.35	0.93	1.12	0.72	4.12	3.73	1.35	0.93	-1.99	-1.74	4.12	3.73
Liquidity restrictions																
Alpha	0.7%	0.64	7.7%	0.59	0.1%	0.03	0.4%	0.35	0.7%	0.78	-0.1%	-0.23	0.3%	0.12	0.6%	0.49
t-statistic	2.13	1.74	2.19	1.58	0.45	0.13	1.06	0.63	1.92	1.75	-0.18	-0.77	0.76	0.23	1.50	1.00

Table 7

Impact of investor constraints on investor's opportunity set.

The table shows the impact of rebalancing (C1), liquidity (C2), diversification (C3), percentage of AuM rule (C4), and the minimum investment (C5) constraints on the proportions of hedge funds, which are available in the investor's opportunity set. We construct three hypothetical investor portfolios whose sizes are assumed to be $100 million ($100 mn.), $500 million ($500 mn.), and $1 billion ($1 bn.) U.S. dollars as of December 2012. To simulate the growth of the hypothetical portfolios' AuM from December 1997 to December 2012, we use the HFRI FoF aggregated index return. We impose the investor's rebalancing frequency constraint (C1) by assuming that the investor's rebalancing frequency is one year. We impose the liquidity constraint (C2) in two phases. We first impose a constraint requiring that the lockup and redemption periods must not exceed 12 months but we leave out constraints for the notice period. In the second phase, we also include the constraint for the maximum acceptable notice period equaling to one month, three months, or six months. The diversification constraint (C3) states that the investor allocates the capital across 30 funds based on the t-statistics of alphas. The invested amount of capital to one fund is measured as a ratio of the portfolio size to the number of funds. The percentage of AuM constraint (C4) states that the investor does not allocate more than 10% of a given fund's AuM. The minimum investment constraint (C5) requires that the minimum investment amount must not exceed the allocation to a given fund. Panel A shows the average number of funds in the investor's opportunity set after the rebalancing (C1) and liquidity (C2) constraints are imposed. Panel B shows the proportions of available funds in the investor's opportunity set after the constraints C1–C3 are imposed. Panel C shows the effects of the constraints C1–C4 on the proportion of investor's available funds. Panel D shows the effects of the constraints C1–C3 and C5 on the proportion of investor's available funds. Panel E shows the effects of five constraints on the investor's opportunity set.

Portfolio	Funds
Baseline: Lockup and Redemption ≤ 12 Months	1,630
Baseline + Notice period ≤ 1 Month	1,076
Baseline + Notice period ≤ 3 Months	1,550
Baseline + Notice period ≤ 6 Months	1,483

	Proportions of Available Funds (%)		
Portfolio	$100 mn.	$500 mn.	$1 bn.
Baseline: Lockup and Redemption ≤ 12 Months	92.8%	74.1%	60.6%
Baseline + Notice period ≤ 1 Month	91.6%	71.0%	57.0%
Baseline + Notice period ≤ 3 Months	93.1%	74.8%	61.6%
Baseline + Notice period ≤ 6 Months	93.4%	75.6%	62.5%
Panel C: Effect of Constraints C3 and C4			
Baseline: Lockup and Redemption ≤ 12 Months	60.6%	25.2%	14.5%
Baseline + Notice period ≤ 1 Month	57.0%	22.4%	12.8%
Baseline + Notice period ≤ 3 Months	61.6%	25.9%	15.2%
Baseline + Notice period ≤ 6 Months	62.5%	26.3%	15.4%
Panel D: Effect of Constraints C3 and C5			
Baseline: Lockup and Redemption ≤ 12 Months	85.6%	72.8%	59.9%
Baseline + Notice period ≤ 1 Month	85.8%	69.9%	56.5%
Baseline + Notice period ≤ 3 Months	85.9%	73.6%	61.0%
Baseline + Notice period ≤ 6 Months	86.0%	74.3%	61.9%
Panel E: Effect of Constraints from C3 to C5			
Baseline: Lockup and Redemption ≤ 12 Months	54.3%	24.5%	14.4%
Baseline + Notice period ≤ 1 Month	52.1%	21.6%	12.6%
Baseline + Notice period ≤ 3 Months	55.3%	25.2%	15.0%
Baseline + Notice period ≤ 6 Months	56.0%	25.6%	15.3%

Table 8.
The performance of hypothetical investor portfolios.

This table shows the performance of assumed hypothetical investor portfolios, which are constructed as in Table 7. We construct three portfolios whose sizes are assumed to be $100 million; $500 million; and $1 billion as of December 2012. Each portfolio satisfies the constraint for rebalancing frequency (C1) stating that each portfolio is formed at the end of the year depending on the maximum acceptable notice period; we then assume that the investor's holding period is one year. We impose the constraint for liquidity needs (C2) given that each portfolio has the maximum acceptable lockup and redemption periods of one year. Additionally, in columns 3 to 5 we impose constraints for the 1-, 3-, or 6-month maximum acceptable notice period. Each portfolio satisties the maximum diversificaton constraint (C3) given that the target number of funds in each portfolio is 30. We compute equal-weighted returns for each portfolio and estimate the post-formation alpha and its *t*-statistic for each of the portfolios. The *t*-statistics of the alpha are reported in parentheses. The time period covered is January 1994 through December 2012.

	Imposed liquidity constraints (C2)			
		Lockup, redemption and notice periods		
Portfolio size	Only lockup and redemption periods	Notice ≤ 1m	Notice ≤ 3m	Notice ≤ 6m
	Panel A: Constraints C1–C3 (Effect of *Diversification Constraint* C3)			
$100 mn.	6.2%	3.6%	4.1%	2.3%
	(8.21)	(4.12)	(4.64)	(2.05)
$500 mn.	5.4%	3.8%	3.1%	1.9%
	(7.22)	(4.13)	(3.58)	(1.72)
$1 bn.	4.8%	2.8%	3.0%	1.9%
	(6.21)	(2.83)	(3.39)	(1.70)
	Panel B: Constraints C1–C3, and C4 (Effect of *Percentage of AuM constraint* C4)			
$100 mn.	4.8%	2.8%	3.0%	1.9%
	(6.21)	(2.83)	(3.39)	(1.70)
$500 mn.	3.8%	1.1%	2.6%	1.4%
	(4.04)	(1.06)	(2.84)	(1.24)
$1 bn.	1.1%	0.7%	2.6%	2.1%
	(0.91)	(0.56)	(2.71)	(1.82)
	Panel C: Constraints C1–C3, and C5 (Effect of *minimum investment* constraint C5)			
$100 mn.	5.8%	3.3%	4.7%	3.6%
	(8.03)	(3.42)	(5.82)	(3.96)
$500 mn.	5.3%	3.9%	3.0%	1.9%
	(7.22)	(4.21)	(3.36)	(1.70)
$1 bn.	4.8%	2.9%	3.1%	1.8%
	(6.03)	(2.90)	(3.50)	(1.62)
	Panels D: Constraints C1–C5 (Effect of *all constraints* simultaneously)			
$100 mn.	4.7%	2.8%	3.6%	3.2%
	(6.31)	(2.81)	(4.60)	(3.52)
$500 mn.	3.8%	1.1%	2.6%	1.6%
	(4.09)	(1.05)	(2.88)	(1.41)
$1 bn.	0.9%	0.5%	2.5%	2.1%
	(0.71)	(0.42)	(2.49)	(1.75)

Figure 1.
Forward-looking and backward-looking size–performance relationship.

For each of the size categories on the x-axis, this figure shows annualized Fung and Hsieh (2004) forward-looking and backward-looking alphas. For December 2012 we calculate the percentiles of funds belonging to the respective nominal fund size category, and for each preceding December we use these percentile boundaries to sort hedge funds into size category portfolios; we then estimate the forward-looking alpha for each of these portfolios. To obtain the backward-looking alphas, hedge funds are sorted into nominal size groups based on the last available AuM observation for each fund. This size sorting is performed only once, but all available return observations for each individual hedge fund are used when we estimate the alphas for each of the size category portfolios. The time period covered is January 1994 through December 2012.

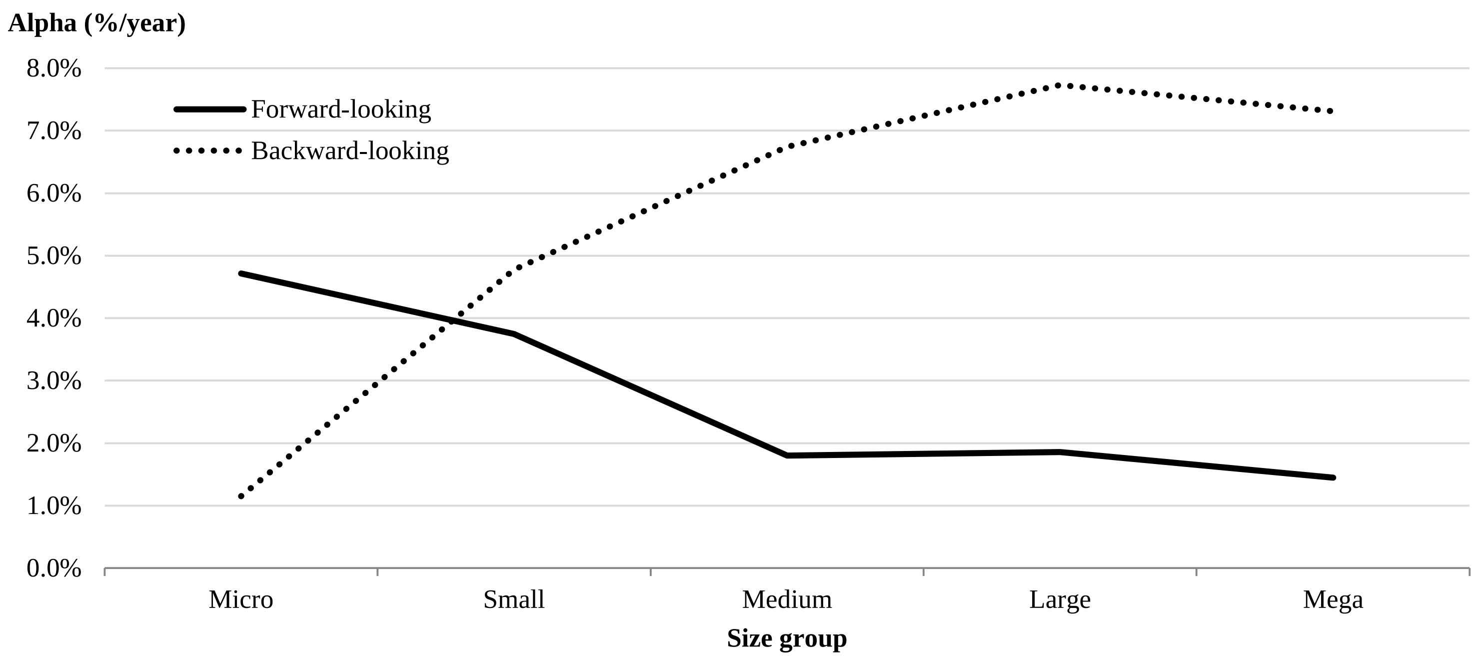
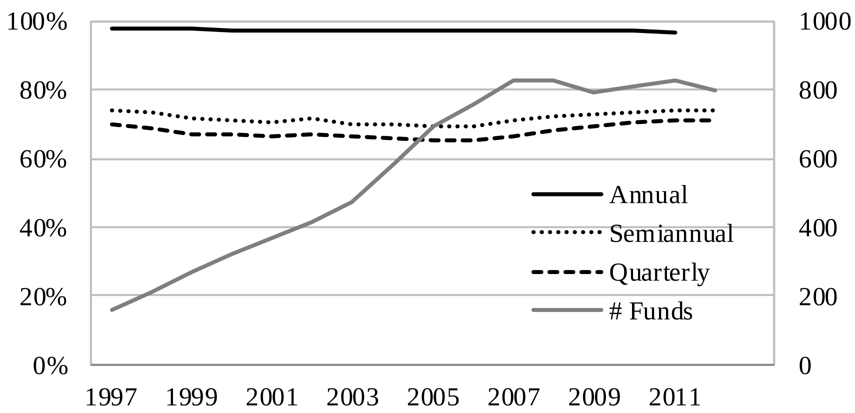


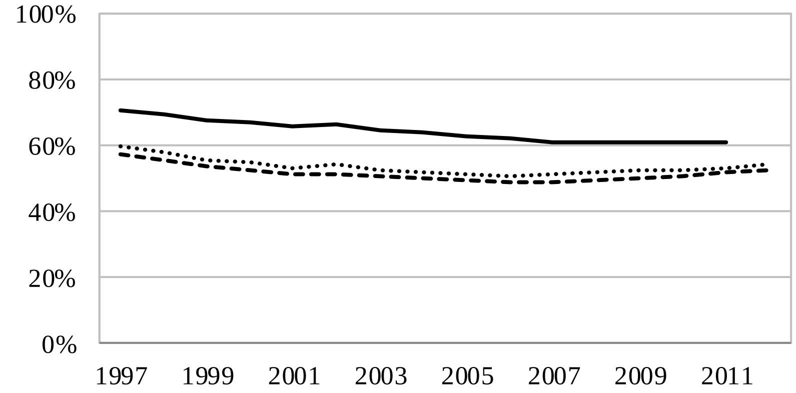
Figure 2.
Proportions of hedge funds in the top-quintile alpha-sorted portfolios after imposing liquidity constraints.

This table shows the proportions of hedge funds that are included in the top-quintile alpha-sorted portfolios after liquidity restrictions (C2) are imposed for lockup, redemption and notice periods. We impose the constraint for rebalancing frequency (C1) and sort hedge funds into quintile portfolios annually, semiannually, and quarterly using the historical t-statistic of the alpha as in Table 4. In each Panel we impose a liquidity constraint (C2) specifying that the lockup and redemption period do not exceed a given holding period. In Panels B, C and D, we specify liquidity constraints for the lockup, redemption and the maximum acceptable notice period, which varies between one and six months, and report the proportions of hedge funds that are included in the top-quintile portfolios after the liquidity constraints are imposed. The sample period covers the years 1997–2012. In Panel A the grey line reports that average number of hedge funds in the top-quintile portfolios when no liquidity constraints are imposed.

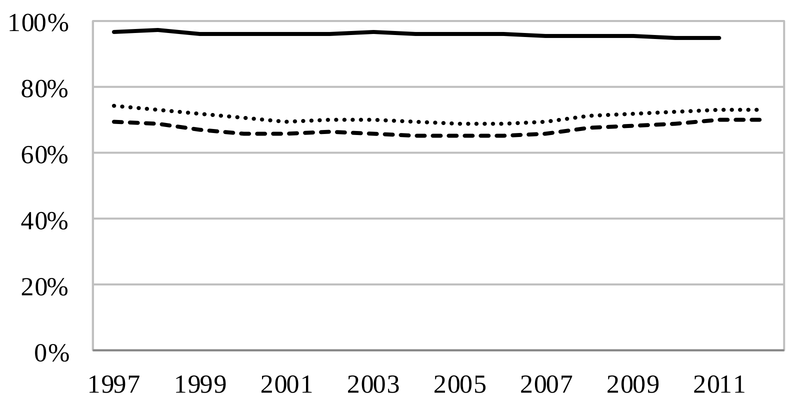
Panel A: Lockup and redemption ≤ 12m



Panel B: Lockup and redemption ≤ 12m, and notice period ≤ 1m



Panel C: Lockup and redemption ≤ 12m, and notice period ≤ 3 m



Panel D: Lockup and redemption ≤ 12m, and notice period ≤ 6m

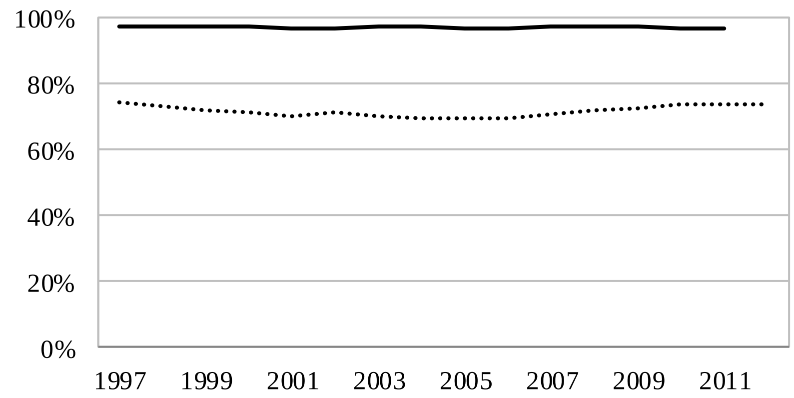
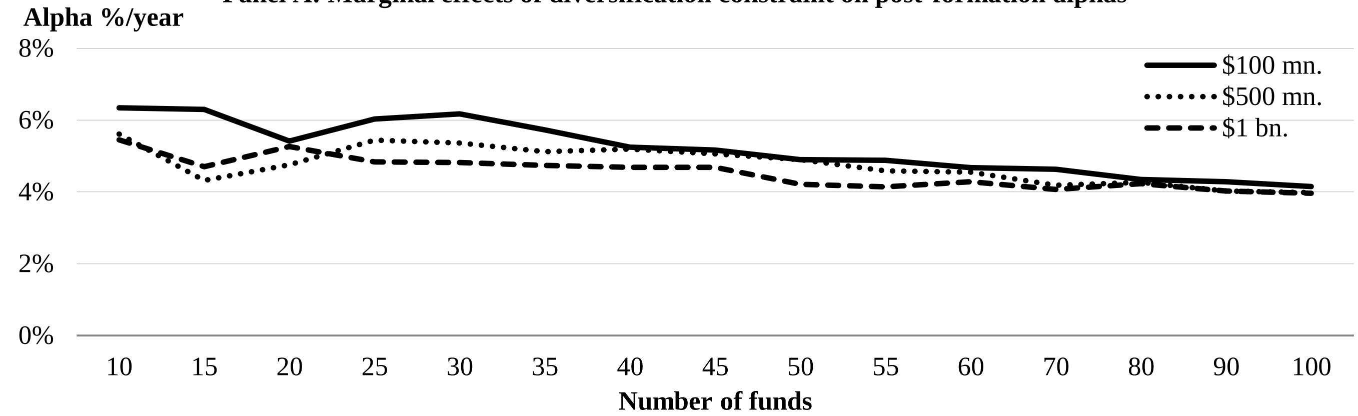


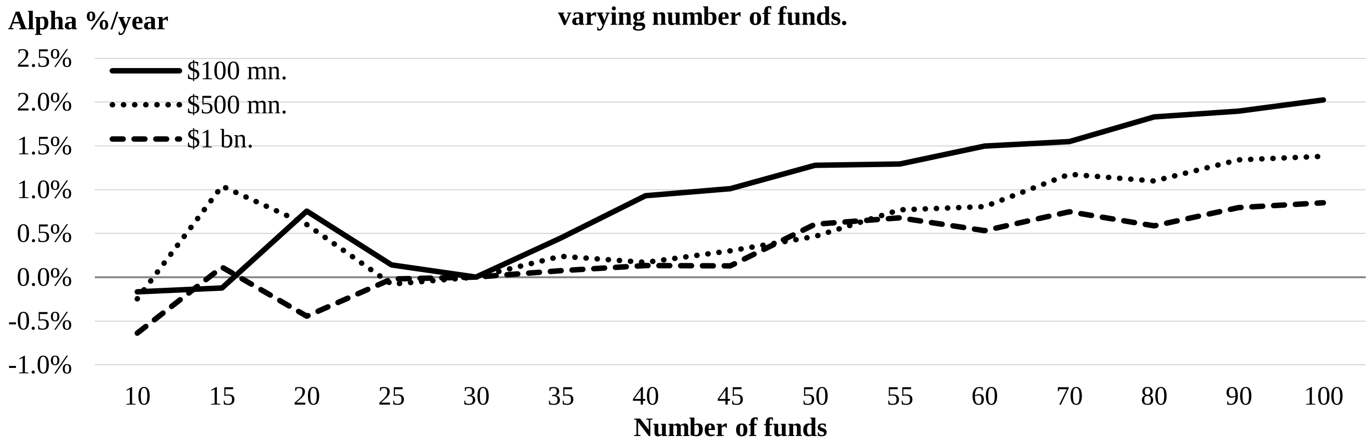
Figure 3.
Marginal effects of diversification requirements and percentage of AuM constraint on investor performance.

This table shows the economic sensitivity of the hypothetical investor portfolio performance to the variation in the constraints C3 and C4. We impose the rebalancing frequency constraint (C1) for each portfolio and sort hedge funds into portfolios every December based on the t-statistic of the alpha. We impose the liquidity constraint (C2) stating that the lockup and redemption periods must not exceed 12 months. In Panel A, we report the post-formation alphas for the portfolios when the diversification constraint (C3) varies between 10 and 100. Panel B measures the spread in the alphas between the top 30 fund portfolio and other portfolios with varying number of funds. In Panel C, we report the post-formation alphas for the portfolios, which are allocated to top 30 funds, and the percentage of AuM constraint (C4) varies between 2% and 34%. Panel D measures the spread in the alphas between the portfolio with the 10% AuM constraint and other portfolios with varying AuM constraint. The y-axis of the figures shows the annualized alphas.

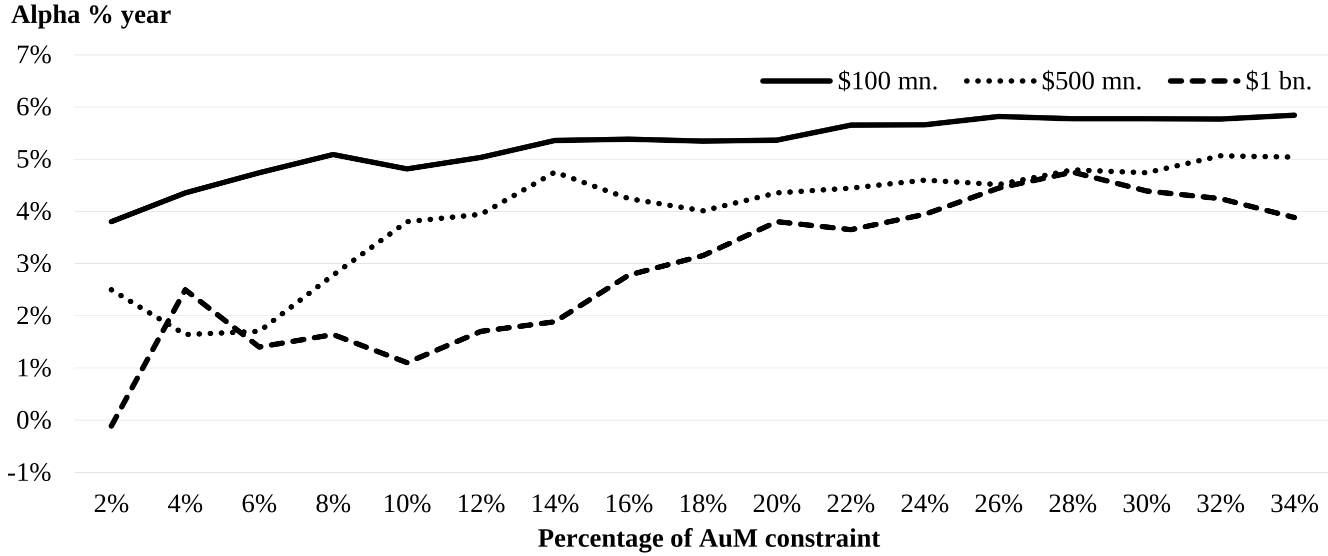
Panel A: Marginal effects of diversification constraint on post-formation alphas



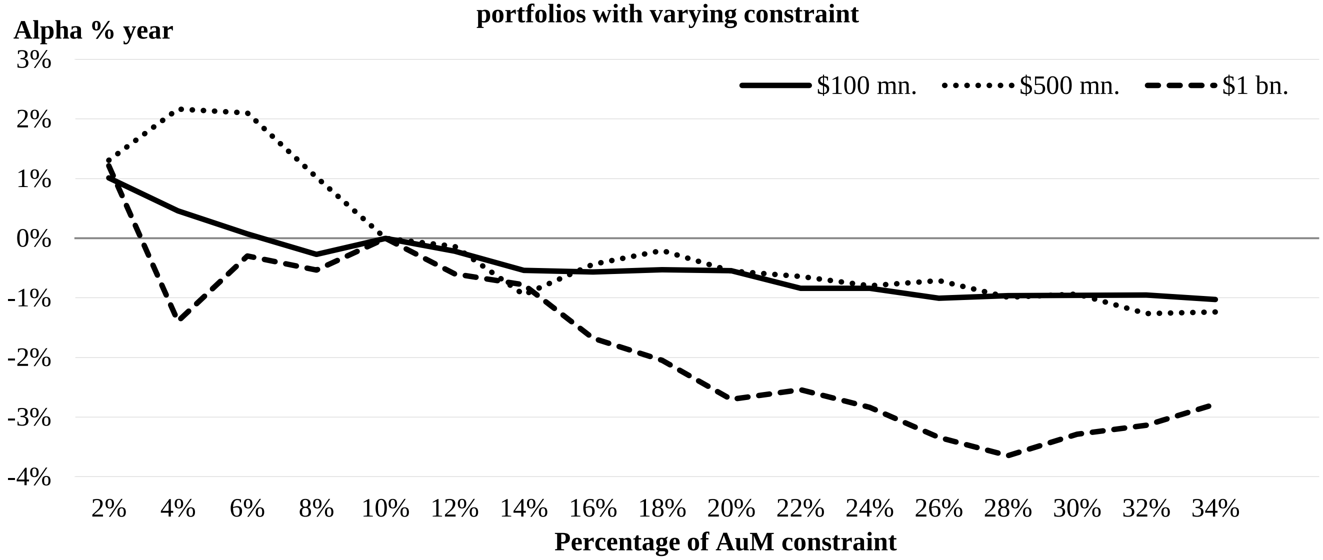
Panel B: Spreads in alphas between portfolio allocated to top 30 funds and other portfolios with varying number of funds.



Panel C: Marginal effects of percentage of AuM constraint (C4) on post-formation alphas



Panel D: Spreads in alphas between portfolio having 10% AuM constraint and other portfolios with varying constraint



Online Appendix for
The Effect of Investment Constraints on Hedge Fund Investor Returns

May 2, 2016

This Online Appendix includes the following supplementary analyses, which are not included to the main paper due to the reasons of space:

Tables

Table A.1. Marginal effects of diversification requirements and percentage of AuM constraint on investor performance.

Figures

Figure A1. Size–performance relationship adjusted for backfill bias.

Figure A1.

Marginal effects of diversification requirements and percentage of AuM constraint on investor performance.

This table shows the economic sensitivity of the hypothetical portfolio performance to the variation in the constraints C3 and C4. We impose the rebalancing frequency constraint (C1) for each portfolio and sort hedge funds into portfolios every December based on the t-statistics of the alpha. We impose the liquidity constraint (C2) stating that the lockup and redemption periods must not exceed 12 months. In Panel A1, we report the post-formation alphas for the portfolios when the diversification constraint (C3) varies between 10 and 100. Panel A2 measures the spread in the alphas between the top 30 fund portfolio and other portfolios with varying number of funds. In Panel B1, we report the post-formation alphas for the portfolios, which are allocated to top 30 funds, and the percentage of AuM constraint (C4) varies between 2% and 34%. Panel B2 measures the spread in the alphas between the portfolio with the 10% AuM constraint and other portfolios with varying AuM constaint. Reported are the annualized alphas. The t-statistics of the alphas are reported in parentheses.

Panel A: Marginal effects of diversification constraint (C3) on investor performance

	Diversification constraint (C3)														
Size	10	15	20	25	30	35	40	45	50	55	60	70	80	90	100
Panel A1: Post-formation alphas of hypothetical portfolios															
$100 mn.	6.3%	6.3%	5.4%	6.0%	6.2%	5.7%	5.2%	5.2%	4.9%	4.9%	4.7%	4.6%	4.3%	4.3%	4.2%
	(6.64)	(7.04)	(5.61)	(7.80)	(8.21)	(8.04)	(7.48)	(7.33)	(6.91)	(6.88)	(6.21)	(5.62)	(5.06)	(4.89)	(4.71)
$500 mn.	5.6%	4.3%	4.8%	5.4%	5.4%	5.1%	5.2%	5.1%	4.9%	4.6%	4.6%	4.2%	4.3%	4.0%	4.0%
	(5.63)	(3.87)	(5.33)	(7.04)	(7.22)	(6.99)	(7.21)	(7.09)	(6.83)	(6.16)	(5.88)	(4.93)	(5.01)	(4.45)	(4.52)
$1 bn.	5.5%	4.7%	5.3%	4.8%	4.8%	4.7%	4.7%	4.7%	4.2%	4.1%	4.3%	4.1%	4.2%	4.0%	4.0%
	(5.94)	(4.60)	(5.88)	(5.80)	(6.21)	(6.38)	(6.33)	(6.48)	(5.60)	(5.14)	(5.33)	(4.64)	(4.86)	(4.46)	(4.52)
Panel A2: Spreads in alphas between portfolio allocated to top 30 and other portfolios															
$100 mn.	-0.2%	-0.1%	0.8%	0.1%	0.0%	0.4%	0.9%	1.0%	1.3%	1.3%	1.5%	1.5%	1.8%	1.9%	2.0%
	(-0.25)	(-0.24)	(1.89)	(0.73)	.	(2.75)	(3.71)	(3.34)	(3.34)	(3.35)	(3.22)	(2.79)	(2.99)	(2.97)	(3.02)
$500 mn.	-0.2%	1.0%	0.6%	-0.1%	0.0%	0.2%	0.2%	0.3%	0.5%	0.8%	0.8%	1.2%	1.1%	1.3%	1.4%
	(-0.38)	(1.77)	(1.73)	(-0.39)	.	(1.04)	(0.67)	(0.98)	(1.27)	(1.92)	(1.75)	(2.13)	(1.87)	(2.10)	(2.17)
$1 bn.	-0.6%	0.1%	-0.4%	0.0%	0.0%	0.1%	0.1%	0.1%	0.6%	0.7%	0.5%	0.7%	0.6%	0.8%	0.9%
	(-1.03)	(0.22)	(-1.38)	(-0.11)	.	(0.35)	(0.47)	(0.38)	(1.49)	(1.49)	(1.14)	(1.31)	(0.99)	(1.25)	(1.36)

Panel B: Marginal effects of percentage of AuM rule (C4) on investor performance																	
	Percentage of AuM constraint (C4)																
Size	2%	4%	6%	8%	10%	12%	14%	16%	18%	20%	22%	24%	26%	28%	30%	32%	34%
Panel B1: Post-formation alphas of hypothetical portfolios																	
$100 mn.	3.8%	4.4%	4.7%	5.1%	4.8%	5.0%	5.4%	5.4%	5.3%	5.4%	5.7%	5.7%	5.8%	5.8%	5.8%	5.8%	5.8%
	(4.04)	(5.23)	(5.68)	(6.58)	(6.21)	(6.61)	(7.07)	(7.23)	(7.14)	(7.22)	(7.53)	(7.53)	(7.65)	(7.58)	(7.59)	(7.58)	(7.70)
$500 mn.	2.5%	1.6%	1.7%	2.8%	3.8%	3.9%	4.8%	4.2%	4.0%	4.4%	4.4%	4.6%	4.5%	4.8%	4.7%	5.1%	5.0%
	(1.86)	(1.27)	(1.60)	(2.62)	(4.04)	(4.36)	(6.03)	(5.28)	(4.90)	(5.23)	(5.33)	(5.59)	(5.25)	(5.78)	(5.68)	(6.24)	(6.20)
$1 bn.	-0.1%	2.5%	1.4%	1.6%	1.1%	1.7%	1.9%	2.8%	3.2%	3.8%	3.6%	3.9%	4.4%	4.8%	4.4%	4.2%	3.9%
	(-0.06)	(1.86)	(1.09)	(1.27)	(0.91)	(1.60)	(1.69)	(2.62)	(3.35)	(4.04)	(3.75)	(4.36)	(4.89)	(6.03)	(5.44)	(5.28)	(4.67)
Panel B2: Spreads in alphas between portfolio having 10% of AuM constraint and other portfolios																	
$100 mn.	1.0%	0.5%	0.1%	-0.3%	0.0%	-0.2%	-0.5%	-0.6%	-0.5%	-0.5%	-0.8%	-0.8%	-1.0%	-1.0%	-1.0%	-1.0%	-1.0%
	(1.76)	(1.50)	(0.37)	(-2.82)	.	(-2.19)	(-3.27)	(-3.23)	(-2.97)	(-3.01)	(-3.96)	(-3.87)	(-4.44)	(-4.25)	(-3.72)	(-3.69)	(-3.90)
$500 mn.	1.3%	2.2%	2.1%	1.0%	0.0%	-0.1%	-0.9%	-0.4%	-0.2%	-0.6%	-0.6%	-0.8%	-0.7%	-1.0%	-0.9%	-1.3%	-1.2%
	(1.18)	(2.50)	(4.18)	(3.10)	.	(-0.51)	(-2.48)	(-1.20)	(-0.52)	(-1.21)	(-1.40)	(-1.70)	(-1.36)	(-1.95)	(-1.75)	(-2.36)	(-2.29)
$1 bn.	1.2%	-1.4%	-0.3%	-0.5%	0.0%	-0.6%	-0.8%	-1.7%	-2.0%	-2.7%	-2.5%	-2.8%	-3.3%	-3.6%	-3.3%	-3.1%	-2.8%
	(0.82)	(-1.44)	(-0.52)	(-0.93)	.	(-1.23)	(-1.62)	(-3.12)	(-3.20)	(-4.09)	(-3.80)	(-4.11)	(-4.72)	(-4.96)	(-4.56)	(-4.34)	(-3.71)

Figure A1.
Size–performance relationship adjusted for backfill bias.

We form size portfolios as in Table 2. This figure shows the annualized Fung and Hsieh (2004) alphas for each of the nominal size groups after returns are adjusted for backfill bias. We exclude 12, 24, or 31 months of fund-level returns in order to control for this bias.