Funding Liquidity Risk and the Dynamics of Hedge Fund Lockups

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Abstract

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JEL classification: G10, G23

Keywords: Hedge Funds, Funding Liquidity Risk, Lockup

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Abstract

We exploit the expiring nature of hedge fund lockups to create a dynamic, fund-level proxy of funding liquidity risk. In contrast to the prior literature, our measure allows us to identify how within-fund changes in funding liquidity risk are associated with performance and risk taking. Lockup funds with lower funding liquidity risk take more tail risk and have better risk-adjusted performance, suggesting reduced funding liquidity risk enables funds to better capitalize on risky mispricing. Surprisingly, lockup funds outperform non-lockup funds even when controlling for restricted capital, suggesting that a portion of the lockup premium is attributable to a "lockup-fixed effect".

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1. Introduction

Theories of efficient capital markets hinge on the concept that mispricing will be arbitraged away by competitive traders. In practice, however, traders are constrained by funding liquidity risk, i.e., their ability to attract and retain the capital necessary to trade against risky mispricing (Shleifer and Vishny, 1997). Funding liquidity risk is a critical friction that reduces a fund manager's ability to take risks, and has wide-reaching implications for not only fund performance, but also asset market liquidity, stability and efficiency (Ben-David, Franzoni, and Moussawi, 2012; Koch, Ruenzi, and Starks, 2016). As such, there is growing interest in understanding how funds manage funding liquidity risk and overcome limits to arbitrage by placing restrictions on investor withdrawals. For instance, there is evidence in the literature that closed-end mutual funds, which do not offer redeemable shares, are better able to invest in illiquid assets and employ risky arbitrage strategies than are open-end funds, which offer daily liquidity to their investors (Cherkes, Sagi, and Stanton, 2009; Deli and Varma, 2002; and Giannetti and Kahraman, 2014).

In addition, because of the importance of hedge funds as arbitrageurs, much attention has been paid to how withdrawal restrictions enable hedge funds to take greater risks and correct mispricings.[1] For example, many hedge funds choose to include an expiring lockup provision in their limited partnership agreements. Lockups are redemption restrictions that prevent new capital from being withdrawn for an initial period (typically 12 months), after which time the lockup expires and the shares become redeemable. These provisions are typically incorporated into fund offering agreements at the fund's inception and maintained throughout the life of the fund. The extant literature has focused its attention on the difference in outcomes between funds with and without a lockup, and evidence from these studies suggest that lockups reduce funding liquidity risk, increase managerial flexibility,

[1] See, for instance, Akbas, Armstrong, Sorescu, and Subrahmanyam (2015), Aragon (2007), Agarwal, Daniel, and Naik (2009), Aragon, Martin, and Shi (2014), Giannetti and Kahraman (2014), and Hombert and Thesmar (2014).

and ultimately lead to an improvement in performance of between 4-7% a year compared to hedge funds that do not impose a lockup (Aragon, 2007).

However, the presence of a lockup is an endogenous and fixed fund characteristic. Thus, it is difficult to disentangle the effects of the presence of the lockup from other time-invariant omitted factors that may affect fund performance and risk characteristics. For example, it could be that higher quality managers have better bargaining power with investors and that these investors are more willing to accept a lockup provision in their contract. Instead of reflecting the effects of reduced funding liquidity risk, the superior performance of lockup funds could reflect superior skill of their managers (or other omitted factors).[2] Moreover, any effects the lockup does have on funding liquidity risk are unlikely to be static, as lockups expire over time. This unique feature of lockups means that the amount of capital a hedge fund has locked up, and thus, its funding liquidity risk, is actually dynamic and varies across funds and through time.

In this paper, we focus on the dynamic nature of the hedge fund lockup and create a time-varying measure of capital restrictions for hedge funds. By comparing the time series of capital inflows relative to a fund's lockup period, we are able to estimate the proportion of fund capital that is restricted from withdrawals at any given time. Doing so allows us to disentangle the effects of binding share restrictions from other omitted factors and helps us to better understand the connection between funding liquidity risk, fund performance, and risk taking.

Our sample includes over 3,800 lockup funds from the union of five different hedge fund databases over the period 1994-2013. We estimate a variable called *dynamic lockup*, which is a proxy measure for the fraction of hedge fund capital locked up for each fund in each month in our sample. For those funds with a lockup, Figure 1 shows the evolution of dynamic lockup over the course of a fund's life, and reveals that the proportion of locked-up capital varies considerably across funds and through time. Although new lockup funds begin operations

[2]A similar argument can be made for a mutual fund's decision to use a closed-end structure.

with 100% of their capital locked up, this percentage steadily declines over time. By the time a fund is five years old, the median fund with a lockup will only have about 10% of its capital locked up, while a quarter of funds have less than 1% of their capital locked up. In fact, more than 70% of the average lockup fund's capital appears to be redeemable at any given time. This raises the question: is the lockup premium attributable to decreased funding risk created by binding withdrawal restrictions, or the endogenous decision to have a lockup in the first place?

To answer this question, we begin by examining the relation between a lockup fund's performance and dynamic lockup in a regression framework. Our results indicate that a one standard deviation increase in dynamic lockup is associated with a 16 basis point (bps) increase in monthly fund returns. The difference in annual performance between a fund without locked-up capital and a fund that is fully locked up is nearly 5%. This result continues to hold up to a series of robustness checks, including different controls for backfill bias and altering the measure of dynamic lockup using duration-based approaches. Collectively, our findings are consistent with the idea that funds with more protected capital have more flexibility to pursue higher expected return strategies.

Further, because the dynamic lockup measure is time-varying, it enables us to employ a fund fixed effects estimator and control for time-invariant factors that could also be driving the outperformance of lockup funds. After including fund fixed effects, we find that within-fund variation in dynamic lockup is positively related to future performance. This means that, within a fund, decreases in funding risk (i.e., increases in locked-up capital) lead to an increase in performance. This is an important contribution to the literature, as most of what we currently know about the relation between funding risk and fund performance is derived from comparative studies of time-invariant contractual designs (i.e., open versus closed-end mutual funds, lockup versus non-lockup hedge funds, etc.) or time-series studies of aggregate funding conditions (such as studies of financial crises).

We also address the potential concern that because our measure of dynamic lockup is calculated from the time series of capital flows, it merely proxies for other fund characteristics, such as a fund's age or size, which have been shown in the literature to be related to future hedge fund returns. In addition to controlling for these characteristics directly in our regressions, we also conduct the following placebo test: we randomly assign a lockup period to non-lockup funds and calculate a placebo value of dynamic lockup using the same methodology as with the lockup funds. We then test for a difference in the relation between the dynamic lockup measure and returns for lockup funds (treated funds) versus non-lockup funds (placebo funds).

The results of this placebo test confirm that the positive relation between fund returns and dynamic lockup is significantly greater for lockup funds as compared to non-lockup funds. In other words, funds with an actual lockup perform better, while there is no performance improvement associated with non-lockup funds that *would* have had more restricted capital if they had the lockup contract feature. The differential effect for lockup funds continues to hold when we include fund fixed effects, meaning it is not driven by time-invariant differences between lockup and non-lockup funds. These findings support the conclusion that our measure captures the relation between returns and funding risk, and not simply other factors that contribute to the dynamic lockup calculation.

Including non-lockup funds in our analysis reveals another interesting pattern. Even when we control for dynamic lockup, lockup funds still outperform non-lockup funds by 108 bps/year. This suggests that the lockup premium documented in prior literature is comprised of two components: a time-varying component related to binding capital restrictions and a time-invariant component related to other differences between lockup and non-lockup funds.

To better understand what is driving both components of the lockup premium, we run portfolio tests using factor models that control for common risks associated with hedge fund investment strategies. We split the sample of lockup funds into terciles of dynamic lockup, and adjust each return for the corresponding placebo portfolio's return. This nets out the characteristics of dynamic lockup that are unrelated to capital restrictions and allows us to identify the differences in risk-adjusted performance and risk loadings between lockup and non-lockup funds.

The portfolio tests reveal that even on a risk- and placebo-adjusted basis, funds in the top tercile of dynamic lockup outperform those in the bottom tercile, meaning that the time-varying component of the lockup premium is not merely driven by differences in factor risk across funds. However, funds in the bottom tercile of dynamic lockup do not outperform placebo funds on a risk-adjusted basis. This suggests that the time-invariant component of the lockup premium (i.e., the component unrelated to dynamic lockup) is driven by increased risk taking by lockup funds versus non-lockup funds.

Although part of the increased risk taking of lockup funds is attributable to their having greater exposure to illiquid assets, surprisingly this increased exposure appears unrelated to the proportion of capital they have locked up. This suggests that the time-varying component of the lockup premium is not driven by increased exposure to illiquid assets. In other words, the fact that lockup funds own more illiquid assets appears to be a lockup fund fixed effect. However, we do find evidence that the time-varying component of the lockup premium is driven by a fund's propensity to pursue strategies that are more likely to suffer during market downturns, when funding liquidity is more likely to dry up. Indeed, we find that funds with high dynamic lockup have significantly higher tail risk as measured by their betas with respect to the tail risk factor created by Agarwal, Ruenzi, and Weigert (2016).

Why would lockup funds own more illiquid assets even if their capital is unrestricted? We argue that the lockup provision may screen for patient investors, and/or create various incentives for investors to remain patient with their capital, even after their lockup expires. For instance, holders of unlocked shares can withdraw capital, but they know that any investments they make in the future will revert to locked-up status. This effectively raises the shadow cost of redeeming unlocked lockup shares.[3] Consequently, the greater risk taking by lockup funds could be due to their having a more stable capital base, beyond that which is induced by the binding restrictions of the lockup. To test this conjecture, we examine the flow pattern of lockup funds versus non-lockup funds, and find that even after controlling for dynamic lockup, lockup funds have lower outflows and lower flow-performance sensitivity than non-lockup funds. This is consistent with patient behavior by lockup investors, and suggests the lockup provision's contribution to capital stability goes beyond merely the strict prohibition of withdrawals.

2. Contribution Relative to Prior Literature

Our work contributes to the growing literature that examines how funding risk affects asset manager performance and risk taking. Agarwal, Daniel, and Naik (2009) argue that hedge funds with redemption restrictions have more flexibility to pursue risky arbitrage opportunities, and find that hedge fund performance is positively related to redemption restrictions. Similarly, Hombert and Thesmar (2014) argue that funds will choose to have more stable capital when they plan to engage in riskier strategies, and find that following low past performance, funds with greater share restrictions and lower flow-performance sensitivity subsequently earn higher returns. Giannetti and Kahraman (2014) find that closed-end mutual funds and hedge funds with greater share restrictions are better able to trade against mispricing than unrestricted funds. Franzoni and Plazzi (2015) find that a hedge fund's ability to provide liquidity is particularly sensitive to funding conditions, but that redemption restrictions mitigate the impact of market-wide funding shocks risk on hedge fund liquidity provision. Collectively, these papers support the idea that redemption restrictions reduce funding risk, which in turn increases a fund's ability to capture higher returns from risky strategies. However, because these studies focus on static withdrawal restrictions, they do

[3] This is similar to the use of share classes in the mutual fund industry. For example, Nanda, Narayanan, and Warther (2000) argue that mutual funds use share classes to screen for investor clienteles with differing liquidity needs.

not disentangle the differential effects of time-varying capital restrictiveness from other omitted differences between restricted and unrestricted funds. Our results support this prior work by showing that even within funds, increases in capital restrictiveness lead to increased fund performance.

In addition, our work contributes to the literature concerning the premium of lockup funds. Aragon (2007) finds that funds that institute a lockup earn a substantial premium of between 4-7% over other hedge funds, and he connects this premium to the lockup fund's ability to more efficiently manage illiquid investments that carry higher returns. Subsequent work has shown that lockup funds are more likely to trade against mispriced securities and provide liquidity than non-lockup funds (Giannetti and Kahraman, 2014; Aragon, Martin, and Shi, 2014), which points to other sources of the lockup premium. By constructing a dynamic measure of locked-up capital, we are better able to identify the role that binding capital restrictions play in determining the outperformance of lockup funds, while holding constant omitted fixed effects that may be correlated with the presence of the lockup. Though we find that binding capital restrictions do lead to higher performance, they are not the only factor that differentiates funds with a lockup from those without a lockup. Our results suggest that funding risk may also be partially mitigated by simply having a lockup provision in the fund's contract, which can attract more patient investors and lead to the formation of a more stable capital base.

Our work is also relevant to the debate about the optimal structure of redemption rights in the asset management industry. Fama and Jensen (1983) argue that demand deposits reduce agency problems and improve fund governance, since investors can vote with their feet. However, the dark side of unrestricted redemptions is that it hinders managerial flexibility to pursue higher expected return investments (Shleifer and Vishny, 1997). As a result, Stein (2005) argues that competitive pressures to remain open-ended lead to an inefficiently low supply of closed-end managers that are free to engage in risky arbitrage, stabilize prices, and contribute to market efficiency. Though the debate concerning redemption rights often centers on the extremes of open-end versus closed-end funds, the heterogeneous structure that has emerged in the hedge fund industry may be a more suitable solution to the problem of excessive open-endedness. In addition to directly restricting investor redemptions through lockups, our finding of the lockup fixed effect, i.e., that investors behave more patiently with unlocked shares than they do with shares in unrestricted funds, suggests that funds can also combat limits to arbitrage by creating contract mechanisms that screen for and incentivize more patient capital.

3. Data and Methodology

The hedge fund data in our paper comes from the union of five hedge fund databases: Lipper TASS, BarclayHedge, HFR, Eureka, and Morningstar. Our sample period covers 1994-2013. We follow Joenväärä, Kosowski, and Tolonen (2012) and merge the databases together to remove duplicate funds and share classes through a name matching and returns correlation algorithm. Because each hedge fund database categorizes investment strategies differently, we use the style-correspondence created by Joenväärä et al. (2012) to condense the investment strategy space to 13 different strategies.[4]

We remove funds of funds and non-US dollar denominated share classes. Our final sample contains 13,115 hedge funds with a total of 776,685 monthly return observations. Of these, 3,712 funds (about 29.8% of fund-months) have a lockup in their contract with an average length of 12 months.

[Insert Table 1 Here]

In Table 1, we present summary statistics for both our full sample (Panel A) and for just those funds with a lockup provision in their contract (Panel B). We note that funds with a lockup have higher average monthly returns than the full sample, which is consistent

[4] The 13 strategies are: CTAs, Emerging Markets, Event Driven, Fund of Funds, Global Macro, Long Only, Long/Short, Market Neutral, Multi-Strategy, Relative Value, Sector, Short Bias, and Others.

with prior literature. Interestingly, lockup funds also have more share restrictions beyond just the lockup, with longer redemption notice periods and redemption frequencies than non-lockup funds. This is consistent with the findings in Aiken, Clifford, and Ellis (2015), who argue that different share restrictions can serve a complementary role in hedge fund contracting. However, it is important to point out that, like the lockup, these restrictions are also fixed-contract provisions that are essentially time-invariant.[5] As such, we control for these restrictions in our tests to ensure that we are isolating the specific effects of the lockup.

3.1. Dynamic Lockup Measure

A primary innovation in this paper is the creation of a dynamic measure of restricted capital that takes into account the flow history of the fund to estimate the amount of capital under lockup. This approach differs from the previous literature that relies on a static indicator of the presence of a lockup provision in the fund's contract. For each fund that has a lockup provision, we calculate the fund's dynamic lockup, which captures the percent of assets the fund has under lockup at a given point of time. We calculate dynamic lockup in the following way: we begin by assuming that a lockup fund's capital is fully locked up at the fund's inception (i.e., dynamic lockup = 100%). This new fund is fully locked up until the lockup period ends. For example, if a fund had a 12 month lockup and received no additional investments, the fund would have a dynamic lockup = 100% for months 1 through 12. In month 13, the lockup period would have expired, and the fund would become fully unlocked (i.e., dynamic lockup = 0%). We treat any additional capital inflows the fund receives as new investments subject to the same 12 month lockup period. We track the timing and size of each inflow to create the following asset weighted percentage of locked-up capital for each

[5] Our database is formed from snapshots of the commercial databases collected in 2013, and thus the contractual terms we observe are fixed through time. It is common in the hedge fund literature to assume these provisions remain fixed in reality, and there is evidence that supports this view (e.g., Aragon, 2007).

$fund_i$:

$$Dynamic\ Lockup_{i,t} = \frac{\sum_{j=1}^{L}(flow_{i,t-L+j} * \prod_{k=j+1}^{L}(1 + r_{i,t-L+k}))}{AUM_{i,t}} \tag{1}$$

where $flow_t$ is the positive net flow received by the fund at the end of each $quarter_t$, r_t is the return in $quarter_t$, L is the length of lockup period measured in quarters, and AUM_t is the assets under management for the fund. If a fund's first reporting month is its inception month, we assume a fund's history begins as 100% locked up. If a fund's first reporting date is subsequent to its inception month, we can not identify its initial lockup fraction. Thus, for these funds, we must let an entire lockup cycle elapse before we can begin calculating the fund's dynamic lockup.

We find that, on average, only 26% of lockup funds' assets are restricted over our sample period. There is a great deal of variation across funds, however, as the 25th percentile of dynamic lockup is only 0.8%, meaning that in over a quarter of our sample, lockup funds have almost no capital locked up. On the other hand, a fund in the 90th percentile is fully locked-up. A static lockup indicator is unable to capture this fact, and would treat both the fully locked and unlocked funds the same. Our goal is to exploit this variation to better understand how a fund's capital restrictiveness is related to a fund's performance and risk.

3.2. Measurement Issues

It is important to note that various issues inherent in empirical hedge fund research, such as database reporting accuracy and unobserved heterogeneity in hedge fund contracts, make it impossible to create a precise measure of each fund's capital restrictiveness. Therefore, we stress that our measure is a proxy for the fund's locked-up capital and is likely measured with error. That being said, we take a number of steps to ensure that dynamic lockup correlates to the underlying construct it is meant to proxy for and that any measurement error does not bias our findings.

One data limitation we face is that gross inflows and outflows are not available in the databases, and thus we are forced to proxy for the gross inflows with positive net inflows. To the extent that some monthly inflows are masked by countervailing outflows in the same month, our dynamic lockup measure would understate the true proportion of locked-up capital.[6] If our proxy understates the true dynamic lockup by some constant fraction α, this will in turn lead to an unadjusted univariate regression coefficient that is overstated by the factor $1/\alpha$. As we standardize the variables in our regressions, however, our analysis should be unaffected (i.e., the standard deviation of the proxy would also be understated by α, leaving the standardized coefficient and t-statistic unaffected by a constant level of mismeasurement).[7] We further address this issue by executing a placebo test in Section 5, whereby we randomly assign a lockup period to non-lockup funds and calculate a placebo value of dynamic lockup using the same methodology as with the lockup funds. We then test for a difference in the relation between the dynamic lockup measure and returns for lockup funds (treated funds) versus non-lockup funds (placebo funds). To the extent that measurement error affects the lockup and non-lockup fund populations similarly, this approach should effectively net out the measurement error related to our proxy.

Another potential issue is that some hedge fund contracts may have additional redemption features, such as side letters and other sources of contract heterogeneity that are not captured by the hedge fund databases and, thus, are not captured by our dynamic lockup measure. To address this, we show results for both the full sample of lockup funds, as well as for the sub-sample of hedge funds that operate in equity-only strategies.[8] Equity-only funds are

[6]Because mutual funds disclose both gross and net flows, we can use this setting to provide some scope for the size and correlation of this effect. We randomly assign lockups to all mutual funds and reconstruct our measure separately using both gross and netflows. While we predictably find that the netflow measure is understated (relative to the gross flow measure), the correlation between the netflow and gross flow measure is 0.85.

[7]If the understating was random, but uncorrelated with the regression variables and error, we would be left with a classic case of errors in variables which would attenuate the observed coefficient. This would effectively reduce our power to reject the null hypothesis. Because we do reject the null, this would only be a problem for the inferences in our study if the frequency with which funds experience countervailing outflows in the same month as inflows is systematically related to the fund's returns.

[8]We thank Narayan Naik for this suggestion.

less likely to hold extremely illiquid assets that could necessitate complex redemption terms that are more difficult to summarize accurately in the databases. Thus, the dynamic lockup measure for equity-only funds is less likely to be contaminated by any unobserved database reporting issues.

We also consider the issue that some fund managers have the option to use their discretion to limit withdrawals during extreme markets with discretionary liquidity restrictions (DLRs), such as side pockets, gates, or withdrawal suspensions (Aiken, Clifford, Ellis, 2015). We are able to calculate dynamic lockup for a small subsample of funds from the Aiken, Clifford, Ellis (2015) study and find that our primary returns results still hold after controlling for DLR use. In addition, we find that funds with higher dynamic lockup are less likely to enact DLRs. This result further bolsters the claim that the dynamic lockup measure captures capital restrictiveness, as funds that have more capital restricted via the lockup mechanism (which is known and agreed to by investors ex-ante) do not need to rely on the more costly ex-post mechanism of the DLR.[9]

To empirically validate our measure, we regress capital outflows on dynamic lockup (for lockup funds only). These results are reported in Table 2. Panel A includes all of the lockup funds in our sample, while Panel B only uses lockup funds with equity-based strategies. The dependent variable in all models is fund outflows, where outflows are defined as min(0, netflow), as in Hombert and Thesmar (2014). The variable of interest is dynamic lockup and we include a standard set of flow determinants, such as fund size, age, performance, fees, and other contractual restrictions on redemptions. In particular, since dynamic lockup varies within a fund, we are able to include fund fixed effects while dropping time-invariant

[9]One concern is that, if funds can simply restrict capital at their discretion, all funds could have an effective dynamic lockup of 100%. However, this view presumes that enacting DLRs is costless and would imply their use to be common. On the contrary, Aiken, Clifford, Ellis (2015) found few funds had ever enacted DLRs outside of the financial crisis in 2007-2009. Moreover, funds that enacted them during the financial crisis suffered ex-post penalties from investors in the form of decreased flows to both the fund and its fund-family affiliates. In other words, managers cannot withhold investor money with impunity, as investors will be far less likely to entrust future dollars to a manager that refused to honor redemption requests in the past. In fact, the coexistence of ex-ante contract features such as lockups and notice periods with ex-post mechanisms such as DLRs speaks to the fact that these features serve different purposes.

fund characteristics, as in Models 3 and 4 of both panels. All models include time fixed effects and standard errors are clustered at the fund level.

[Insert Table 2 Here]

We document a strong negative relationship between dynamic lockup and fund outflows, even when employing fund fixed effects. For example, in Model 4 of Panel A, we find that a one standard deviation increase in dynamic lockup is associated with a 37 bps decrease in monthly outflows. Based on the average outflow for our sample, this represents a 19% decrease in fund outflows, holding other fund characteristics constant and including both time and fund fixed effects. Since fund fixed effects absorb typical static capital restriction proxies such as redemption notice periods and the lockup indicator, this helps to verify that changes in dynamic lockup correlate to changes in a fund's capital restrictiveness.

4. Dynamic Lockups and Fund Returns

We start by investigating the relationship between the returns of lockup funds and the proportion of locked-up capital (dynamic lockup). As discussed, previous work has focused on the average differences between funds with a closed structure and those that choose to allow investors to withdraw their capital. However, our dynamic lockup measure allows us to study within-fund variation in funds with a lockup feature to more clearly identify the link between changes in funding risk and asset manager performance.

4.1. Multivariate Regression

We begin by estimating a pooled, monthly return regression, where we restrict our sample to just those hedge funds that use a lockup. These results are presented in Table 3. Our regression model is given in equation (2) as

$$Return_{i,t+1} = \alpha + \beta \times Dynamic\ Lockup_{i,t} + \gamma \times Controls_{i,t} + \theta_i + \tau_t + \epsilon_{i,t} \qquad (2)$$

where the dependent variable, $Return_{i,t+1}$, is the fund's return in the subsequent month t+1 and the variable of interest, $Dynamic\ Lockup_{i,t}$, is the percentage of the fund's capital under contractual lockup in month t.

$Controls_{i,t}$ is a vector of time-varying controls, including the fund's past performance, flow, age, and size, as well as time-invariant controls, including the fund's minimum investment, fees and other capital restriction features, such as redemption frequency and notice period. All continuous variables are normalized to a mean of zero and a standard deviation of one. The unit of observation is a fund-month and we include time fixed effects in all models. Standard errors are clustered at the fund-level. θ_i includes style or fund fixed effects, as noted.

[Insert Table 3 Here]

We find that dynamic lockup is positively related to future fund returns in all model specifications. In Model 1, we find that a one standard deviation increase in dynamic lockup is associated with a 16 bps/month (t-statistic of 10.54) increase in the fund's future performance. In Model 2, where we control for fund characteristics shown to be related to fund performance, we again find a positive and significant relation between dynamic lockup and future fund performance. Specifically, a one standard deviation increase in dynamic lockup is associated with a 9 bps increase in monthly returns (t-statistic of 5.86).

One of the advantages of our dynamic lockup measure is that we can capture within-fund variation. As such, in Models 3 and 4 we perform similar tests but include fund-level fixed effects to control for unobservable, time-invariant fund characteristics that may be related to the performance of lockup funds.[10] Using this within-fund methodology, we continue to find a significant and positive relation between dynamic lockup and returns. For example, a one standard deviation increase in dynamic lockup leads to a 6 bps/month increase in average returns (Model 4) within a given fund. Our results are similar if we focus on equity-only funds

[10]To remove concern of a dynamic panel bias, we ran a specification of Model 4 of Table 3 where we excluded the lagged dependent variable (untabulated), our inferences are unchanged.

in Models 5-8. Overall, this result is consistent with a greater degree of capital stability (i.e. a reduction in funding risk) allowing managers to pursue strategies with greater expected returns. We argue this is an important finding given the lack of within-fund evidence for a link between funding liquidity risk and performance in the prior literature.

4.2. Robustness

We examine the robustness of our findings in Table 4. In Panel A, we include all funds in our sample, while, in Panel B, we include just equity funds. We are again only including funds with a lockup. The same set of control variables as in Table 3 are included, but omitted for brevity. Style and time fixed effects are included in all models. Model 1 shows our baseline model results for comparability.

[Insert Table 4 Here]

One particular concern is that our results could be driven by backfill bias. Funds have the option to start reporting to commercial databases after a successful incubation period, and can backfill their performance history with the good performance from the incubation period. This causes the well-known backfill bias, which means the returns of young funds are biased upwards on average. Because dynamic lockup tends to be highest when funds are young (e.g., see Figure 1), our measure may simply be a proxy for the high returns of very young funds.

We address this in two ways. First, in Model 2, we add fund age (in years) fixed effects to our main regression. This approach nets out the average performance of funds for every age cohort, and only captures the relation between dynamic lockup and performance within each year of age group. Second, in Model 3, we simply remove all observations that are backfilled from the analysis. To do this, we can only use data from TASS and HFR, as both give the date when a fund started reporting to the database. The advantage of this method is that we are sure the data are not backfilled. However, we are forced to drop a large fraction of observations, including many where the fund is still young and, thus, has higher levels of dynamic lockup. In both approaches, we continue to find that dynamic lockup is positively related to future returns.

Previously, we calculated dynamic lockup using quarterly flows data to reduce the noise in monthly flow calculations.[11] As a further robustness check, we estimate the dynamic lockup variable using monthly flows in Model 4, and find similar results. In Model 5, as an alternative to the percentage of assets locked up, we define dynamic lockup using a duration-based measure similar to the measure used in Hombert and Thesmar (2014).[12] This approach addresses the limitation that a percentage based dynamic lockup measure ignores the length of time the capital is expected to remain locked up. We define duration in this context as the length of time in quarters that the fund's assets will remain under lockup, or:

$$Duration_{i,t} = \frac{\sum_{j=1}^{L}(j * flow_{i,t-L+j} * \prod_{k=j+1}^{L}(1 + r_{i,t-L+k}))}{AUM_{i,t}} \tag{3}$$

where $flow_t$ is the positive net flow received by the fund at the end of each $quarter_t$, r_t is the gross return in quarter t, L is the length of lockup period measured in quarters, and AUM_t is the assets under management for the fund. We find very similar results with this duration based measure. Thus, our results appear to be robust to a variety of sample choices and variable definitions.

5. Placebo Approach

In this section, we also include all non-lockup funds in our analysis. We do this for two reasons. First, we wish to connect our results to the prior literature which only compared the performance of lockup and non-lockup funds. Doing so allows us to understand if the return differences found in Section 4 are driven entirely by our dynamic measure, or if there

[11]Some funds report AUM at irregular frequencies even if returns are reported monthly.

[12]In unreported analysis, we create the duration measure exactly as described in Hombert and Thesmar (2014) and find similar results.

is a residual, fixed difference between lockup and non-lockup funds. Second, including funds without a lockup in our sample also serves as a robustness check for our dynamic lockup measure. Our measure is created using the past flow history of the fund and will mechanically be related to the age, size, performance, and net inflows of the fund. Because these factors have been shown to predict hedge fund performance (e.g., see Boyson (2008) and Aggarwal and Jorion (2010)), one concern could be that our dynamic lockup measure is simply a proxy for these factors. Though we control for these factors in our regression, there remains a potential for nonlinear confounding effects.

To mitigate concern that our dynamic lockup measure is a proxy for other fund characteristics rather than a proxy for funding liquidity risk, we use a placebo approach and randomly assign a pseudo-lockup period to non-lockup funds. By year of fund founding, we obtain the frequency distribution of lockup periods for lockup funds and apply that distribution to non-lockup funds founded in the same year. In 2000, for example, 76% of newly founded lockup funds in our sample have a one-year lockup period. Accordingly, we randomly assign a one-year pseudo-lockup period to 76% of the non-lockup funds founded in 2000. We repeat the process for each lockup length/frequency combination for each year in the sample. This way each non-lockup fund has a pseudo-lockup period and the distribution of pseudo-lockup periods matches the actual lockup distribution of the lockup fund sample. We then use these pseudo-lockup periods to create a placebo version of dynamic lockup for non-lockup funds using the definition of dynamic lockup given in equation (1).[13]

Next, we re-run our performance regressions on the combined sample of lockup and non-lockup funds. We augment our regression model from Table 3 by interacting each variable (including the unreported control variables) with an indicator for whether the observation comes from a lockup fund or a non-lockup fund. This model setup allows us to identify the differential effect of the dynamic lockup measure across the lockup and non-lockup sample,

[13] In unreported analysis, we have also assigned pseudo-lockup periods by matching on observable fund characteristics using a propensity score matching algorithm and find very similar results.

as well as estimate the average difference in returns between the two samples after controlling for dynamic lockup. The results of these regressions are reported in Table 5.

Dynamic Lockup $\times$ *Lockup Fund* represents the real dynamic lockup measure for lockup funds. *Dynamic Lockup* $\times$ *Non-Lockup Fund* represents the placebo measure of dynamic lockup for non-lockup funds. Because the non-lockup funds do not actually have restricted capital, the placebo measure is only picking up (perhaps nonlinear) effects related to age, size, or recent inflows. By controlling for this placebo measure, we can net out any biases related to the dynamic lockup calculation and identify the effects of dynamic lockup on performance that come from the fund actually having restricted capital. Specifically, we estimate this effect as the difference in the coefficients *Dynamic Lockup* $\times$ *Lockup Fund* - *Dynamic Lockup* $\times$ *Non-Lockup Fund*. We report the differences and associated F-test below each model. All controls, time fixed effects, and style/fund fixed effects are included but omitted from the table for brevity.

[Insert Table 5 Here]

Model 1 of Table 5 includes the same controls as in our main specification in Table 3. The results for the lockup funds are similar to those in Table 3. *Dynamic Lockup* $\times$ *Lockup Fund* is positive and highly significant (9 bps, t-stat=5.50). Turning to the non-lockup funds, *Dynamic Lockup* $\times$ *Non-Lockup Fund* is also positive and significant, though its magnitude is much smaller and is only marginally significant at conventional levels (2 bps, t-stat=1.78). That said, this placebo result does support the concern that the dynamic lockup calculation picks up some effects on returns that are unrelated to actual capital restrictions. However, the difference between lockup and placebo groups is 7 bps, which is significant at the less than 1% level, indicating the majority of the dynamic lockup effect is coming from funds that actually have restricted capital. The contrast between the two samples becomes even stronger in Model 2, when we include fund fixed effects. Now, *Dynamic Lockup* $\times$ *Non-Lockup Fund* is approximately zero, and is not significant at conventional levels (t-stat=-0.07). On the other hand, *Dynamic Lockup* $\times$ *Lockup Fund* remains positive and highly significant (6 bps, t-stat=3.03). The results using fund fixed effects help to confirm that the positive association between dynamic lockup and fund performance is driven by reduced funding liquidity risk within a fund. We repeat the analysis for equity-only funds in Models 3 and 4 and find largely similar results. In fact, dynamic lockup is no longer significant for the placebo group in either model, while it remains positive and significant for the lockup group in both models. Collectively, the results in Table 5 support the notion that the positive relation between returns and dynamic lockup is driven by increased capital stability, rather than the components of the dynamic lockup calculation.

Perhaps the most interesting result from Table 5 can be seen by inspection of the *Lockup Fund* indicator variable in Models 1 and 3. Despite controlling for dynamic lockup, *Lockup Fund* remains positive and statistically significant. This means that there is a positive return difference between lockup and non-lockup funds that is not explained by lockup funds' restricted capital. For example, the coefficient from Model 1 of Table 5 indicates that a lockup fund that has had its lockup completely expire still earns a return premium of 108 bps/year when compared to a non-lockup fund. This, of course, raises the question: Why do lockup funds earn a premium in the absence of locked-up capital? We explore this question in the next section.

6. Lockup Premiums, Risk, and Patient Capital

6.1. Risk Models

We demonstrate that the lockup premium is a function of two separate mechanisms. One is dynamic and related to how much capital the manager has under contractual lockup. The other is time-invariant and associated with the presence of a lockup feature in the fund's contract. In this section, we ask if this return premium is related to manager skill, or if more restricted capital allows funds to take more risk. For example, perhaps managers who are able to negotiate a lockup *ex ante* are also more skilled. If this is the case, then we should observe positive alpha for managers with a lockup, independent of the percentage of capital under contractual restriction. However, perhaps limits to arbitrage are relaxed and managers are better able to engage in more complex arbitrage activities without the fear of investor outflows. In this case, estimates of alpha should increase as the percentage of capital under lockup increases. Finally, managers with less fragile capital might also earn higher returns from increased factor exposures. In this situation, lockup funds would have larger betas and these betas might increase as the amount of capital under lockup is increased.

In Table 6, we perform calendar-time factor regressions in order to test these hypotheses. Among those funds with a lockup, we form equal-weighted monthly portfolios based upon the fund's lagged dynamic lockup tercile. Furthermore, we adjust each portfolio's return by netting out the average placebo portfolio's return in that tercile. For example, if lockup and placebo funds in the high dynamic lockup tercile share certain characteristics that are associated with higher returns (e.g. both are smaller and younger funds), then subtracting placebo returns will adjust for that source of premium. All alpha and factor betas reported in Table 6 are, therefore, in excess of the abnormal return earned or the risks taken by the placebo group in that tercile.

[Insert Table 6 Here]

The first set of models in Panel A exclude any risk factors and thus illustrate the gross return spreads across the terciles of dynamic lockup. We find that Low, Mid, and High Dynamic Lockup portfolios earn alphas of 15, 20, and 34 bps/month, respectively. The difference between the High and Low portfolios is 19 bps/month. Each of these coefficients are statistically significant at conventional levels. Given that portfolio returns are net of the returns of the placebo funds, these coefficients reveal two effects. First, fund returns increase monotonically with the amount of capital under lockup. Second, all lockup funds earn a premium, regardless of the amount of locked-up capital the fund has, indicating the presence of a fixed lockup effect. Both of these effects are consistent with our findings in Table 5.

To begin addressing how funding liquidity risk affects risk taking, in the second model we include the market return premium as a risk factor, as well as the lagged market return premium to account for autocorrelation in hedge fund returns (Asness, Krail, and Liew, 2001; Getmansky, Lo, and Makarov, 2004). Autocorrelation in fund returns is often interpreted as a sign that a fund owns illiquid and/or difficult-to-value securities. In this simple model, alpha estimates fall by 9-12 bps/month and are no longer statistically different than zero for the low tercile portfolio. Estimated coefficients for the market factor are positive and statistically significant. Since fund returns are placebo adjusted, these estimates reflect the *incremental* risk taking by lockup funds over placebo funds that are in the same tercile. This suggests that the lockup fixed effect is related to an increased ability to take risk, independent of the amount of capital locked-up.

We also note that the coefficient on lagged market returns is positive and significant in all models. This suggests that funds with a lockup own more illiquid or difficult-to-price assets with greater transactions costs than the placebo funds in their tercile. This finding is consistent with the findings in Aragon (2007), who shows that lockup funds have greater returns autocorrelations. However, the lagged market factor loading does not increase when moving from the low to the high tercile, indicating that this increase in illiquid assets is independent of the amount of capital under lockup. This result is striking, as a common conjecture made in the literature is that lockup funds own more illiquid assets because they have more illiquid capital. We address this point further in Sections 6.2 and 6.3.

Finally, these findings hold when we add the six additional factors from the Fung and Hsieh (2004) model for hedge fund returns.[14] We also note that, in the Fung and Hsieh model, funds with a lockup take on more small stock risk than the placebo funds. Furthermore, the factor loading on *sizespread* increases as the amount of capital under lockup increases.

[14] The Fung and Hsieh (2004) model includes the following returns: the S&P 500 total return, a size spread return (Wilshire Small Cap 1750 - Wilshire Large Cap 750), a bond market factor (quarterly change in the 10-year constant maturity treasury yield), a credit spread factor (quarterly change in the Moody's Baa yield less the 10-year treasury constant maturity yield), and three trend-following factors for the bond market, the currency market, and the commodities market. See David Hsieh's web page at `http://faculty.fuqua.duke.edu/%7Edah7/HFRFData.htm` for a complete description.

Both facts suggest that at least a portion of the excess returns observed for lockup funds is associated with an ability to earn the size premium when capital is more stable. Our results are similar in Panel B, when we focus only on equity funds.

Regardless of model, we find that funds in the highest tercile portfolio earn larger alphas than funds in the lowest tercile portfolio. For example, the high minus low portfolio alpha when including all risk factors is 18 basis points per month for both the complete set of funds and the equity-only sample. Thus, while lockup funds seem to take more risk, they also tend to earn abnormal risk-adjusted returns when their capital is restricted from withdrawals. With a more stable capital base, this additional alpha could be related to a reduction in the limits to arbitrage, or perhaps to an omitted risk premium that managers with more restricted capital can better capture. We explore a possible additional risk premium in the next section.

6.2. Dynamic Lockup and Tail Risk

There are several studies in the literature that show that hedge funds have significant exposures to nonlinear systematic risk factors.[15] Indeed, many hedge fund strategies are characterized as "picking up nickels in front of bulldozers",[16] which is to say they pursue strategies that have high Sharpe ratios or positive alphas, but are also more likely to incur a substantial loss, especially in periods of market stress. In particular, Agarwal, Ruenzi, and Weigert (2016) (henceforth ARW), document a strong link between a hedge fund's returns and its exposure to market crashes, which they refer to as "tail risk". Funds with higher tail risk have higher average returns, but are more likely to suffer losses during market downturns.

High tail risk could be particularly problematic for funds that are exposed to funding liquidity shocks. Large losses during periods of market stress are more likely to trigger redemption requests that could lead to loss spirals, as in Brunnermeier and Pedersen (2009)

[15]Some examples include Fung and Hsieh (1997, 2004), Mitchell and Pulvino (2001), Agarwal and Naik (2004), Brown, Gregoriou, and Pascalau (2012), Jiang and Kelly (2012), and Bali, Gokcan, and Liang (2007).

[16]From Roger Lowenstein's account of the collapse of Long Term Capital Management, "When Genius Failed".

(i.e., redemption requests cause fire sales, which hurt performance, which cause more redemption requests, etc.). Thus, funds with a more fragile capital structure should be less willing to pursue higher tail risk strategies. Accordingly, ARW find that funds with lockups are likely to have higher tail risk exposure, consistent with lockups increasing managerial discretion to invest in risky arbitrage that could be susceptible to fire sale risk (Agarwal, Daniel, and Naik, 2009).

ARW also find that funds connected to Lehman Brothers experienced a spike in tail risk during the financial crisis as Lehman collapsed. Because tail risk spikes coincide with market downturns, this implies that funds that experience funding shocks during downturns suffer even more extreme losses than funds that are relatively insulated from funding shocks. This finding is also consistent with the loss spirals-view of tail risk: funds that have high tail risk and fragile equity capital are more likely to suffer during a market downturn, as performance induced redemption requests will beget even more damaging fire sales. Understanding these consequences *ex ante*, we would expect funds to manage their tail risk exposure to be aligned with their funding liquidity risk. Thus, funds with greater (less) funding liquidity risk should be less (more) willing to pursue high tail risk strategies.

We examine whether funds with higher dynamic lockup have greater exposure to tail risk using the placebo-adjusted factor model methodology. We closely follow ARW and create a tail risk factor defined as the difference in returns of funds in the top quintile of tail risk and the returns of the funds with zero tail risk (henceforth, *Tail*).[17] We then measure tail risk exposure as the beta of the dynamic lockup tercile portfolios with respect to *Tail*.[18]

[17]See Agarwal, Ruenzi, and Weigert (2016) for more details on how to construct the tail risk factor.

[18]Note that although Agarwal, Ruenzi, and Weigert (2016) create the tail risk factor from fund-level measures of tail risk, we do not use fund-level tail risk measures in our analysis. The reason is that ARW's fund-level measures reflect a fund's trailing tail risk over the past 24 months, whereas dynamic lockup changes rapidly through time as lockups expire. Thus, the relation between a fund's dynamic lockup and its fund-level tail risk measure in fact reflects the relation between a fund's historical average tail risk and its current proportion of locked-up capital, which is not the relation we are interested in studying. Because we change the composition of the dynamic lockup portfolios every month based on their current dynamic lockup, the correlation between the dynamic lockup tercile portfolio returns and the tail risk factor is more likely to reveal contemporaneous relation between dynamic lockup and tail risk exposures.

We report our factor model results in Table 7. Each model includes the Fung and Hsieh (2004) seven factors, as well as the *Tail* Factor. We report both the model's alpha and the beta for *Tail* for each of the dynamic lockup tercile portfolios, as well as the high minus low portfolio for the full set of hedge funds in Panel A and for the sample of equity-oriented hedge funds in Panel B.

[Insert Table 7 Here]

Table 7 reveals that tail risk exposure is positively related to dynamic lockup in the cross section of funds. Tail risk betas for the bottom tercile of dynamic lockup are insignificant for the full sample and significantly negative for the equity-only sample. On the other hand, funds in the top tercile of dynamic lockup have positive tail risk betas that are significant at the 1% level for both samples. The difference between the high and low terciles is also positive and significant at the 1% level for both samples. This implies that funds with more locked-up capital increase their exposure to tail risk, which is consistent with the idea that greater funding stability should provide a fund manager additional flexibility to pursue risky arbitrage.

Why would *Dynamic Lockup* be related to tail risk, but not the decision to hold illiquid assets? We believe this asymmetric result could be due to the different nature of the two premiums. As mentioned previously, the liquidity premium essentially comes from amortizing a large expected transaction cost. Because lockups expire, dynamic lockup represents a relatively short-term measure of binding withdrawal restrictions. For example, suppose a fund has 100% of its capital locked up for the next two months, but afterwards will revert to an unlocked fund. Buying more illiquid assets today will not necessarily be an attractive strategy for this fund, as the manager should still expect to liquidate some proportion of the illiquid assets and bear the high transactions costs in two months when the fund becomes unlocked.

On the other hand, the premium earned from holding greater tail risk stems from the possibility that a fund will hold the asset in a state of the world where the market crashes and withdrawal requests appear at the same time. In this case, a relatively short-term withdrawal restriction could be quite effective. The same fund whose lockup is expiring in two months could hold high tail risk assets this month with the knowledge that if the market experiences a shock and their assets decline in value, the fund will not be forced to sell at the bottom and get caught in a short-term loss-spiral (Brunnermeier and Pedersen, 2009). Once the fund reverts to unlocked status, it can reduce its tail risk to an appropriate level given the change in its funding liquidity risk. As we explore in the next section, it could be that lockups encourage a more patient investor clientele on average, but even patient investors can become impatient during a crisis. Therefore, lockup funds can afford to take more tail risk when they know that their capital is restricted from withdrawals.

6.3. Patient Capital

So far we have demonstrated that lockup funds with more locked up capital earn higher returns than lockup funds with less restricted capital, and that some of this return premium comes from fund's increased risk taking, including an increased exposure to tail risk. Furthermore, we find evidence of a fixed lockup premium (lockup fixed effect) - lockup funds appear to earn a risk-related premium relative to non-lockup funds that is unrelated to the proportion of capital that is locked up. In other words, lockup funds outperform non-lockup funds, even when their investors can withdraw their capital.

We posit that this fixed lockup premium could, in part, be due to lockup funds having a more patient capital base than non-lockup funds. There are several reasons why investors in lockup funds may be more patient than other investors. Investors that are willing to accept a lockup *ex ante* might be long horizon investors who understand that earning a risk premium over the long run (such as an illiquidity premium) entails suffering lower returns in some states of the world. Thus, a lockup could serve as a screening device to attract investors that are less likely to react quickly to poor performance. In addition, the presence of a lockup raises the cost to re-enter the fund. Investors may be less willing to withdraw capital if they know that any capital they choose to reinvest with the fund will again be subject to a lockup. Finally, investors may be more patient with their own unlocked capital if they know that other investors' restricted assets are enabling all investors in the fund to earn a risk or liquidity-based premium.

We test this conjecture in Table 8 by exploring how the presence of a lockup relates to fund outflows and the relationship between outflows and fund performance. Following the same placebo approach as in Section 5, we regress a fund's forward monthly outflow on lockup characteristics and other fund controls known to affect fund flows. Because we are interested in the flow-performance relation across lockup and non-lockup funds, in each model we include a measure of lagged annual fund performance interacted with an indicator for whether the observation comes from a lockup fund or a non-lockup fund. The rest of our (unreported) controls include the same independent variables as those in Table 2, including dynamic lockup. Similar to our approach in Table 5, we also interact each control variable with an indicator for whether the observation comes from a lockup fund or a non-lockup fund. We examine all funds in Models 1 and 2 and repeat the analysis for equity-only funds in Models 3 and 4.

[Insert Table 8 Here]

We begin by examining the coefficient on *Lockup Fund*. Because we control for *Dynamic Lockup* in each model, the *Lockup Fund* indicator reflects the average differences in outflows between lockup and non-lockup funds after controlling for the contractually restricted capital of lockup funds. Across each model, *Lockup Fund* is negative and statistically significant at less than the 1% level. For example, the coefficient from Model 1 suggests that the outflows of lockup funds are 41 bps per month lower than non-lockup funds, all else equal. This implies that even lockup funds with very little contractually restricted capital are less likely to receive redemption requests than non-lockup funds, supporting the notion that lockup funds have more stable capital.

Next, we turn to the relation between flows and performance. If lockup fund investors are more patient, we expect their redemption requests to be less sensitive to performance. We find robust evidence that this is indeed the case. In Model 1, where we measure performance using trailing twelve month returns, the relation between flows and performance is negative for both lockup and non-lockup funds. That is, that on average, as performance decreases, outflows increase for both sets of funds.

However, lockup fund outflows are significantly less sensitive to performance than are the outflows of non-lockup funds. The coefficient on performance for lockup funds (-26 bps) is more than 43% lower in absolute value than the coefficient for non-lockup funds (-46 bps). Our inferences are similar when we use a low return indicator (defined as below median returns) as our measure of performance in Model 2. Again, both lockup and non-lockup funds have higher outflows if they have low returns, but non-lockup funds lose significantly more capital than the lockup funds do (135 bps for non-lockup funds vs. 99 bps for lockup funds). The differences in the flow-performance relationship across both samples is significant in both models at the less than 1% level. We find similar effects in Models 3 and 4 when we examine only equity-oriented hedge funds.[19]

Collectively, the results of Table 8 suggest that lockup funds are less likely to receive redemption requests, and their investors are less sensitive to performance when requesting redemptions, even after controlling for the amount of capital that lockup funds have contractually restricted through the dynamic lockup. Thus, our findings suggest that in addition to maintaining stable capital through direct capital restrictions from the lockup, lockup contracts also allow funds to maintain a more stable base of unrestricted capital. Viewed from the limits to arbitrage perspective, the patient unlocked capital of lockup funds helps explain how lockup funds are able to realize superior performance even after their lockups expire.

Of course, if lockup funds outperform non-lockup funds, a natural question may be, why don't all funds have a lockup? It is important to remember that lockups do not come without

[19] We also find similar differences in flow-performance sensitivity when we examine implied net flows instead of outflows (unreported).

a cost. Namely, increased realized performance comes at the cost of more illiquid shares (Aragon, 2007). Moreover, as discussed above, the presence of a lockup is the endogenous outcome of an unobserved bargain between managers and investors. Investors may only be willing to accept a lockup from superior managers.

7. Conclusion

Funding liquidity risk, i.e., the risk that traders will not be able to source outside funding to take advantage of attractive investment opportunities, is a central friction in models of financial market disequilibrium and limits to arbitrage. It is crucial that we understand how funding risk influences the performance and risk taking of hedge funds because of their key role as arbitrageurs that provide liquidity, stabilize markets, and help push prices to their fundamental value. In this paper, we create a novel proxy of funding liquidity risk (dynamic lockup) that is both a fund-level and time-varying measure, which allows us to better identify the connections between funding liquidity risk, performance, and risk-taking in the cross section of hedge funds.

We document a strong positive association between dynamic lockup and hedge fund performance and risk taking. This effect is robust to including several fund-level control variables, different sample formations, and changes in how we measure dynamic lockup. Moreover, our result holds when we include fund-fixed effects in the regressions, meaning that within-fund changes in capital restrictions are associated with improvements in fund performance.

We also find that regardless of how much capital lockup funds have restricted, they still outperform non-lockup funds by approximately 1% per year (9 bps per month). This lockup fixed effect appears to be driven by increased risk taking by lockup funds as compared to non-lockup funds, including an increased exposure to illiquid investments. We conjecture that lockup funds take greater risk perhaps because the lockup provision screens for patient investors and incentivizes incumbent investors to be patient after the lockup expires. This allows lockup funds to retain more stable *unrestricted* capital, even after the lockup expires. Consistent with this conjecture, we find that lockup funds have lower outflows and their flows are less sensitive to performance, even after controlling for dynamic lockup. Collectively, our results suggest that funds can combat limits to arbitrage by not only directly restricting their investors' withdrawals, but also by creating mechanisms that incentivize a more patient investor base.

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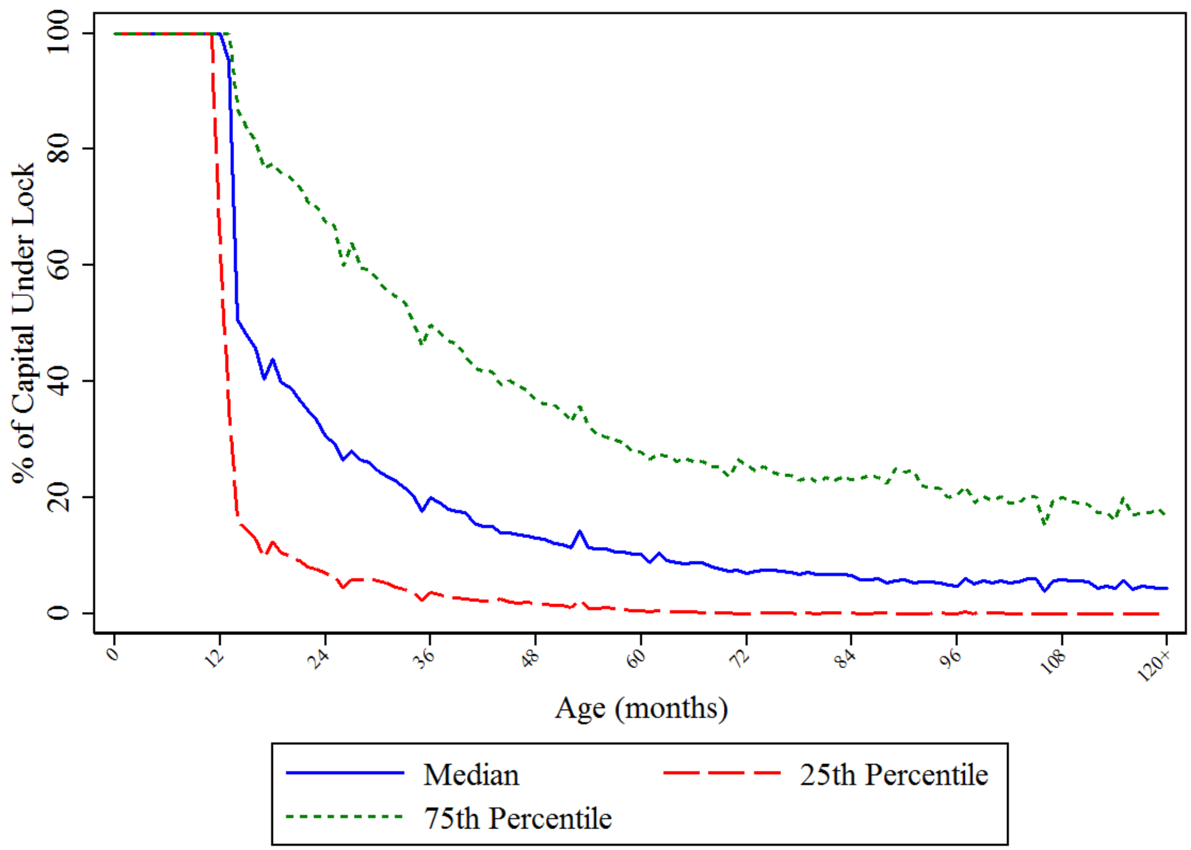

Figure 1
Percentage of Capital Under Lockup by Fund Age
Figure 1 presents the percentage of capital under lockup (*Dynamic Lockup*) based on a fund's age (months). We separately report *Dynamic Lockup* for the 25th percentile, median, and 75th percentile of *Dynamic Lockup*.

Table 1
Summary Statistics

This table presents the summary statistics for the hedge funds in our sample. The unit of observation is a hedge fund-month. Our sample period is 1994-2013. In Panel A, we examine the full sample of funds. In Panel B, we only examine the sample of funds with a lockup. *Lockup Fund* is an indicator variable equal to one if the fund has a lockup, and zero otherwise. *Dynamic Lockup* equals the percent of capital the fund has locked up (see equation 1). *AUM* is a fund's reported assets under management at the end of each month ($ millions). *Age* measures years since fund's first reported AUM. *Return* is the monthly return net of fees (%). *Flow* is a fund's implied, monthly net flows scaled by AUM (%). *Management fee* is the annual fee charged to investors as a percent of AUM (%). *Incentive fee* is the annual performance-based fee charged to investors (%). *Redemption notice* is the number of days of advance notice an investor must provide the fund to withdraw capital. *Redemption frequency* is the number of days between withdrawal periods. *Minimum Investment* is the minimum investment required to invest in the fund ($ millions). The full sample includes 13,115 funds and 776,685 fund-months.

Panel A: Full Sample

	Mean	10th	25th	50th	75th	90th	sd
Lockup Fund %	29.81	0.00	0.00	0.00	100.00	100.00	45.74
AUM ($MM)	168.74	2.94	10.00	34.99	116.84	351.00	634.43
Age (years)	4.91	0.92	1.83	3.67	6.75	10.67	4.27
Return %	0.67	-3.86	-1.00	0.63	2.34	5.21	5.35
Flow %	1.11	-5.12	-0.41	0.00	1.30	7.65	10.95
Management fee %	1.47	1.00	1.00	1.50	2.00	2.00	0.62
Incentive fee %	18.17	10.00	20.00	20.00	20.00	20.00	5.88
Redemption notice (days)	36.51	2.00	15.00	30.00	45.00	90.00	34.28
Redemption frequency (days)	68.27	7.00	30.00	30.00	90.00	90.00	79.74
Minimum Investment ($MM)	1.18	0.10	0.20	0.50	1.00	2.00	3.88

Panel B: Lockup Sample Only

	Mean	10th	25th	50th	75th	90th	sd
Dynamic Lockup %	26.45	0.00	0.81	11.31	40.69	100.00	32.80
AUM ($MM)	160.59	3.00	9.94	34.20	111.70	337.19	559.21
Age (years)	4.93	0.92	1.83	3.75	6.92	10.67	4.05
Return %	0.77	-3.87	-0.90	0.73	2.47	5.33	5.54
Flow %	1.24	-3.64	-0.19	0.00	1.27	6.95	9.96
Management fee %	1.39	1.00	1.00	1.50	1.80	2.00	0.48
Incentive fee %	19.20	18.00	20.00	20.00	20.00	20.00	3.98
Redemption notice (days)	51.65	30.00	30.00	45.00	60.00	90.00	41.83
Redemption frequency (days)	106.31	30.00	30.00	90.00	90.00	180.00	98.39
Minimum Investment ($MM)	1.11	0.10	0.25	1.00	1.00	2.00	1.69

Table 2
Hedge Fund Outflows and Dynamic Lockup

This table reports the results of regressions of forward monthly outflows on dynamic lockup. The dependent variable, *Outflow*, is defined to be the $-min(0$, monthly net flow), as in Hombert and Thesmar (2014). The unit of observation is a hedge fund-month. All control variables are defined in Table 1. In Panel B, we repeat our analysis on equity-only funds, as defined by Agarwal, Ruenzi, and Weigert (2016). All continuous control variables are normalized to mean of zero and a standard deviation of one. We include time fixed effects throughout and style/fund fixed effects where indicated. We cluster standard errors at the fund level. We report t-statistics in square brackets. ***, **, * represents statistical significance at the 1%, 5%, and 10% level respectively.

Panel A: All Lockup Funds

	1	2	3	4
Dynamic Lockup$_{t-1}$	-0.0021***	-0.0015***	-0.0046***	-0.0037***
	[-8.635]	[-5.718]	[-17.163]	[-12.534]
Log Age$_{t-1}$		0.0003		0.0043***
		[1.148]		[5.285]
Log AUM$_{t-1}$		0.0014***		0.0043***
		[6.281]		[8.107]
Minimum Investment$_{t-1}$		-0.0014***		
		[-3.094]		
Management Fee$_{t-1}$		0.0020***		
		[3.325]		
Incentive Fee$_{t-1}$		0.0010***		
		[3.566]		
Redemption Frequency$_{t-1}$		-0.0009***		
		[-4.076]		
Redemption Notice$_{t-1}$		-0.0002		
		[-1.249]		
Annual Return$_{t-1}$		-0.0026***		-0.0028***
		[-6.452]		[-6.241]
Flow$_{t-1}$		0.0038***		0.0007**
		[13.625]		[2.507]
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	-	-
Fund FE	-	-	Yes	Yes
Observations	208,338	208,338	208,338	208,338
R^2	0.026	0.035	0.085	0.089

Table 2, Continued

Panel B: Equity-only Lockup Funds

	1	2	3	4
Dynamic Lockup$_{t-1}$	-0.0016***	-0.0011***	-0.0042***	-0.0033***
	[-5.536]	[-3.422]	[-13.064]	[-9.230]
Log Age$_{t-1}$		0.0002		0.0045***
		[0.595]		[4.623]
Log AUM$_{t-1}$		0.0019***		0.0048***
		[6.438]		[7.260]
Minimum Investment$_{t-1}$		-0.0015**		
		[-2.340]		
Management Fee$_{t-1}$		0.0024***		
		[3.492]		
Incentive Fee$_{t-1}$		0.0003		
		[0.652]		
Redemption Frequency$_{t-1}$		-0.0008***		
		[-3.405]		
Redemption Notice$_{t-1}$		-0.0004		
		[-1.323]		
Annual Return$_{t-1}$		-0.0028***		-0.0028***
		[-5.287]		[-4.940]
Flow$_{t-1}$		0.0038***		0.0008**
		[11.218]		[2.517]
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	-	-
Fund FE	-	-	Yes	Yes
Observations	149,176	149,176	149,176	149,176
R^2	0.028	0.038	0.085	0.090

Table 3
Hedge Fund Performance and Dynamic Lockup

This table reports the results of regressions of forward monthly returns on dynamic lockup. The unit of observation is a hedge fund-month. All control variables are defined in Table 1. In Models 5-8, we repeat our analysis on equity-only funds, as defined by Agarwal, Ruenzi, and Weigert (2016). All continuous control variables are normalized to mean of zero and a standard deviation of one. We include time fixed effects throughout and style/fund fixed effects where indicated. We cluster standard errors at the fund level. We report t-statistics in square brackets. ***, **, * represents statistical significance at the 1%, 5%, and 10% level respectively.

	All Lockup Funds				Equity-only Lockup Funds			
	1	2	3	4	5	6	7	8
Dynamic Lockup$_{t-1}$	0.0016***	0.0009***	0.0014***	0.0006***	0.0016***	0.0009***	0.0015***	0.0007**
	[10.543]	[5.855]	[7.281]	[2.978]	[8.804]	[4.444]	[6.134]	[2.530]
Flow$_{t-1}$		0.0009***		0.0006***		0.0010***		0.0008***
		[5.633]		[3.813]		[5.020]		[3.758]
Log Age$_{t-1}$		-0.0002		-0.0014***		-0.0002		-0.0013**
		[-0.971]		[-2.688]		[-0.873]		[-2.159]
Log AUM$_{t-1}$		-0.0012***		-0.0077***		-0.0013***		-0.0081***
		[-7.290]		[-17.457]		[-6.847]		[-16.302]
Return$_{t-1}$		0.0066***		0.0052***		0.0065***		0.0052***
		[16.567]		[12.696]		[14.104]		[11.029]
Minimum Investment$_{t-1}$		0.0013***				0.0012***		
		[5.316]				[3.923]		
Management Fee$_{t-1}$		0.0007				0.0008		
		[1.636]				[1.631]		
Incentive Fee$_{t-1}$		0.0005***				0.0008***		
		[3.679]				[3.499]		
Redemption Frequency$_{t-1}$		0.0001				0.0001		
		[0.552]				[0.574]		
Redemption Notice$_{t-1}$		0.0000				0.0005***		
		[0.047]				[3.909]		
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	-	-	Yes	Yes	-	-
Fund FE	-	-	Yes	Yes	-	-	Yes	Yes
Observations	231,516	231,516	231,516	231,516	164,346	164,346	164,346	164,346
R^2	0.166	0.180	0.193	0.203	0.208	0.220	0.230	0.240

Table 4
Hedge Fund Performance and Dynamic Lockup – Robustness

This table reports the results of regressions of forward monthly returns on dynamic lockup. The unit of observation is a hedge fund-month. Model 1 of *Panel A(B)* is intended for reference and is identical to that of Model 2(6) from Table 3. In an effort to mitigate concerns of backfill bias, we follow two approaches. In Model 2, we include age fixed effects to study the within age cohort effects of dynamic lockup on future returns. In Model 3, we use date the fund started reporting to a database from TASS and HFR to explicitly remove all return observations that were backfilled. In Model 4, we estimate *Dynamic Lockup* using monthly flows. In Model 5, we alter our definition of dynamic lockup using a duration approach (see equation 3). In Panel B, we repeat our analysis on equity-only funds, as defined by Agarwal, Ruenzi, and Weigert (2016). We include time and style fixed effects throughout. We cluster standard errors at the fund level. We report t-statistics in square brackets. ***, **, * represents statistical significance at the 1%, 5%, and 10% level respectively.

Panel A: All Lockup Funds

	1	2	3	4	5
	Baseline	Age Fixed Effects	Remove Backfill	Monthly Dynamic Lockup	Duration
Dynamic Lockup$_{t-1}$	0.0009***	0.0007***	0.0008***	0.0009***	0.0012***
	[5.855]	[4.380]	[3.333]	[5.969]	[5.729]
Controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes
Observations	231,516	231,516	123,333	231,516	231,516
R-squared	0.180	0.180	0.193	0.180	0.180

Panel B: Equity Only Lockup Funds

	1	2	3	4	5
	Baseline	Age Fixed Effects	Remove Backfill	Monthly Dynamic Lockup	Duration
Dynamic Lockup$_{t-1}$	0.0009***	0.0006***	0.0006**	0.0008***	0.0014***
	[4.444]	[3.159]	[2.045]	[4.226]	[5.290]
Controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes
Observations	164,346	164,346	89,048	164,346	164,346
R-squared	0.220	0.220	0.233	0.220	0.220

Table 5
Hedge Fund Performance and Dynamic Lockup – Placebo Approach

This table reports the results of regressions of forward monthly returns on dynamic lockup. The unit of observation is a hedge fund-month. We randomly assign a pseudo-lockup period to non-lockup funds and calculate a placebo value of dynamic lockup using the same methodology as with the lockup funds. We then test for a difference in the relation between the dynamic lockup measure and returns for lockup funds versus non-lockup funds. In the table, *Lockup Fund* is an indicator variable equal to one if the fund has a lockup, and zero otherwise. *Dynamic Lockup* × *Lockup Fund* captures the effect of reduced funding liquidity risk for lockup funds. *Dynamic Lockup* × *Non-Lockup Fund* captures any residual effect that our methodology has in predicting future returns for placebo funds. In Models 3-4, we repeat our analysis on equity-only funds, as defined by Agarwal, Ruenzi, and Weigert (2016). We include identical control variables (omitted) to those in Table 3. We include time, style and fund fixed effects where indicated. Standard errors are clustered at the fund level. t-statistics are reported in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	All Funds		Equity-only Funds	
	1	2	3	4
(1) Dynamic Lockup$_{t-1}$× Lockup Fund	0.0009***	0.0006***	0.0009***	0.0007***
	[5.497]	[3.033]	[4.355]	[2.813]
(2) Dynamic Lockup$_{t-1}$× Non-Lockup Fund	0.0002*	-0.0000	0.0001	0.0001
	[1.774]	[-0.074]	[0.766]	[0.429]
Lockup Fund	0.0009***		0.0004*	
	[4.415]		[1.796]	
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	-	Yes	-
Fund FE	-	Yes	-	Yes
Observations	776,685	776,685	477,240	477,240
R^2	0.137	0.161	0.190	0.211
(1)-(2)	0.0007***	0.0006***	0.0008***	0.0006***
F-test	[15.04]	[7.21]	[11.07]	[4.65]

Table 6
Dynamic Lockup Placebo-Adjusted Performance - Portfolio Approach

This table reports factor exposures for a series of equal-weighted, placebo-adjusted portfolios. Each month, funds are sorted into terciles based on their lagged *Dynamic Lockup*. We placebo-adjust each tercile by subtracting the monthly return for the placebo portfolio (*Lockup Fund = 0*) from the monthly return of the lockup portfolio (*Lockup Fund = 1*). We consider raw returns, a market model (with a lagged market factor) and the Fung and Hsieh (2004) 7-factor model (with a lagged market factor). High-Low represents a long-short portfolio that invests long in high dynamic lockup funds and short low dynamic lockup funds. In Panel B, we repeat our analysis on equity-only funds, as defined by Agarwal, Ruenzi, and Weigert (2016). t-statistics are reported in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: All Lockup Funds, Placebo-Adjusted

	alpha	mktrf	lag mktrf	sizespread	bondmarket	creditspread	ptfsbd	ptfsfx	ptfscom	R^2
Low Dynamic Lockup$_{t-1}$	0.0015**									-
	[2.120]									
Mid Dynamic Lockup$_{t-1}$	0.0020***									-
	[3.094]									
High Dynamic Lockup$_{t-1}$	0.0034***									-
	[4.578]									
High - Low	0.0019***									-
	[3.199]									
Low Dynamic Lockup$_{t-1}$	0.0004	0.1283***	0.0408***							0.332
	[0.764]	[9.955]	[3.164]							
Mid Dynamic Lockup$_{t-1}$	0.0011**	0.1159***	0.0280**							0.309
	[2.016]	[9.696]	[2.337]							
High Dynamic Lockup$_{t-1}$	0.0022***	0.1645***	0.0396***							0.461
	[3.853]	[13.413]	[3.229]							
High - Low	0.0017***	0.0362***	-0.0012							0.031
	[2.824]	[2.733]	[-0.089]							
Low Dynamic Lockup$_{t-1}$	0.0004	0.1076***	0.0381***	0.0419**	0.7151***	0.6432*	-0.0041	-0.0086***	-0.0155***	0.467
	[0.803]	[8.071]	[3.023]	[2.550]	[3.110]	[1.914]	[-1.114]	[-2.806]	[-3.809]	
Mid Dynamic Lockup$_{t-1}$	0.0011**	0.0923***	0.0238**	0.0762***	0.4257**	0.3844	-0.0020	-0.0075***	-0.0130***	0.461
	[2.247]	[7.541]	[2.056]	[5.047]	[2.017]	[1.246]	[-0.586]	[-2.657]	[-3.483]	
High Dynamic Lockup$_{t-1}$	0.0022***	0.1395***	0.0344***	0.0902***	0.3411	0.2747	-0.0017	-0.0077***	-0.0097**	0.575
	[4.289]	[11.051]	[2.881]	[5.792]	[1.567]	[0.864]	[-0.480]	[-2.624]	[-2.522]	
High - Low	0.0018***	0.0319**	-0.0037	0.0482***	-0.3741	-0.3686	0.0024	0.0010	0.0058	0.077
	[2.898]	[2.126]	[-0.263]	[2.610]	[-1.448]	[-0.976]	[0.587]	[0.287]	[1.266]	

Table 6, Continued

Panel B: Equity-only Lockup Funds, Placebo-Adjusted

	alpha	mktrf	lag mktrf	sizespread	bondmarket	creditspread	ptfsbd	ptfsfx	ptfscom	R^2
Low Dynamic Lockup$_{t-1}$	0.0013**									-
	[2.033]									
Mid Dynamic Lockup$_{t-1}$	0.0015***									-
	[2.926]									
High Dynamic Lockup$_{t-1}$	0.0034***									-
	[4.608]									
High - Low	0.0022***									-
	[3.040]									
Low Dynamic Lockup$_{t-1}$	0.0006	0.0892***	0.0158							0.184
	[1.085]	[7.023]	[1.239]							
Mid Dynamic Lockup$_{t-1}$	0.0010**	0.0626***	0.0216**							0.157
	[2.024]	[6.024]	[2.077]							
High Dynamic Lockup$_{t-1}$	0.0022***	0.1661***	0.0305**							0.452
	[3.948]	[13.390]	[2.460]							
High - Low	0.0016**	0.0769***	0.0148							0.107
	[2.329]	[5.088]	[0.978]							
Low Dynamic Lockup$_{t-1}$	0.0006	0.0803***	0.0169	0.0325*	0.4324*	0.5930*	-0.0015	-0.0044	-0.0112**	0.252
	[1.024]	[5.689]	[1.271]	[1.871]	[1.778]	[1.669]	[-0.378]	[-1.363]	[-2.588]	
Mid Dynamic Lockup$_{t-1}$	0.0010**	0.0505***	0.0178	0.0313**	0.2410	0.1241	-0.0017	-0.0013	-0.0090**	0.217
	[2.094]	[4.344]	[1.622]	[2.185]	[1.203]	[0.424]	[-0.524]	[-0.471]	[-2.533]	
High Dynamic Lockup$_{t-1}$	0.0024***	0.1429***	0.0212*	0.0820***	0.1581	-0.2172	0.0019	-0.0030	-0.0076*	0.527
	[4.395]	[10.700]	[1.676]	[4.976]	[0.687]	[-0.646]	[0.520]	[-0.981]	[-1.864]	
High - Low	0.0018**	0.0627***	0.0042	0.0494**	-0.2744	-0.8102*	0.0034	0.0014	0.0036	0.146
	[2.583]	[3.658]	[0.260]	[2.340]	[-0.929]	[-1.878]	[0.718]	[0.358]	[0.678]	

Table 7
Tail Risk and Dynamic Lockup

This table reports tail-risk factor exposures for a series of equal-weighted, placebo-adjusted portfolios. Each month, funds are sorted into terciles based on their lagged *Dynamic Lockup*. We placebo-adjust each tercile by subtracting the monthly return for the placebo portfolio (*Lockup Fund = 0*) from the monthly return of the lockup portfolio (*Lockup Fund = 1*). We augment the Fung and Hsieh (2004) 7-factor model (omitted) with a tail risk factor from Agarwal, Ruenzi, and Weigert (2016). We report both the alpha and factor loading on the tail risk factor for each portfolio. High-Low represents a long-short portfolio that invests long in high dynamic lockup funds and short low dynamic lockup funds. We repeat our analysis on equity-only funds, as defined by Agarwal, Ruenzi, and Weigert (2016). t-statistics are reported in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Placebo-Adjusted			
	All Lockup Funds		Equity-only Lockup Funds	
	Alpha	Beta	Alpha	Beta
Low Dynamic Lockup$_{t-1}$	0.0007	-0.0313	0.0008	-0.0711***
	[1.316]	[-1.323]	[1.357]	[-2.930]
Mid Dynamic Lockup$_{t-1}$	0.0012**	0.0431**	0.0011**	-0.0005
	[2.527]	[2.018]	[2.363]	[-0.024]
High Dynamic Lockup$_{t-1}$	0.0024***	0.0574***	0.0025***	0.0624***
	[4.689]	[2.598]	[4.663]	[2.701]
High - Low	0.0017***	0.0887***	0.0017***	0.1334***
	[2.844]	[3.478]	[2.615]	[4.670]

Table 8
Hedge Fund Flows and Dynamic Lockup

We test for differences in the flow-performance sensitivity of *Lockup* and *Non-Lockup* funds. The dependent variable, *Outflow*, is defined to be the $-min(0$, monthly net flow), as in Hombert and Thesmar (2014). We estimate *Dynamic Lockup* for all funds following the placebo approach in Table 5 and control for *Dynamic Lockup* throughout (as well as all controls from Table 2). *Lockup Fund* is an indicator variable equal to one if the fund has a lockup, and zero otherwise. *Annual Return* is the fund's holding period return over the prior twelve months. *Low Return Indicator* is an indicator equal to one if the fund's holding period return over the prior twelve months was below the sample median, and zero otherwise. In Models 3-4, we repeat our analysis on equity-only funds, as defined by Agarwal, Ruenzi, and Weigert (2016). We include time and style fixed effects throughout. Standard errors are clustered at the fund level. t-statistics are reported in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	All Funds		Equity-only Funds	
	1	2	3	4
Lockup Fund	-0.0041***	-0.0022***	-0.0040***	-0.0019***
	[-14.164]	[-7.778]	[-11.068]	[-5.360]
(1) Lockup Fund × Annual Return$_{t-1}$	-0.0026***		-0.0027***	
	[-6.937]		[-5.699]	
(2) Non-lockup Fund × Annual Return$_{t-1}$	-0.0046***		-0.0043***	
	[-13.153]		[-8.937]	
(3) Lockup Fund × Low Return Indicator$_{t-1}$		0.0099***		0.0096***
		[30.814]		[26.095]
(4) Non-lockup Fund × Low Return Indicator$_{t-1}$		0.0135***		0.0138***
		[58.298]		[45.449]
(1) - (2)	0.0021***		0.0016***	
(3) - (4)		-0.0036***		-0.0042***
F-stat	18.48	86.20	6.943	83.81
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Observations	699,426	699,426	431,955	431,955
R^2	0.040	0.046	0.045	0.051