HEDGE FUND LIQUIDITY MANAGEMENT[1]

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ABSTRACT

We find that asset illiquidity in hedge funds is typically lower than combined liabilities and equity illiquidity, i.e., hedge funds tend to exhibit negative liquidity mismatch. Using hedge fund regulatory filings of Form PF over 2013-2015, we find that negative liquidity mismatches are more pronounced among larger funds, funds with lower leverage, funds in which managers have a greater personal stake, and when market volatility is lower. We also find support for existing theories of liquidity management: Funds holding more illiquid assets are associated with longer committed periods of investor financing, and the absence of long-term commitments from investors and lenders predicts greater cash holdings and unused borrowing capacity, respectively. Finally, quarterly changes in cash holdings and unused borrowing are negatively related to current and future investor flows and fund returns, suggesting that managers increase liquidity buffers in response to investor outflows, negative performance and ahead of financial distress. Our findings of a negative relation between cash buffer changes and outflows contrast sharply with recent mutual funds studies. We find that hedge funds' right to enact so-called "discretionary" liquidity restrictions plays an important role in explaining this difference.

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1. Introduction[2]

The recent financial crisis has highlighted the importance of sound liquidity risk management to guarantee the viability of financial institutions, especially during severe market downturns. The large liquidity mismatch between the assets and liabilities of financial intermediaries fueled investor runs and triggered distressed asset sales that threatened insolvencies across the entire financial system. The potential inability of financial institutions to effectively manage their liquidity in times of need created concerns among policymakers that ultimately resulted in significant regulatory reforms around the globe.

An analysis of liquidity management inside hedge funds is critical to our understanding of financial markets. Despite calls for further research, there currently exists little public evidence on the role of liquidity management in hedge funds.[3] In this paper, we use information extracted from Form PF filings that are submitted confidentially with the SEC. These disclosures provide details information about hedge funds operations that allow us to investigate heretofore unanswered questions.[4] While some previous studies investigate the relation between hedge funds' portfolio liquidity and investor liquidity (e.g. Aragon 2007; Agarwal, Aragon, and Shi, 2015) our study is the first to include most crucial components of hedge funds' overall liquidity profile: asset liquidity,

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[2] The Form PF information and statistics discussed in this study are aggregated and/or masked to avoid potential disclosure of proprietary information of individual Form PF filers.

[3] An understanding of how hedge funds manage liquidity can inform regulation of other segments of the asset management industry, like open-end mutual funds.

[4] A comprehensive picture of hedge funds and advisers that file form PF is provided in the quarterly statistics produced by the SEC Division of Investment Management and available here: https://www.sec.gov/divisions/investment/private-funds-statistics.shtml

investor liquidity, financing liquidity, cash, and unused borrowing capacity (e.g., excess margin and lines of credit).[5]

Our analysis addresses several research questions related to liquidity management in hedge funds. First, we examine the extent of liquidity mismatches across funds and over time. To do this we construct a global measure of liquidity mismatch for each fund and quarter equal to the illiquidity of the fund's assets including cash (asset illiquidity) minus the illiquidity of the fund's liabilities (financing illiquidity) and equity (investor illiquidity). A fund's asset illiquidity is a weighted-average of the time it takes to liquidate the fund's portfolio.[6] Similarly, financing and investor illiquidity are weighted-averages of the time that creditors and investors have committed their loan facilities and equity capital to the fund, respectively. Both sides of balance sheet liquidity are measured in the same units (days), and are reported by the fund manager on Form PF.

We find that liquidity mismatches in hedge funds are typically negative (-85 days, on average), meaning that hedge funds hold relatively liquid assets compared to the

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[5] Prior studies rely on liquidity proxies that allow only a partial view of the hedge funds' overall liquidity profile and/or covered only a limited sample of the funds' population. These proxies often lack important components and/or were polluted with other factors unrelated to funds' liquidity. Getmansky, Lo, and Makarov (2004), for instance, construct a joint measure of asset liquidity and return smoothing, thus only indirectly providing an assessment of hedge funds' asset liquidity. The commercially available TASS database, often used in the literature to gauge investor liquidity, does not provide an overall investor liquidity variable: first, it does not provide any information on gates; second, some funds have separate information on lock-ups, redemption notice periods, and redemption frequency and this information is often missing; third, share restrictions are very static and do not change overtime in TASS. Finally, commercial databases also do not provide information about a hedge fund's unencumbered cash holdings or available borrowing– two significant elements of liquidity management.

[6] Our measure of a fund's asset liquidity is a weighted average between the liquidity of the investment portfolio (Q32 on form PF) and cash. In principle, the sum of percentage values entered across all periods in Q32 (portfolio illiquidity) should be 100%. However, we observe some observations where these sums are very different from 100%. Therefore, we drop observations where either sum is either less than or equal to 90% or greater than or equals to 110%.

combined liquidity of its liabilities plus equity, though there exists a number of funds in our sample with positive liquidity mismatches. Our results display significant variation across funds and market conditions. Highly levered funds, in particular, are associated with significantly greater mismatches.[7] This finding is interesting because higher leverage amplifies returns on assets and makes hedge funds more exposed to margin calls and redemptions by their prime brokers and investors, respectively. At the same time, liquidity mismatches can create so-called strategic complementarities whereby fund investors pre-emptively withdraw their capital in anticipation of outflows by other investors, to avoid significant costs from asset fire sales.[8] Taken together, our evidence suggests that an increase in leverage could make hedge funds more prone to asset fire sales that propagate funding shocks throughout the financial system.

We also find that larger mismatches are more pronounced among smaller funds, funds having the ability to enact discretionary liquidity restrictions, funds with a larger number of prime brokers, and funds in which managers have a smaller personal stake. In addition, hedge fund mismatches are positively correlated with market volatility (78% with VIX, see Figure 3). As we show, the positive relation between mismatch and VIX is driven by the asset side of the balance sheet, i.e., as VIX increases, portfolio illiquidity tends to increase. In sum, while hedge funds generally aim to hold assets that are more

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[7] As we show, the terms of committed financing that a hedge fund arranges with its creditors are much shorter, on average, as compared to those of its equity investors. Therefore, a higher leverage ratio places relatively more weight on a fund's short-term liabilities, and this creates a greater mismatch *ceteris paribus*.

[8] See, e.g.,Chen, Goldstein, and Jiang (2010), Liu and Mello (2011, 2016), Goldstein, Jiang, and Ng (2015). On the investor side, many hedge funds can enact gates and suspend redemptions outright to prevent investor runs. We account for such discretionary liquidity restrictions in our analysis of liquidity mismatch.

liquid than their liabilities (negative mismatch), the degree of mismatch is strongly related to fund characteristics and market conditions.

To shed further light on liquidity management inside hedge funds, we further test whether funds pursuing investment strategies that are long-term in nature are more likely to require long-term commitments from their investors. The conceptual framework underlying our analysis is illustrated in Figure 1. Prior to fund inception (i.e., t = -1), a fund manager decides on an investment strategy and thus a general asset allocation reflective of her fundamental skillset and attributes (e.g., shareholder activist vs. high-frequency trader). The liquidity of a fund's non-cash asset holdings (i.e., portfolio liquidity) is a function of this decision and is taken as exogenous in our analysis.[9] Second, after portfolio liquidity is established, the fund manager (at time = 0, i.e., inception of a hedge fund) simultaneously decides on investor (with investors) and financing (with brokers) liquidity terms. Specifically, the manager, with the help of legal staff, write fund governing documents that establish lock-up, redemption, and other investor liquidity provisions and create relationships with prime brokers to obtain financing, thus establishing financing liquidity terms. Understanding the type of assets the hedge fund invests into and the type of strategy the manager is going to follow is important in establishing investor liquidity terms and negotiating favorable financing liquidity terms.

We use an instrumental variables approach to examine whether a fund's financing and investor illiquidity are jointly determined on the basis of the illiquidity of its non-cash portfolio assets. Our evidence strongly shows that funds pursuing more illiquid

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[9] See Section 4.1 for a further discussion of this assumption.

strategies have more stable funding sources. Specifically, a one standard deviation increase in portfolio's average illiquidity is associated with a 0.57 standard deviation increase in investor illiquidity (see Table 4). Interestingly, the committed period of financing from a fund's creditors is unrelated to portfolio illiquidity. A possible interpretation for this "non-result" is that, while funds pursuing illiquid strategies have a greater demand for longer-term financing, its creditors are less willing to extend long-term loans due to the illiquid nature of the fund's assets.

We next examine whether, in the absence of long-term capital commitments, funds manage their liquidity needs by maintaining larger liquidity buffers in the form of unencumbered cash holdings and unused borrowing capacity. According to Figure 1, once investor and financing liquidity terms are set (at time=0), hedge fund managers use cash and unused borrowing (at time >0) to dynamically manage liquidity needs. Unencumbered cash holdings permit the fund to fill investor redemption orders without having to liquidate their non-cash assets. Therefore, we test whether cash holdings are greater when investors have committed their equity capital for shorter periods. Also, a hedge fund's unused borrowing capacity refers to undrawn lines of credit and free credit balances the fund has in its margin account. This facility is a useful liquidity buffer in case the fund needs to roll-over short-term debt or avoid a sudden margin call. Therefore, we expect a negative relationship between unused borrowing capacity and the period that a fund's creditors have contractually committed to provide their financing.

We find empirical support for these predictions (see Table 5): a one standard deviation increase in investor illiquidity is associated with a drop in unencumbered cash (as a percentage of net assets) of 2.83 percentage points (0.12 standard deviations); and a one standard deviation increase in financing illiquidity is associated with a drop in unused borrowing capacity (as a percentage of used plus unused borrowing) of 6.27 percentage points (0.18 standard deviations). Our evidence resonates well with theories of corporate liquidity management according to which cash and unused lines of credit provide liquidity insurance against future financing constraints.[10]

The final part of our analysis examines dynamic liquidity management – specifically, how hedge funds manage over time the liquidity of their funds by adjusting the amount of cash and available borrowing in response to financial distress as measured by poor performance and investor outflows. Consistent with hedge funds drawing down cash to meet redemptions, we find that cash holdings drop by $0.18 for every dollar of net outflows in the same quarter (see Table 6). Interestingly, however, we find that changes in a fund's cash holdings *as a proportion of NAV* ("cash buffer") are negatively related to investor outflows, as well as fund returns. Our findings of a negative relation between cash buffer changes and outflows in hedge funds contrast sharply with recent evidence that mutual funds reduce their cash buffers concurrently with outflows. As we show, the right to enact so-called "discretionary" liquidity restrictions, like gates and side pockets, plays an important role in explaining this difference. In fact, for a small number of hedge funds in our sample with "mutual fund-like" liquidity offered to fund investors, the dynamics of cash buffers are similar to the mutual fund evidence (see Table 6).

Why do hedge funds increase their cash buffers in response to outflows? We argue that managers increase their cash ratios during periods of liquidity stress in anticipation of future stress. Consistent with this prediction, we find that the negative

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[10] For a review of this literature see Almeida et al. (2014).

relation between cash buffers and outflows is most pronounced during periods of greater macroeconomic uncertainty (measured by VIX, see Table 6). Moreover, when we decompose outflows into an expected and unexpected component, we find that cash buffers actually decline during periods of higher *expected* outflows, an indication that managers temporarily increase cash buffers above target levels when outflows are expected to be high and subsequently use this cash when *expected* outflows realize. In contrast, negative outflow *surprises* are associated with an increase in cash buffers and, therefore, drive the overall negative relation between cash buffers and outflows. Finally, and, most directly, we find that increases in cash buffers predict investor outflows and a greater likelihood of fund liquidation in the following quarter (see Table 7).

We then run a parallel analysis using changes in a hedge fund's unused borrowing capacity. Our conclusions are similar: the dollar amount of unused borrowing declines with investor flows and fund returns, but unused borrowings *as a proportion of used and unused borrowing* (margin buffer) are greater following poor fund performance (see Table 8). Moreover, consistent with fund managers increasing their margin buffers in anticipation of future liquidity stress, we find that increases in unused borrowing capacity predict a greater likelihood of negative returns and fund liquidation in the following quarter (see Table 9).

Our analysis is related to empirical work on liquidity mismatches in commercial banks, especially by Berger and Bouwman (2009).[11] In contrast to our findings of

[11] The main difference of our measure from Berger and Bouwman (2009) is that our measure is based on hedge fund managers' own assessments of the liquidity of its balance sheet (as reported on Form PF) and is not dependent on our judgment of the liquidity of specific balance sheet items. Berger and Bouwman (2009) construct several alternate measures using different ways of classifying a bank's balance sheet items

negative mismatches in most hedge funds, they find that banks tend to have positive mismatches and, hence, "create" liquidity. Their findings support prior theories of capital structure that help rationalize why banks mainly finance illiquid assets with liquid demand deposits. By allowing depositors to force liquidation, demand deposits provide a disciplining force against a bank's incentive to take actions against the interest of depositors.[12] Our findings of negative mismatches among hedge funds suggest that funds can adopt alternative devices, besides a "fragile" capital structure, to mitigate conflicts between fund managers and investors.

Our work also contributes to recent efforts to measure liquidity mismatches among asset managers. Agarwal, Aragon, and Shi (2016) study registered funds of hedge funds (FoFs) and compute mismatch as the difference between the average redemption frequency of their investments in underlying hedge funds (assets) and the redemption frequency they offer to its own investors (equity). Compared to their study, we focus on mismatches in hedge funds (versus registered FoFs) and extend their measure to incorporate leverage. This is important because leverage is used extensively by hedge funds and, as we show, the committed period of a fund's borrowings (financing illiquidity) is typically much lower than its investor illiquidity. We also examine a different set of research questions related to the determinants of financing and investor

as liquid, semi-liquid, or illiquid. Other empirical studies of liquidity mismatches in banks include Deep and Schaefer (2004) and Bai, Krishnamurty, and Weymuller (2015).

[12] See, e.g., Diamond and Dybvig (1983), Gorton and Pennacchi (1990), Calomiris and Kahn (1991), Flannery (1994), and Diamond and Rajan (2000, 2001).

illiquidity, as well as the use of unencumbered cash and unused borrowing capacity as liquidity buffers.[13]

We contribute to prior work showing that cash holdings of asset managers play a major role in providing liquidity to fund investors. Chordia (1996) predicts that mutual funds with a greater exposure to investor redemptions will hold more cash as a liquidity buffer. Consistent with this prediction, we find that hedge fund cash holdings are negatively related to investor illiquidity. Focusing on changes in cash holdings, Chernenko and Sundarem (2016) find that mutual funds reduce their cash (as a percentage of NAV) during periods of investor outflows. Our main findings contrast with the mutual fund evidence in that hedge funds actually *increase* their cash buffers when outflows occur, an indication that hedge funds adjust cash buffers in anticipation of future liquidity needs. Further, we show that a hedge fund's ability to enact discretionary liquidity restrictions, like side pockets and gates, helps explain the difference in our findings from the mutual fund literature.[14]

Finally, theories of corporate liquidity management argue that available lines of credit, like cash holdings, provide insurance against liquidity risk.[15] To our knowledge,

[13] Related work includes Teo's (2010) finding of significant liquidity risk-taking among hedge funds that offer generous liquidity terms to their investors. Sadka (2010) finds that hedge funds with greater liquidity risk earn higher average returns. Liu and Mello (2011) present a theory of financial fragility in hedge funds. Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2015) find a greater sensitivity of investor flows to fund performance among mutual funds with a greater exposure to illiquid assets.

[14] See Aiken, Clifford, and Ellis (2015) for a discussion of discretionary liquidity restrictions in hedge funds. Several papers highlight the role of cash in corporate liquidity management (e.g., Opler et al., 1999; Almeida et al., 2004; Faulkender and Wang, 2006; Bates, Kahle, and Stulz, 2009; and Falato, Kadyrzhanova, and Sim, 2015).

[15] See, e.g., Boot et al., (1987) and Holmstrom and Tirole (1998). Kashyap et al. (2002) and Gatev and Strahan (2006) argue that banks have a comparative advantage in providing lines of credit compared to other institutions.

our analysis is the first to show that hedge funds maintain significant levels of unused credit, especially when they face a greater liquidity risk in the form of short commitments of financing from their creditors. In fact, 63% of funds have some available borrowing at some point in our sample period. For comparison, Sufi (2009) finds that the majority (85%) of his sample of industrial firms have a line of credit.

The rest of the paper is organized as follows: Section 2 discusses the data and summary statistics. Section 3 discusses our findings for liquidity mismatches in hedge funds. Section 4 discusses our findings on the determinants of investor and financing illiquidity, and on changes in hedge fund cash holdings and unused borrowing capacity. Section 5 concludes.

2. Data and summary statistics

2.1. Form PF and other data sources

The main data in our analysis come from Form PF regulatory filings. Since mid-2012, Form PF filings are required by all Securities and Exchange Commission (SEC)-registered investment advisers with at least $150 million in private fund (PF) assets. [16] The information reported in Form PF is nonpublic and contains information about each individual private fund under management, including the fund's identity, investment strategy and performance, assets under management, borrowing, and balance sheet liquidity.

[16] As noted in the adopting release (17 CFR Parts 275 and 279 – Release No. IA–3308), "The information contained in Form PF is designed, among other things, to assist the Financial Stability Oversight Council in its assessment of systemic risk in the U.S. financial system."

Our analysis focuses on the subsample of private funds that report their fund type as "Hedge Fund" and answer Section 2b of Form PF[17]; this Section provides fund-level information that is central to our analysis, such as the fund's asset illiquidity, unencumbered cash, available borrowing, and the committed periods of investor and lender financing. Furthermore, this information is available on a quarterly basis; therefore, we can study how hedge funds manage their liquidity in a dynamic setting at a relatively high frequency. Our final sample contains 12,384 quarterly filings over 2013-2015 made by 1,809 funds of 559 advisers.[18]

We also use data from the public Form ADV regulatory filings of hedge fund advisers in our sample, including the adviser's percentage ownership stake in the fund, whether the fund uses an independent administrator to value the fund's assets, and the number of prime brokers used by the fund. Finally, we use VIX data supplied by DataStream. All variables used in our analysis are defined in the Appendix.

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[17] Only the so-called *Qualifying Hedge Funds*, which have at least $500 million in net assets, answer Section 2b. Note that the Form requires aggregating all master-feeder funds, parallel funds, and dependent parallel managed accounts associated with a fund to determine whether it is a Qualifying Hedge Fund or not. However, advisers are allowed to report fund level data separately as well as on an aggregated basis; thus, some Qualifying Hedge Funds may have net assets less than $500 million (see Form PF General Instructions for reporting and aggregation requirements). Some results in this paper, and the conclusions we draw from them, could conceivably change if our sample included information from all funds, not just the Section 2b filers.

[18] Our sample contains a cross-section of both small and large funds (see Table 1 for details).

Figure 2 plots the number of advisers and hedge funds in our estimation sample. The number of advisers grows from 331 to 436 over 2013Q1-2015Q3, while the number of corresponding funds grows from 891 to 1,292.[19]

2.2. Method of measuring liquidity mismatches in hedge funds

The main objective of our study is to measure liquidity mismatches in hedge funds – that is, differences between a hedge fund's asset illiquidity and the illiquidity of its liabilities and equities. The Form PF data makes this possible because it provides detailed data on a hedge fund's asset holdings and capital structure, two critical components of liquidity mismatch. Moreover, the Form PF filings include information about the illiquidity of a fund's assets, liabilities, and equity, all measured in the same units.[20] The following subsection provides a detailed discussion of our methodology.

2.2.1. Asset illiquidity

As illustrated in Figure 1, asset illiquidity is a function of a hedge fund strategy and its underlying assets, and is the first type of liquidity being established and calculated. We first obtain information about the illiquidity of a hedge fund's non-cash assets from Question 32 of Form PF. This question asks each fund to report the percentage of non-cash assets that could be liquidated assuming no fire-sale discounting within each of the following intervals of days: 1 or fewer, 2-7, 8-30, 31-90, 91-180, 181-

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[19] Our sample excludes quarterly filings with missing or extreme values for our variables of interest (see Section 2.3 for a detailed explanation of the filters applied).

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365, and 365 or more.[21] We calculate the illiquidity of a hedge fund's non-cash assets (*PortIlliq*) by summing up the products of the reported percentage and the midpoint of the corresponding interval.[22] Intuitively, *PortIlliq* is greater for funds that hold more illiquid assets, because such a fund would require more time to liquidate its assets in absence of fire sales. For example, the value of *PortIlliq* for a hedge fund holding the most liquid (illiquid) non-cash assets would be one (365) days.

Next we create an overall asset illiquidity measure by combining *PortIlliq* with unencumbered cash and cash equivalents (*Cash*).

$$AssetIlliq = PortIlliq \times \left(1 - \frac{Cash}{GAV}\right) + 1 \times \left(\frac{Cash}{GAV}\right)$$

The above expression is a weighted average of the illiquidity of a fund's non-cash assets (*PortIlliq*) and the illiquidity of its cash (one day). The weight applied to *PortIlliq* is essentially the value of a fund's non-cash assets as a percentage of gross asset value (*GAV*). We assign *Cash* the lowest possible time-to-liquidate of just one day (i.e., most liquid).[23]

2.2.2. *Financing and Investor Illiquidity*

We focus on unencumbered cash since it is freely available to the manager to meet margin calls or investor redemptions and provides a liquidity buffer. In contrast, a fund's total cash position may include cash posted as margin. Even so, for robustness, we repeated our analysis of liquidity mismatch (Table 3) after replacing *Cash* with total cash (from Form PF Q26 or Q30) in our calculation of *Mismatch*. The results from this robustness check are qualitatively unchanged from those using unencumbered cash.

According to Figure 1, once the planned asset liquidity is established (at time = -1), both investor and financing liquidity are negotiated and established at hedge fund's inception (time=0). Advisers for each hedge fund report in Q46(b) the percentage of a fund's total available (i.e., used and unused) borrowing that has been contractually committed to the fund for the same set of intervals listed in Question 32. [24] This provides a measure of financing illiquidity (*FinIlliq*), which is calculated as the weighted average of the interval midpoints. Likewise, for the same set of intervals, respondents to Question 50 report the percentage of equity capital that is contractually committed to the fund. The latter intends to account for all relevant investor liquidity, such as lock-up periods, imposed gates, redemption frequency, and notice periods. We calculate investor illiquidity (*InvIlliq*) as the weighted average of interval midpoints. Finally, we combine financing and investor illiquidity to create an overall measure of the illiquidity of a fund's equity and liabilities:

$$FinInvIlliq = \left(\frac{NAV}{GAV}\right) \times InvIlliq + \left(1 - \frac{NAV}{GAV}\right) \times FinIlliq$$

FinInvIlliq is simply a weighted-average of *InvIlliq* and *FinIlliq*, where the weight on *InvIlliq* is the inverse of the fund's leverage ratio. [25]

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[24] We understand that hedge funds that may not report obligations under derivatives contracts as "borrowings" in Q12, Q43 or Q46(b) of Form PF. To the extent that funds do not include these obligations in their PF filings, the liquidity terms reported in Q46(b) may understate a fund's liquidity exposure, hence causing to underestimate its overall "liquidity mismatch".

[25] For robustness, we compute the inverse of the fund's leverage ratio by replacing GAV with NAV + *UsedBrw* (where *UsedBrw* is actual used borrowing from Form PF, Q43 or, if missing, Q12). We then repeat our analysis of liquidity mismatch (Table 3). The results from this robustness check are qualitatively unchanged from those using GAV.

We then construct a global measure of liquidity mismatch for each fund and quarter equal to the illiquidity of the fund's assets including cash (asset illiquidity) minus the illiquidity of the fund's liabilities (financing illiquidity) and equity (investor illiquidity). Both sides of balance sheet liquidity are measured in days. Thus, *Mismatch* is measured as the difference between *AssetIlliq* and *FinInvIlliq*:

$$Mismatch = AssetIlliq - FinInvIlliq$$

Intuitively, positive values of *Mismatch* will occur when a fund pursues a long-term investment strategy while maintaining shorter-term commitments from its investors and creditors. A fund that "borrows short" therefore has *Mismatch* > 0. In contrast, a fund that is financing very liquid assets with relatively long-term capital will show negative values of *Mismatch*. A fund that "borrows long" therefore has *Mismatch* < 0.

2.3. *Summary statistics*

Our final sample excludes fund/quarter observations with missing values for net asset value (*NAV*), gross asset value (*GAV*), non-cash asset illiquidity (*PortIlliq*), fund investor illiquidity (*InvIlliq*), unencumbered cash (*Cash*), unused borrowing capacity (*UnuBrwRatio*), and investment strategy. We also drop observations where *Cash* or *UnuBrwRatio* have negative values, *GAV* is either strictly less than either *NAV* or *Cash*, or *NAV* is less than or equal to zero. In principle, the sum of percentage values entered across all periods in Q32 (portfolio illiquidity), Q46(b) (Financing Illiquidity), and Q50 (Investor Illiquidity) should be 100%. However, we observe some observations where these sums are very different from 100%. Therefore, we drop observations where either sum is either less than or equal to 90% or greater than or equals to 110%.[26] All variables (except *VIX* and dummies) are winsorized each quarter at the 1% and 99% levels.

Table 1 Panel A shows that the mean illiquidity of a fund's assets (65.9 days) is lower than the illiquidity of its liabilities plus equity (145.9 days). The average *Mismatch* in our sample is -85.5 days, indicating that the typical hedge fund in our sample has a "liquidity cushion."[27] In other words, it takes a shorter time for the typical fund to liquidate its assets than it takes for its stakeholders to reclaim their financing and redeem equity shares. This is consistent with Agarwal, Aragon, and Shi's (2016) finding of a negative illiquidity gap, on average, in their sample of funds of funds over 2004-2011.[28] The top panel of Figure 3 plots the average value of *Mismatch* over our sample period. We see that liquidity mismatches in hedge funds co-vary positively with market volatility, as measured by a pairwise correlation between *Mismatch* and *VIX* of 0.78. The bottom panel of Figure 3 shows that greatest (i.e., least negative) mismatches are found among the smaller hedge funds. We investigate these relations further in a multivariate setting.

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[26] For robustness, we repeated our analysis after applying more (less) restrictive filters by dropping observations where either sum in Q32, Q46(b), or Q50 is either less than or equal to 95% (85%) or greater than or equals to 105% (115%). The results from this robustness check are qualitatively unchanged from those using the 90% – 110% thresholds.

[27] The average *Mismatch* is not the difference between the average *AssetIlliq* and *FinInvIlliq* because *FinIlliq* is missing for 3,159 observations in our final sample. For these observations, we can compute *AssetIlliq* but neither *FinInvIlliq* nor *Mismatch*.

[28] Agarwal, Aragon, and Shi (2016) report a greater (i.e., less negative) mismatch of -20 days, suggesting that the liquidity cushion in registered funds of funds is lower than that of large individual hedge funds. A close comparison of the two papers shows that this difference is mainly coming from greater asset illiquidity among funds of funds. This makes sense given that the main assets held by funds of funds are investments in hedge funds, which are inherently illiquid.

A further partitioning of *AssetIlliq* yields additional insights. Table 1 Panel A shows that the illiquidity of a hedge fund's non-cash assets (*PortIlliq*) is greater than that of total assets. This is unsurprising since *PortIlliq* does not account for a fund's cash holdings. The ratio of unencumbered cash to net asset value (*CashRatio*) has a sample median of 6.9%. This is comparable to Chernenko and Sunderam's (2016) finding that equity and bond mutual funds have a median cash ratio of 4.38% and 7.52%, respectively.

A comparison of *InvIlliq* and *FinIlliq* provides a richer understanding of *FinInvIlliq*. Table 1 Panel A shows that, while fund investors typically commit their capital for a mean period of 173 days, a fund's creditors commit their financing for only 52.9 days. Strikingly, *FinIlliq* has a median value of just one day implying that hedge funds largely rely on very short-term loans.[29] The disparity between investor and financing illiquidity highlights the dependence of a hedge fund's liquidity mismatch on its leverage ratio, with a greater leverage ratio placing more weight on *FinIlliq* and, hence increasing *Mismatch*.

Table 1 also summarizes the ratio of unused borrowing to total (used plus unused) borrowing (*UnuBrwRatio*).[30] The dollar amount of unused borrowing reflects the credit

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[29] Some filers may report their financing terms as "1 day or less" despite having longer-term agreements in place. According to form PF instructions: "(If a creditor […] is permitted to vary unilaterally the economic terms of the financing or to revalue posted collateral in its own discretion and demand additional collateral, then the financing should be deemed uncommitted for purposes of this question. Uncommitted financing should be included under "1 day or less.")". The data does not allow us to distinguish between filers that agree on one-day-term loans vs. filers that agree on longer terms but are subject to daily revaluation of collateral.

[30] Unused borrowing is taken as the difference between available borrowing and actual borrowing. Available borrowing is reported in Question 46(a), which asks each fund to report the "aggregate dollar amount of borrowing by and cash financing available to the reporting fund (including all drawn and

available through a committed line of credit and/or the fund's free credit balance in its margin account – that is, the excess of the value of margin securities over the margin requirement.[31] In our sample, *UnuBrwRatio* has a sample mean of 28.7%. To put this number into perspective, we compute a measure of publicly-reported margin loan capacity from the aggregate margin balances reported by member organizations of the New York Stock Exchange.[32] Specifically, for each quarter in our sample, we divide the total credit balances in margin accounts (i.e., unused margin borrowing) by the total available margin borrowing (i.e., credit balances in margin accounts plus margin debt balances). We find (not tabulated) that this NYSE-based variable has a sample mean of 26% and a correlation with *UnuBrwRatio* of 73%. This suggests that *UnuBrwRatio* – which includes undrawn lines of credit and credit balances in margin accounts – is comparable to and correlated with aggregate margin loan capacity among customers of broker-dealers.

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undrawn, committed and uncommitted lines of credit as well as any term financing)." Actual borrowing is reported in Questions 43. Specifically, we compute actual borrowing as the sum of the responses to the subcategories of Question 43. In some cases, where, responses to Question 43 are missing, we use the response to Question 12. Lastly, we drop observations with negative values of unused borrowing. We do not have an economic interpretation for negative values of unused borrowing and, therefore, attribute these observations to reporting error.

[31] Suppose a hedge fund has $100 worth of margin securities, a debit balance (i.e., margin borrowing) of $25, and the remaining $75 is equity. If the maintenance margin requirement is 50%, then the fund could withdraw cash up to $25, reducing its equity down to $50, and increasing its debit balance to $50. Alternatively if the margin requirement is only 25% the fund could withdraw cash up to $50, reducing its equity to $25, and increasing its debit balance to $75. In other words, the fund has an excess margin, or, free credit balance, of $25 and $50, respectively. See Fortune (2000) for additional discussion of margin accounting.

[32] The data are from the Margin Debt and Stock Loan, Securities Market Credit segment of the NYSE Facts and Figures website (http://www.nyxdata.com/nysedata/asp/factbook/main.asp). The NYSE notes, "NYSE member organizations are required to report monthly their aggregate debits (amount borrowed by customers to purchase securities) in margin accounts, as well as aggregate free credits (cash balances) in cash and margin accounts."

Table 1 Panel B shows basic summary statistics for other variables in our analysis. The median fund has gross assets value (*GAV*) of $1.249 billion and net asset value (*NAV*) of $907.9 million. In comparison, Aragon and Nanda (2016) and Agarwal, Daniel, and Naik (2011) report a median size of $29 million and $25 million, respectively. The difference shows that our sample contains more funds with larger assets under management compared to the prior study. [33]

The equal-weighted mean leverage of hedge funds in our sample is 1.6, which is lower than the few existing estimates of hedge fund leverage.[34] Jiang (2015) combines the gross asset values from Form ADV filings with the net asset values from client brochures to infer the leverage levels of hedge fund advisers over 2011-2013. He reports mean leverage of 1.96 (i.e., aggregated across an adviser's underlying hedge funds). Ang, Gorovyy, and van Inwegen (2011) report an average leverage of 2.13 using a proprietary sample of hedge funds obtained from a fund of fund investor. They also report a downward trend in leverage use since the financial crisis, which could partly explain why our estimate (from a more recent sample) is lower.

Quarterly returns (1.6%) and net flows (1.0%) are positive, on average, over our sample period, but there is a considerable variation in outcomes. For example, the standard deviation of returns and flows is 5.3% and 16.7%, respectively, across both time and filers. We exploit this variation later to see how funds adjust their cash and unused borrowing in response to and in anticipation of negative flows and returns.

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[33] This is, of course, partially due to the fact that only QHFs (as defined in Form PF) are reported in Section 2b. This essentially places a soft floor of $500 million on the NAV of the funds in our sample.

[34] The asset-weighted mean leverage of hedge funds in our sample is 1.77.

Table 1 Panels C and D summarize other Form PF variables used in our sample. Hedge funds allocate 36.2% of their assets to equity strategies, on average, as compared to just 2.0% for managed futures strategies. *HHI* is a Herfindahl-Hirschman Index calculated as the sum of squared percentage allocations to seven portfolio strategies. This captures the fund's strategy concentration and can take a maximum value of unity (most concentrated). Our sample has a median *HHI* of unity, suggesting that hedge fund portfolios are typically focused on a single investment strategy. On average, the top five investors and the hedge fund adviser have ownership stakes in the fund of 61.3% and 12.5%, respectively, suggesting that many hedge funds are majority owned by a few investors. Lastly, the quarter-end level of *VIX* has a sample mean of 16.5% and ranges from 11.6% to 24.5% over our sample period.

3. Liquidity mismatches in the cross-section and over time

The above discussion shows that liquidity mismatches are negative, on average, indicating that a fund's assets are more liquid than its liabilities and equity. In this section we examine how liquidity mismatches vary across hedge funds and time. We also examine the separate components of liquidity mismatches to shed light on how hedge funds manage liquidity.

3.1. *Liquidity mismatches: Univariate comparisons*

Table 2 shows the average characteristics of funds with low (bottom quartile), medium (middle quartiles), and high (top quartile) values of *Mismatch*. A few interesting patterns emerge. First, high liquidity mismatches are associated with smaller funds (*Ln(NAV)*) and funds in which the adviser has a small ownership stake (*AdvOwner*). Teo

(2011) argues that such funds face strong incentives to raise capital and, in line with an agency explanation, are more prone to take excessive liquidity risk. Second, large mismatches are associated with greater leverage. This makes sense in light of our earlier findings that the illiquidity of a fund's creditors (*FinIlliq*) is typically much lower than that of its investors.[35] Ceteris paribus, a higher leverage ratio places more weight on the former and increases *Mismatch*. Finally, low mismatches are associated with certain investment strategies, such as Credit and Event Driven. On one hand, these strategies typically involve greater asset illiquidity (e.g., fixed income securities and merger arbitrage), which would increase mismatch. However, in our sample, these strategies are associated with a greater liability plus equity illiquidity, and the net effect is a lower mismatch.

3.2. *Liquidity mismatches: Regression framework*

Next we assess these relations more closely in a multivariate regression framework. The first two columns of Table 3 present results in which the dependent variable is $Mismatch_{iq}$ – that is, the liquidity mismatch of fund i at the end of quarter q. All explanatory variables are measured at the end of quarter q. The results largely confirm our univariate findings: liquidity mismatches are greater among smaller funds, and funds with greater leverage.[36] The latter result contrasts with Berger and Bouwman's (2009) finding of a positive relation between a bank's equity capital ratio and liquidity

[35] This result is largely dependent on the fact that most filers report their financing terms as "1 day or less".

[36] The investment strategy variables *Credit* and *EventDriven* (not tabulated to save space) are associated with significantly lower mismatches, as we find in Table 2.

mismatch in large banks.[37] Rather, our evidence shows that hedge funds tend to have a higher mismatch (worse liquidity condition) when they have a higher leverage ratio. Higher mismatch is also present among funds where advisers have a lower ownership stake. A possible interpretation is that funds that are more prone to agency problems take on “excessive” liquidity risk, as argued by Teo (2011).

Bai, Krishnamurthy, and Weymuller (2015) show that aggregate liquidity mismatch in banks – i.e., the difference between asset illiquidity and liability illiquidity – increased significantly during the crisis. The reason is that drops in market-wide measures of liquidity can significantly impact the liquidity weights assigned to the assets and liabilities on the bank’s balance sheet, thereby increasing the vulnerability of banks to liquidity stress. While our sample period lies outside the crisis period, we exploit time variation in market conditions by including a measure of market illiquidity (*VIX*) as an additional explanatory variable in our *Mismatch* regression.

Consistent with hedge funds being more susceptible to liquidity runs during periods of market stress, we find a positive and significant relation between mismatches and *VIX*.[38] Specifically, a one standard deviation increase in *VIX* is associated with an increase in *Mismatch* of 3.11 days. Furthermore, Columns (3) and (4) run separate regressions for each component – *AssetIlliq* and *FinInvIlliq* – of mismatch. The results show that the significant positive relation between *VIX* and *Mismatch* is driven by a

[37] We again find a positive relation between mismatches and leverage when we repeat the regression on subsamples of funds in the bottom, middle, and top quartiles of *NAV*. Our results are qualitatively similar when we replace *NAV* with *GAV* in Table 3 regressions.

[38] We find qualitatively similar results when we replace *VIX* with either the TED spread or Pastor and Stambaugh’s (2003) market liquidity measure.

positive relation between *VIX* and asset illiquidity. This makes sense given that *AssetIlliq* depends directly on *PortIlliq* and, according to Question 32 of Form PF, *PortIlliq* is based on the manager's "good faith estimates for liquidity [of non-cash assets] based on market conditions over the reporting period."[39]

Interestingly, some variables (*Ln(AdvNAV) and Top5Owner*) explain the *AssetIlliq* and *FinInvIlliq* components of mismatch, but do not have much statistical power in predicting *Mismatch* itself in Column (2).[40] This provides preliminary evidence of hedge funds matching the maturity structure of their assets with that of their equity and liabilities. In the next section we examine the components of hedge fund liquidity management in greater detail.

4. Liquidity management and its components

The evidence above shows that asset illiquidity is lower than the illiquidity of its liabilities and equity, and that these negative mismatches are related to fund characteristics and market conditions. In this section we test theoretical predictions about specific aspects of liquidity management. First, we examine how the contractually committed term of creditor and investor financing is related to asset illiquidity. Second, we study the determinants of hedge funds' cash holdings and unused borrowing capacity.

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[39] The coefficients in Column (2) of Table 3 do not exactly equal the difference in coefficients between Columns (3) and (4) due to the winsorization of *Mismatch*, *AssetIlliq*, and *LiabEqIlliq*.

[40] That is because these variables load up on each component with the same sign and similar statistical significance, hence their net effect on *Mismatch* becomes null.

Third, we examine whether managers dynamically adjust cash and borrowing capacity to protect against investor outflows and poor fund performance.

4.1. *Does asset illiquidity impact the term of creditor and investor financing?*

Existing theories posit that the maturity structure of a firm's liabilities and equity are related to the illiquidity of its assets. For example, Diamond (1991) argues that longer-maturity debt reduces the risk that a borrower will be forced to liquidate its assets in the event that short-term debt cannot be rolled over. Moreover, in a mutual fund setting where investors can redeem their shares in the fund for cash, Chordia (1996) argues that back-end fees and lockup periods can help fund managers dissuade investor redemptions.[41] Therefore, we examine whether the terms of committed financing on the equity (*InvIlliq*) and liability (*FinIlliq*) sides are greater among hedge funds with illiquid assets (*PortIlliq*).

An important concern in empirical tests of the relation between the terms of commitments of equity capital or loan facilities and portfolio illiquidity is that *InvIlliq*, *FinIlliq*, and *PortIlliq* are endogenous. However, note that *PortIlliq* is the illiquidity of a fund's non-cash assets, rather than the illiquidity of the fund's entire (i.e., cash plus non-cash) portfolio. Thus, assuming *portIlliq* to be exogenously determined does not preclude cash holdings and unused borrowing capacity from being impacted by investor and financing illiquidity (as we examine in Section 4.2). Moreover, it is plausible that a

[41] Nanda, Narayanan, and Warther (2000) and Lerner and Schoar (2004) present models in which redemption restrictions allow funds to attract investors with low liquidity needs. The disadvantages of longer-maturity debt include sending a negative signal about asset quality (Flannery, 1986), underinvestment and debt overhang (Myers, 1977) and asset substitution problems (Leland and Toft, 1996). The disadvantage of longer lockups on investor capital is that investors will demand an illiquidity premium (Aragon, 2007).

fund's investment strategy is a fundamental attribute of the manager (e.g., whether to be a shareholder activist vs. high-frequency trader), rather than a choice by the manager to pursue strategies that differ substantially in their liquidity. Therefore, we treat *PortIlliq* as an exogenous variable in our *FinIlliq* and *InvIlliq* regressions.[42] Figure 1 illustrates the time-line of strategy and liquidity management decisions for a typical hedge fund.

We use an instrumental variables approach to control for the endogeneity of *FinIlliq* and *InvIlliq*. Both equations include *PortIlliq, Ln(NAV), Ln(AdvNAV), IndepAdmin, HHI,* and investment strategy variables. In the *FinIlliq* equation, we also include the square of *Ln(NAV)* because Diamond (1991) predicts a positive, concave relation between debt maturity and firm size. We also include #*Brokers* based on motivation from the portfolio margining system.[43] In this system, brokers set margin requirements based on the riskiness of the fund's portfolio that they can observe. We posit that spreading a fund's trades across multiple prime brokers reduces the diversification benefits of portfolio margining for each individual broker and, in turn, brokers will demand shorter-term financing.[44]

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[42] Support for this assumption is provided by Table 1's finding that the average strategy *HHI* equals 0.8 an indication that hedge funds in our sample show a great deal of specialization in their investment strategies. We also find that funds generally exhibit stickiness in their investment strategy and that fund fixed effects explain 98.2% of the total pooled variation in *PortIlliq*, suggesting that the illiquidity of a fund's non-cash assets does not change much over time.

[43] This variable is likely over-representative of the prime brokers actually used by the fund. Advisers often report in form ADV the entire set of prime brokers with whom the fund has legal agreements in place but actively use only a time-varying subset.

[44] Another motivation for including *#Brokers* in the *FinIlliq* equation is that, by directing more of their brokerage through a fewer number of brokers, funds can potentially negotiate longer-term commitments. This channel would also predict a negative relation between the two variables.

We include *Top5Owner*, *DiscRestrict*, *AdvOwner* as additional explanatory variables in the *InvIlliq* equation. We argue that these variables plausibly capture a fund manager's (dis)incentive to restrict the liquidity of investors through longer commitment periods. We expect a negative relation between *InvIlliq* and *Top5Owner* because Chen, Goldstein, and Jiang (2010) argue that the presence of large investors can lower the chance of investor runs in mutual funds. Also, a small number of larger investors can potentially negotiate better liquidity terms (i.e., lower *InvIlliq*) as compared to funds with more diffuse ownership. Second, we expect a negative relation between *InvIlliq* and *DiscRestrict* because managers' ability to raise gates on fund investors at their discretion reduces the need to contract for longer investment periods (Aiken, Clifford, and Ellis, 2015). Finally, we expect a positive relation between *InvIlliq* and *AdvOwner* since investors may be more willing to commit to a longer-investment horizon when the fund manager has significant skin in the game.

Columns (1) and (2) of Table 4 present the results for the two stage least squares (2SLS) estimation of the simultaneous equation system. All variables (except dummies) are standardized to have a zero mean unit variance. We first note that the coefficients on our instrumental variables are significant and have the predicted signs. Our main results are provided by the estimated coefficients of *PortIlliq*. Consistent with theoretical predictions on liquidity management, we find that hedge funds with more illiquid assets are associated with longer term commitments by fund investors. Specifically, a one standard deviation increase in portfolio illiquidity is associated with a 0.565 standard deviations increase in *InvIlliq*. This suggests that managers investing in more illiquid market segments have more stable funding sources.

Aragon (2007) and Aragon, Liang, and Park (2013) find that lockup and redemption periods imposed on fund investors (i.e., a measure of investor illiquidity) are more common among hedge funds with greater return autocorrelation (i.e., a measure of asset illiquidity). Compared to these studies, our findings are based on a measure of asset illiquidity that is reported directly by fund managers.

Table 4 Column (1) also shows that *FinIlliq* is estimated to increase by 0.0758 standard deviations per one standard deviation increase in *PortIlliq*; however, this estimate is not significant (t=0.86). A possible explanation for this "non-result" is that, while a greater illiquidity of a fund's non-cash assets might lead funds to prefer longer-term financing, its creditors are less willing to commit to a longer financing period when the fund's collateral is relatively illiquid. We also find a positive and significant coefficient on *InvIlliq*, indicating that funds with stricter redeeming rights tend to have longer term financing from creditors. Perhaps, a hedge fund's lenders are reassured when investors make long-term commitments, and may be more willing to lend for a longer term.

Finally, Columns (3) and (4) of Table 4 present the results from running ordinary least squares (OLS) separately on the *InvIlliq* and *FinIlliq* equations. Again, we find a positive and significant coefficient on *PortIlliq* in both equations. However, the relation between *FinIlliq* and *PortIlliq* is now significant in the OLS equation, which highlights the importance of controlling for the endogeneity of *InvIlliq* and *FinIlliq* as we do in Columns (1) and (2).

4.2. *What determines a hedge fund's cash holdings and unused borrowing capacity?*

Dai and Sundaresan (2010) argue that a hedge fund manager writes to its stakeholders: 1) a redemption option that allows fund investors to redeem their stakes in the fund; and 2) a funding option that allows prime brokers to withdraw their lines of credit or increase margins. As discussed above, hedge funds can manage the liquidation risk inherent in these two options by contracting for longer-term commitments from investors and creditors. However, a fund's financing and investor illiquidity are contractually set and, therefore, are not easily adjusted in response to market conditions.[45] Following Figure 1, once asset, investment, and financing liquidity parameters are set, hedge fund managers use cash holdings and unused borrowing capacity to dynamically manage fund liquidity. Taking financing illiquidity as given, we now examine whether hedge funds use unencumbered cash holdings and unused borrowing capacity as additional liquidity buffers against fire sale risk.[46]

In Chordia's (1996) model, funds that do not impose redemption fees or other restrictions hold more cash. By holding more cash, a fund can meet the liquidity demands of investors without having to engage in asset fire sales. Chernenko and Sunderam (2016) develop a model of mutual funds that predicts a positive relation between cash holdings and asset illiquidity, due to the greater costs of fire sales when assets are illiquid. We adapt these predictions to our setting by positing that cash holdings are greater among

[45] To avoid forced sales of illiquid assets at unfavorable prices funds can decide to enact discretionary liquidity restrictions (DLRs) such as gates and side pockets. Despite the fact that most hedge fund agreements give the manager the option to restrict investor liquidity by invoking DLRs, previous studies have shown that funds exercise this option only in extreme market conditions as DLRs negatively impact fund family reputation making hard to subsequently raise capital and more likely to cut fees (Aiken, Clifford and Ellis (2015)).

[46] Note that, by taking a hedge fund's financing illiquidity (i.e., term of committed financing) as given in our analysis of unused borrowing capacity, our setting differs from prior corporate finance studies in which both leverage and maturity are jointly determined (Barclay, Marx, and Smith, 2003; Johnson, 2003).

funds with lower investor illiquidity (*InvIlliq*) and greater asset illiquidity (*PortIlliq*). We focus on the ratio of unencumbered cash to net asset value (*CashRatio*) because unencumbered cash represents cash equivalent assets that have not been pledged as collateral. Therefore, *CashRatio* is the cash available to be freely deployed to meet investor redemptions as a percentage of investor capital.[47]

Unused borrowing in hedge funds represents undrawn lines of credit and margin capacity still available to the fund.[48] Either source can help the manager avoid costly deleveraging and asset fire sales by providing a type of liquidity insurance. For example, funds can use lines of credit to roll over short term debt without having to liquidate its assets. Unused borrowing capacity is created when the value of collateral held in a fund's margin account exceeds the maintenance margin. In this situation, the fund is at a lower risk of a margin call and, hence, a forced deleveraging. Therefore, similar to our predictions for hedge fund cash holdings, we expect greater unused borrowing capacity among funds with low financing illiquidity (*FinIlliq*) and greater asset illiquidity (*PortIlliq*). In our empirical analysis, we measure unused borrowing capacity as the ratio of unused borrowing and total (i.e., used and unused) borrowing (*UnuBrwRatio*).[49]

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[47] More broadly, the theoretical literature argues that one important benefit of cash is to eliminate the need to liquidate assets to meet payments in the future (Chordia, 1996; Opler et al., 1999). Cash also allows firms to make new investments while avoiding costly external finance (Froot, Scharfstein and Stein, 1993). Disadvantages of cash include its opportunity cost (i.e., "liquidity premium") and potential agency costs of "free-cash flow" in which managers waste resources on bad projects.

[48] Existing theories of lines of credit in corporate finance argue that lines of credit provide liquidity insurance because they allow firms to obtain funds when financing needs arise (see, e.g., Boot et al., 1987; Holmstrom and Tirole, 1998, Martin and Santomero, 1997). In the hedge fund setting, Sufi (2009) provides an empirical study of corporate cash holdings and lines of credit.

[49] Specifically, *UnuBrwRatio* equals *UnuBrw*/*TotBrwAvail* if *TotBrwAvail* is greater than zero, and equals zero if *TotBrwAvail* equals zero.

Table 5 presents the results from testing the above hypotheses. Consistent with theoretical predictions, we find greater cash holdings and unused borrowing among funds that have relatively short-term commitments from investors and creditors. Our estimates in Column (2) indicate that a one-standard deviation increase in *InvIlliq* is associated a drop in *CashRatio* of 0.0283 (0.12 standard deviations). Similarly, Column (4) shows that the ratio of unused borrowing to total borrowing decreases by 0.0627 (0.18 standard deviations) per one standard deviation increase in *FinIlliq*. In contrast, we do not find a significant relation between *CashRatio* and *FinIlliq*, nor between *UnuBrwRatio* and *InvIlliq*. This suggests that cash holdings and unused borrowing capacity provide a type of liquidity insurance against funding shocks from fund investors and creditors, respectively.

Table 5 also reveals a positive and significant relation between *UnuBrwRatio* and *PortIlliq* (*t*-statistic = 1.94), which is consistent with the above prediction that funds maintain greater levels of reserve borrowing when potential fire sale costs are greater. However, in contrast to Chernenko and Sunderam's (2016) evidence for mutual funds, we do not find that asset illiquidity is associated with greater cash holdings in hedge funds. This suggests that hedge funds are more concerned about potential fire sale costs resulting from forced deleveraging by its creditors rather than from investor redemptions.

Finally, Table 5 shows that cash holdings are greater during periods of high VIX, whereas the relation between unused borrowing capacity and VIX is not significant. One possible explanation is that managers hold more cash in anticipation of future liquidity stress, such as periods of greater market volatility. In contrast, a similar increase in unused borrowing capacity is not observed due to higher margins and spreads charged on lines of credit by banks during periods of high VIX (Acharya, Almeida, and Campello, 2013). In the following, we examine whether managers dynamically adjust cash holdings and unused borrowing in response to and in anticipation of liquidity stress.

4.3. Dynamic cash management and investor flows

The above results show that hedge funds maintain greater cash holdings when they are exposed to investor redemptions (i.e., low investor illiquidity). In this section we examine how changes in cash holdings are related to investor flows. To address this we follow prior literature and define net flows (*NetFlow*) as the difference between the percentage growth in net asset value and fund returns. We compute quarterly flows since hedge funds are required to report assets under management on a quarterly basis.

Table 6 shows the results from regressing quarterly changes in cash on net flows during the same quarter. The dependent variable in the first three columns is the quarterly change in *Cash* divided by *NAV* in the prior quarter. All specifications include quarter dummies and style category variables. From Model (1) we see that the coefficient on *NetFlow* is 0.1796; thus, a decrease in net flows by $1 is associated with a decrease in cash by $0.18. This estimate is comparable to those reported in earlier studies. For example, Chernenko and Sundarem (2016) report that cash holdings of mutual funds change in response to net flows over the most recent quarter at a rate of about $0.13 and $0.21 per dollar for equity and bond funds, respectively.[50] We also illustrate our findings

[50] Chernenko and Sundarem (2016, Table 2) regress semi-annual changes in mutual fund cash on the six monthly net flows over the same period, whereas we regress hedge fund cash changes on net flows at a

graphically in Figure 4. The top panel shows that the average percentage change in cash increases monotonically as we move from the lowest to the highest flow deciles.

The above finding might simply reflect hedge funds scaling back their entire portfolio ("vertical cut") in response to flows. However, if a manager anticipates future redemptions then she might choose to disproportionately liquidate her non-cash assets so that the fund has a larger cash position relative to the remaining investor capital ("horizontal cut"). Therefore, in the final three columns of Table 6 we repeat the analysis using the quarterly change in cash ratio (*CashRatio*) as the dependent variable. Strikingly, the relation between changes in *CashRatio* and net flows is negative, indicating that managers increase their cash buffers in response to net outflows. Models (5) and (6) further show that this relation is only significant for the negative part of net flows, denoted by min(*NetFlow*,0). This indicates that the managerial response to net outflows is driving the overall negative relation. This is illustrated in the bottom panel of Figure 4, which shows that the largest increase in cash ratio (1.2 percentage points, on average) is, indeed, concentrated in the lowest flow decile.

Panel A of Table 6 also shows that fund returns are positively related to percentage changes in cash. This makes sense to the degree that fund managers rebalance their portfolios to maintain a constant percentage allocation to safe assets (i.e., cash). Hence, cash positions will fall following negative returns, as shown in Column (3), since otherwise a drawdown in returns would increase the fund's portfolio weight in cash. It also seems reasonable that rebalancing is imperfect due to trading costs so that funds may

quarterly frequency. To make our comparison, we average the three coefficients corresponding to the most recent three months of net flows.

still show a higher cash ratio following poor returns. This could help explain the negative coefficient on min(*NetReturn*,0) in Column (6).[51]

In Panel B of Table 6 we repeat the regressions of changes in cash ratio on various fund subsamples. We find that the evidence of hedge funds increasing cash buffers during periods of outflows is stronger during periods of high VIX. This is consistent with Jiang, Li, and Wang's (2016) evidence that the tendency for mutual fund cash ratios to fall during periods of outflows is weaker when macroeconomic uncertainty is high. The rationale is that during these periods managers are more averse to liquidity risk exposure and, as a result, maintain greater cash buffers in anticipation of future distress. We also find stronger evidence among funds with low investor illiquidity, suggesting that managers increase cash buffers especially when the threat of redemptions is more severe (Low *InvIlliq*). In addition, we find that the tendency to increase cash buffers during periods of outflows is significantly weaker among funds that are managed by larger advisers (Low Ln(*AdvNAV*)). One interpretation of this finding is that larger advisers can provide a backstop to member funds in case of a liquidity emergency, and so their funds have less of a need to increase their cash buffers in anticipation of future liquidity needs.[52]

[51] Consistent with this interpretation, we find that the negative coefficient on min(*NetReturn*,0) in (6) is no longer significant when we look at the subsample of funds that have low portfolio illiquidity – for those funds, it should be easier to maintain target cash ratios. Also, the positive coefficients on returns in (3) are larger in magnitude for this subsample, consistent with such funds having lower adjustment costs.

[52] Agarwal and Zhao (2016) find that larger mutual fund families are more likely to seek participation in inter-fund lending whereby family funds can borrow from member funds to meet investor redemptions.

Our finding that hedge funds' cash ratios rise during periods of outflows differs from recent evidence that the cash ratios of mutual funds fall with outflows (Chernenko and Sundarem, 2016; Jiang, Li, and Wang, 2016). A possible explanation for the disparate findings is related to Zeng's (2016) theory of cash management in mutual funds. He argues that fund managers face a tradeoff in choosing the speed with which they reestablish a cash buffer after outflows. On one hand, rebuilding a cash buffer at a faster rate allows the fund to avoid future liquidation costs in the event of further outflows. On the other hand, rapidly restoring cash buffers might entail significant costs from liquidating non-cash assets in the fund's portfolio. As a result, fund investors have an incentive to exit the fund pre-emptively to avoid these costs, thereby triggering a run.

One difference from the mutual fund setting is that most hedge funds reserve the right to temporarily suspend investor redemptions (70%, see Table 1). These discretionary restrictions (i.e., gates and/or side pockets) should curtail the threat of an investor run in the event that a manager maintains or increases the fund's cash buffers during periods of outflows. Therefore, we predict that our evidence for the full sample would be weaker (or, perhaps, in reverse) for the subsample of hedge funds that offer "mutual-fund-like" liquidity terms to investors – that is, funds with low *InvIlliq* and without discretionary restrictions. Support for this hypothesis is provided in the final two columns of Table 6 Panel B. Similar to the mutual fund evidence cited above, Column (7) shows that the coefficient on min(*NetFlow*,0) is positive (*t*-stat=1.09) for the subsample of hedge funds that offer "mutual-fund-like" liquidity terms. In contrast, our main finding for the full sample of hedge funds is driven by the larger sample of hedge funds with the ability to enact gates or side pockets.[53]

To shed further light on our evidence of cash management we ask whether fund managers respond differently to expected or unexpected outflows. The idea is that managers build up their cash buffers in anticipation of outflows during the following quarter. In this case, the portion of outflows that were anticipated would be associated with a drop in concurrent cash ratios as cash ratios fall back to target levels. In contrast, an outflow surprise could signal further outflows over subsequent quarters and trigger a cash buffer buildup. In this case, we would expect a negative relation between cash buffer changes and unexpected flows. To measure expected flows we regress *NetFlow* on lagged values of max(*NetFlow*,0), min(*NetFlow*,0), max(*NetReturn*,0), min(*NetReturn*,0), and *InvIlliq* (results not tabulated). We define expected ($NetFlow^{E}$) and unexpected ($NetFlow^{U}$) flows as the predicted and residual values from the regression, respectively.

Panel C of Table 6 presents the results from regressing Δ*CashRatio* on concurrent $NetFlow^{E}$ and $NetFlow^{U}$ flows. We either use a one-time, pooled estimation to construct $NetFlow^{E}$ (Columns (1)-(2)), or a recursive, backward-looking procedure to construct $NetFlow^{E}$ (Columns (3)-(4)). The coefficient on min($NetFlow^{E}$,0) is generally positive and significant, indicating a positive relation between cash buffer changes and expected outflows. This is consistent with a mean reversion in cash buffers following periods when managers accumulate cash in expectation of outflows. In contrast, the coefficient on

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[53] In Panel B of Table 6 there are 114 unique hedge funds that do not enact discretionary restrictions and have below-the-median investor illiquidity (i.e., of the 614 observations in Column (7)).

min(*NetFlow*^{U},0) is negative and significant, suggesting that managers respond to surprise outflows by increasing cash buffers

4.4. Do changes in cash holdings predict financial distress?

The results above show that hedge funds increase their cash ratios in response to outflows. One possible explanation is fund managers increase the fund's cash buffer in anticipation of future distress within the fund, as indicated by further outflows, low returns, or fund closure. For example, Liu and Mello (2011) present a theoretical model in which hedge funds increase their cash buffers in anticipation of future liquidity needs to lower potential liquidation costs and to reduce investors' fears of a possible run. Therefore, in Table 7 we report the results from regressing distress-related variables on lagged changes in cash ratios. Column (1) shows that *ΔCashRatio* is a negative and significant predictor of future flows. An increase in cash ratio of ten percentage points is associated with subsequent net flows of -1.153%. Column (2) shows that this predictability goes above and beyond the information contained in lagged flows, returns, or assets under management. Column (3) further shows that the significance of this finding is concentrated among increases (versus decreases) in cash buffers.[54]

Next we report the results from a Probit regression in which the dependent variable is a dummy that equals one if the fund is defunct after the following quarter – that is, it ceases filing Form PF and drops from our sample. It is possible that the defunct status indicates that the manager is liquidating the fund and returning money to fund

[54] Prior studies of hedge fund flows include Agarwal et al. (2006), Goetzmann et al. (2003), and Getmansky et al. (2015).

investors. In this case, we would expect an increase in cash buffers to predict the likelihood of a fund becoming defunct.[55] Column (7) shows that changes in cash buffers are positively and significantly related to the defunct fund dummy. An increase in cash ratio of 10 percentage points is associated with a 0.51% higher chance of becoming defunct. This number may seem small in absolute terms, but represents 27% of the overall frequency of defunct status (=0.51%/1.91%). Overall, the evidence is consistent with managers increasing cash buffers in anticipation of liquidation or distress as measured by investor outflows and fund closure.

Finally, we test whether changes in cash buffer predict either the level (Columns (4)-(5)) or sign (Column (6)) of net returns. In contrast to our evidence for net flows and defunct status, we find no evidence that changes in cash ratio have predictive power for net returns. This makes sense given that outflows and fund closure are direct measures of a fund's liquidity needs, whereas a higher cash ratio is not necessary to absorb negative fund returns.

4.5. Dynamic adjustment of unused borrowing capacity

In Table 8 we present the results from regressions of changes in unused borrowing capacity on fund flows and returns. Panel A shows the results for the full sample. In the first three columns, the dependent variable is the quarterly change in unused borrowing as a percentage of total available borrowing in the prior quarter. The

[55] Note that becoming defunct does not necessarily indicate fund liquidation. A fund can drop from our sample simply because the adviser's and/or the fund's size may fall below their respective Form PF reporting thresholds. However, our focus is on how changes in cash buffers impact likelihood of becoming defunct, rather than on the overall frequency of defunct status.

results show a positive and significant relation between dollar changes in unused borrowing and both net flows and returns. For example, the coefficient on max(*NetReturn*,0) is 0.5648. This indicates that a 1% increase in positive fund returns is associated with a 0.56% increase in unused borrowing. A possible interpretation is that higher fund returns reflect an increase in the market value of margin securities, which produces excess margin.

The final three columns in Panel A of Table 8 show the regression results where the dependent variable is the quarterly change in a fund's margin buffer – the unused borrowing as a proportion of total available borrowing (*UnuBrwRatio*). In contrast to our findings from Models (1)-(3), the evidence in Models (4)-(6) show that hedge funds increase their margin buffers following poor fund performance (min(*NetReturn*,0)). For example, Model (6) shows that a -10% quarterly fund return is associated with an increase in *UnuBrwRatio* of 1.655 percentage points. We interpret this evidence similarly to our evidence above regarding changes in hedge funds' cash buffer: managers strategically increase their margin buffers to avoid a margin call in anticipation of continuing poor performance. We test this directly in the following section.

In Table 8 Panel B we repeat our regressions of changes in *UnuBrwRatio* for different subsamples where funds plausibly have a greater incentive to hedge against margin calls by increasing their margin buffers – specifically, periods of high market volatility (High *VIX*), funds with short-term commitments from their creditors (low *FinIlliq*), funds that are managed by smaller advisers (Low Ln(*AdvNAV*)), and funds with greater leverage (High *Leverage*). Overall, the point estimates on min(*NetReturn*,0) are in the predicted directions (except in columns (3) and (4)), but the differences between subsamples within each sorting variable are not significant.

4.6. Do changes in unused borrowing capacity predict financial distress?

The results above show that hedge funds increase their unused borrowing ratios in response to poor performance. One possible explanation is fund managers anticipate a continuation of poor performance, and so increase the amount of "buffer" to avoid a forced deleveraging. Table 9 reports the results from regressing distress-related variables on lagged changes in *UnuBrwRatio*. Columns (3) and (4) show some evidence that *ΔUnuBrwRatio* is a negative predictor of fund returns, especially when one conditions on increases in unused borrowing capacity. However, this result is not significant (*t*-stat=-1.34).

In Columns (5) and (6) we report the results from Probit regressions of the sign of fund returns and whether the fund stops filing Form PF, respectively. The evidence shows that increases in *UnuBrwRatio* predict a greater likelihood of negative returns (*t*-stat=2.37) and becoming defunct (*t*-stat=2.06). This evidence is consistent with managers increasing margin buffers in anticipation of distress. Finally, in contrast to our evidence for negative returns and defunct status, we find no evidence that changes in *UnuBrwRatio* have predictive power for net investor flows (Columns (1) and (2)). This makes sense given that fund returns (rather than flows) are more directly linked to the value of a fund's margin securities and, hence, the likelihood of margin calls.

5. Conclusions

Using a comprehensive hedge fund dataset (Form PF), we construct a global measure of liquidity mismatches in hedge funds over 2013-2015. Our analysis sheds new light on hedge fund liquidity management. First, hedge funds typically hold assets that are more liquid than the combined liquidity of their liabilities and equity (i.e., negative liquidity mismatches). Second, liquidity mismatches are more pronounced during periods of high market volatility, and among smaller funds, funds with high leverage, and funds in which the manager owns a smaller proportion of the fund. Third, hedge funds that pursue longer-term investment strategies arrange for longer terms in their contractual commitments with creditors and fund investors. Fourth, consistent with theories of corporate liquidity management, we find evidence that cash holdings and unused borrowing capacity provide insurance against liquidity shocks, and that changes in these “liquidity buffers” predict future liquidity stress.

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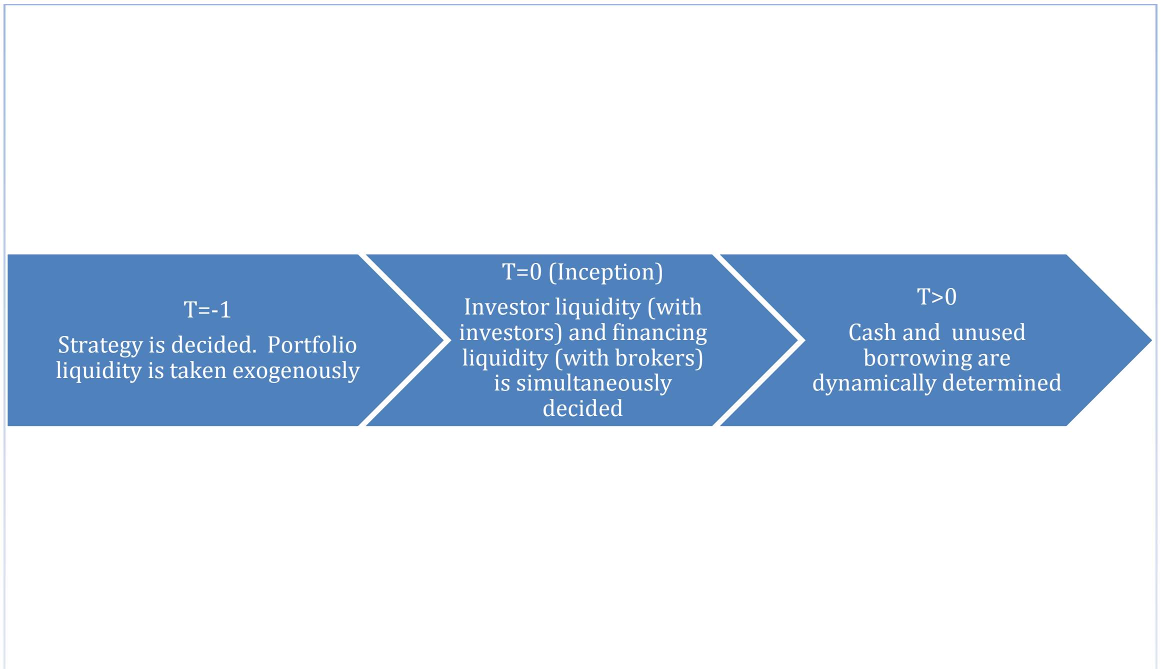

Figure 1. The figure plots the time-line of strategy and liquidity management decisions for a typical hedge fund.

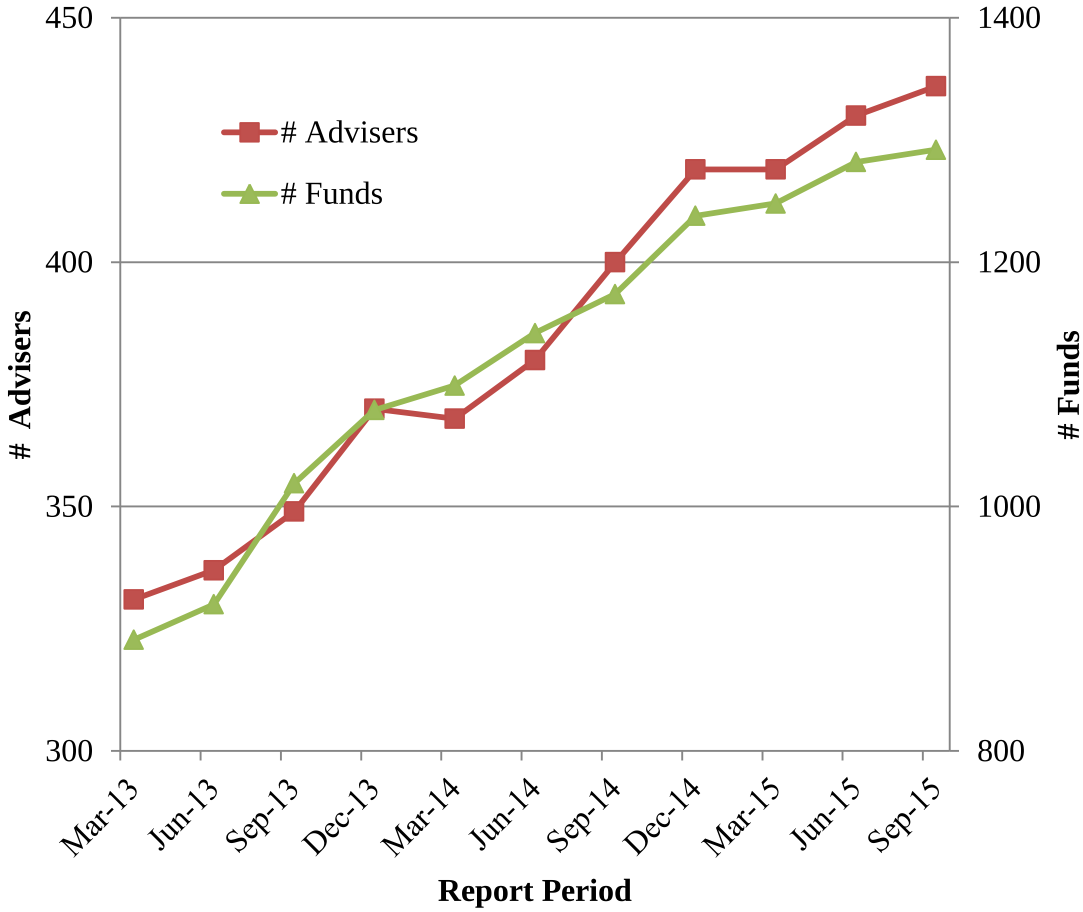

Figure 2. The figure plots the number of hedge funds and advisers in our estimation sample for each quarter of our sample period 2013Q1-2015Q3.

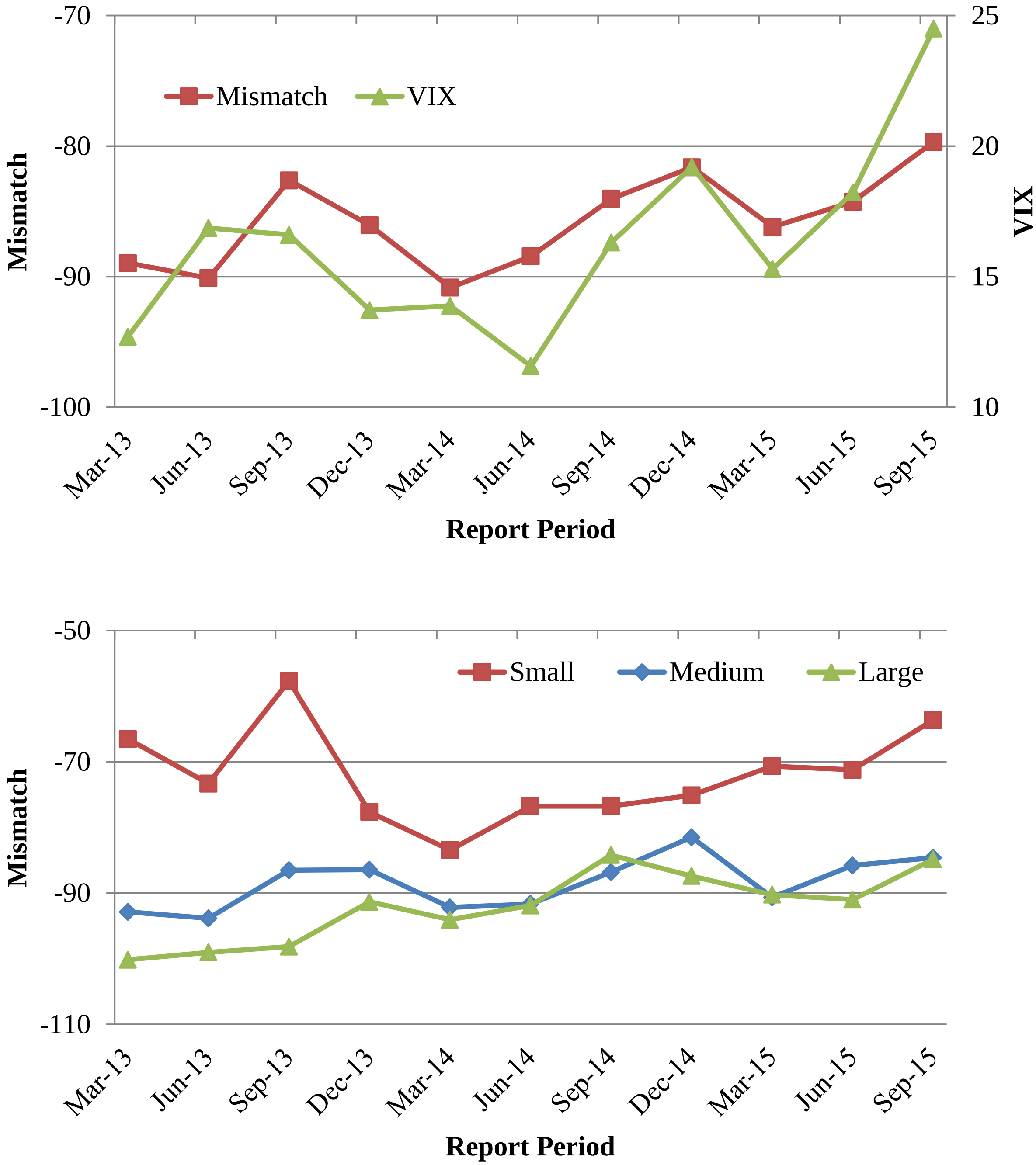

Figure 3. Top panel shows the average liquidity mismatch of hedge funds (squares) and the level of VIX (triangles) at the end of each quarter of our sample period 2013Q1-2015Q3. Bottom panel shows the average liquidity mismatch for small (squares), medium (diamonds), and large (triangles) hedge funds. Small, medium, and large funds are those in the bottom, middle, and top quartiles based on quarter-end net asset values.

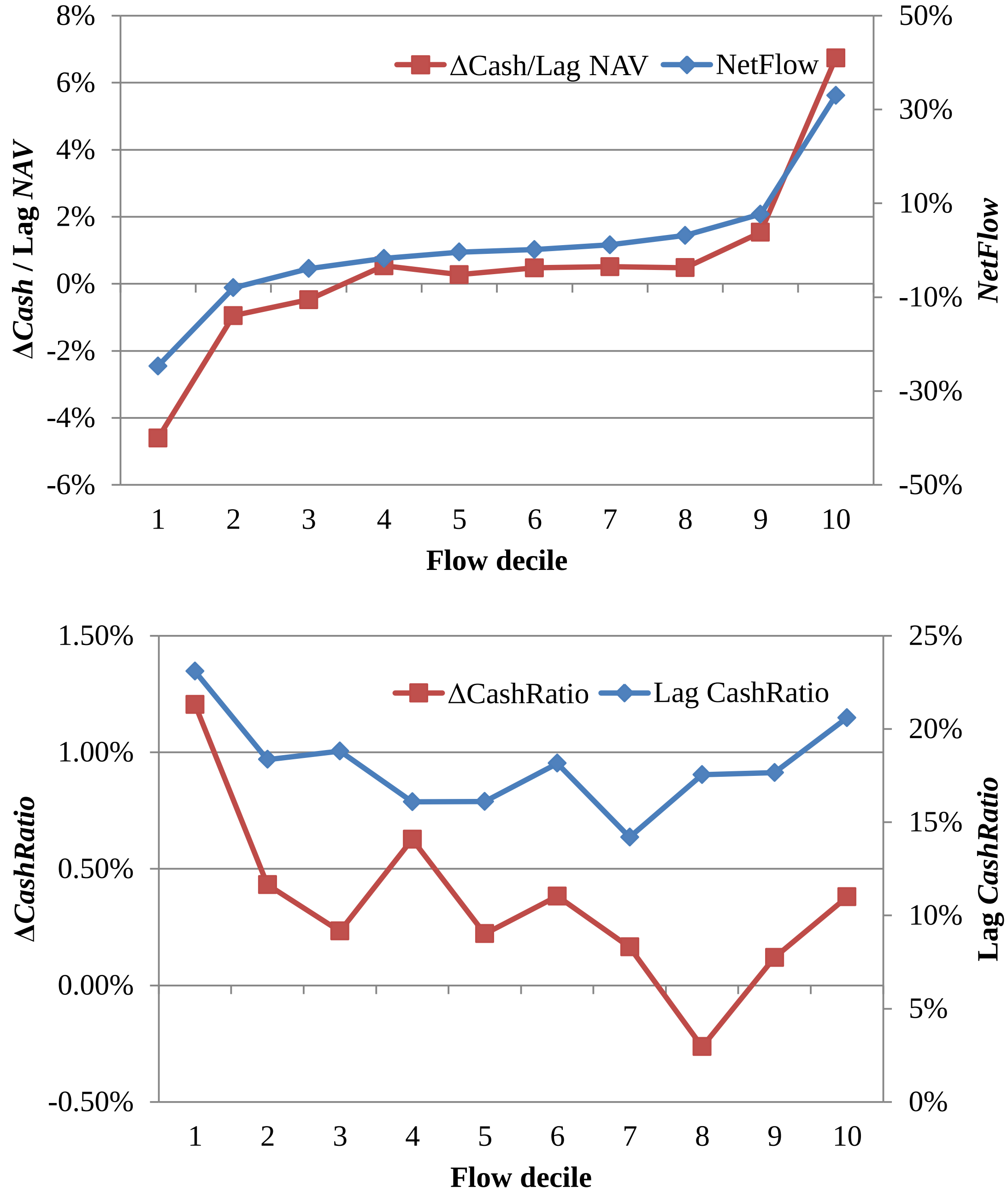

Figure 4. Hedge fund quarterly observations of *NetFlow* are sorted into deciles over our sample period 2013Q1-2015Q3. Top panel shows the average contemporaneous change in hedge fund cash as a percentage of lagged net asset value (squares) and average net flow (diamonds) within each decile. Bottom panel shows the average contemporaneous change in cash ratio (squares) and average lagged cash ratio (diamonds) within each decile.

Appendix: Variable definitions

Variable	Description and data source
#Brokers	Number of prime brokers used by the fund
AdvNAV	Adviser HFs AUM.
AdvOwner	Ownership % of Adviser and Related Persons. Form ADV.
AssetIlliq	Asset illiquidity is defined as *PortIlliq**(1-(*Cash*/*GAV*))+1*(*Cash*/*GAV*).
Cash	Unencumbered cash available to the fund at the end of the quarter. Form PF, Q33
CashRatio	*Cash*/*NAV*
Credit	Percentage of fund’s NAV following Credit strategy. Form PF, Q20.
DiscRestrict	Dummy equal to 1 if fund can enact discretionary liquidity restrictions. Form PF, Q49(b,c).
Equity	Percentage of fund’s NAV following Equity strategy. Form PF, Q20.
EventDriven	Percentage of fund’s NAV following Event Driven strategy. Form PF, Q20.
FinIlliq	Average commitment period of available borrowing. Form PF, Q46(b).
GAV	Gross asset value (millions). Form PF, Q8.
HHI	Herfindahl-Hirschman Index using NAV percentage weights of seven portfolio strategies. It is defined as *Credit*^2 + *Equity*^2 + *EventDriven*^2 + *InvestsOtherFunds*^2 + *Macro*^2 + *ManagedFutures*^2 + *OtherStrategy*^2.
IndepAdmin	Dummy variable equal 1 if fund uses an independent administrator. Form ADV.
InvestsOtherFunds	Percentage of fund’s NAV following Investment in Other Funds strategy. Form PF, Q20.
InvIlliq	Average commitment period of equity investors. Form PF, Q50.
Leverage	Fund leverage: *GAV*/*NAV*
FinInvIlliq	Liability and equity illiquidity is defined as *InvIlliq***NAV*/*GAV*+*FinIlliq**(1-*NAV*/*GAV*).
Macro	Percentage of fund’s NAV following Macro strategy. Form PF, Q20.
ManagedFutures	Percentage of fund’s NAV following managed Futures strategy. Form PF, Q20.
Mismatch	The difference between the illiquidity of a hedge fund’s assets (*AssetIlliq*) and the illiquidity of its liabilities and equity (*FinInvIlliq*).
NAV	Net asset value (millions). Form PF, Q9.
NetFlow	Quarterly net flows computes as [*NAV*(q)-*NAV*(q-1)*(1+*NetReturn*(q))]/*NAV*(q-1)
NetReturn	Quarterly net-of-fees returns computed as the product of (one plus) the monthly returns within the quarter, minus one.
OtherStrategy	Percentage of fund’s NAV following Other strategy. Form PF, Q20.
PortIlliq	Average number of day needed to liquidate fund's non-cash assets. Form PF, Q32.
RelativeValue	Percentage of fund’s NAV following Relative Value strategy. Form PF, Q20.
Top5Owner	Percentage of fund’s equity own by top 5% owners. Form PF, Q15.
TotBrwAvail	Total borrowing available. Form PF, Q46 (a).
UnusedBrw	Unused borrowing. Equals *TotBrwAvail* - *UsedBrw*.
UnuBrwRatio	*UnusedBrw* / *TotBrwAvail*
UsedBrw	Actual used borrowing. Form PF, Q43 or, if missing, then Q12.
VIX	Level of VIX

Table 1: Characteristics of the hedge fund sample over 2013Q1-2015Q3
This table reports summary statistics. All variables are winsorized at 1% and 99% levels and defined in the Appendix.

Variable	N	mn	sd	p25	p50	p75
Panel A: Liquidity variables						
Mismatch	9298	-85.5	85.9	-135.6	-62.7	-17.4
AssetIlliq	12384	65.9	105.4	3.5	13.7	64.1
LiabEqIlliq	9298	145.9	119.5	45.0	110.9	238.5
PortIlliq	12384	71.2	112.2	4.3	14.9	72.3
InvIlliq	12384	172.8	135.1	60.5	143.7	306.1
FinIlliq	9298	52.9	96.7	1.0	1.0	60.5
CashRatio	12384	16.7%	22.9%	0.7%	6.9%	22.7%
UnuBrwRatio	12384	28.7%	35.6%	0.0%	7.8%	52.8%
Panel B: Size, leverage, and flow variables						
GAV	12384	2955.6	5328.9	577.5	1249.3	2847.7
NAV	12384	1723.6	2397.6	472.1	907.9	1900.2
Leverage	12384	1.6	1.3	1.0	1.2	1.7
NetReturn	10779	1.6%	5.3%	-0.7%	1.6%	4.0%
NetFlow	9612	1.0%	16.7%	-3.7%	0.0%	3.3%
Panel C: Investment strategy variables						
Credit	12384	9.1	25.4	0.0	0.0	0.0
Equity	12384	36.2	45.4	0.0	0.0	100.0
EventDriven	12384	11.0	27.7	0.0	0.0	0.0
InvestOtherFunds	12384	2.1	12.2	0.0	0.0	0.0
Macro	12384	7.6	24.2	0.0	0.0	0.0
ManagedFutures	12384	2.0	13.0	0.0	0.0	0.0
RelativeValue	12384	10.6	27.7	0.0	0.0	0.0
Other	12384	21.4	38.5	0.0	0.0	18.0
HHI	12384	0.8	0.3	0.6	1.0	1.0
Panel D: Other variables						
Ln(AdvNAV)	12384	22.8	1.3	21.6	22.7	23.9
DiscRestrict	12384	0.7	0.4	0.0	1.0	1.0
IndepAdmin	12384	0.6	0.5	0.0	1.0	1.0
#Brokers	9200	2.2	2.6	0.0	2.0	3.0
Top5Owner	12384	61.3	28.1	37.0	58.0	92.0
AdvOwner	9200	12.5	23.5	0.0	3.0	11.0
VIX	12384	16.5	3.5	13.7	16.3	18.2

Table 2: Characteristics of hedge funds with high and low liquidity mismatches
The table reports sample averages of hedge fund characteristics for different subsamples based on a fund's end-of-quarter liquidity mismatch. Low, Medium, and High mismatch categories are those with *Mismatch* values in the bottom, middle two, and top quartiles, respectively. All variables are defined in the Appendix.

	Low *Mismatch* (bottom 25th pct)	Medium *Mismatch* (25th-75th pct)	High *Mismatch* (top 25th pct)
Panel A: Liquidity variables			
Mismatch	-209.22	-68.22	3.76
AssetIlliq	46.65	48.24	100.53
FinInvIlliq	256.67	116.45	94.09
PortIlliq	52.39	53.86	104.90
InvIlliq	297.71	151.19	112.04
FinIlliq	77.13	42.67	49.22
CashRatio	13.67%	16.46%	19.72%
UnuBrwRatio	43.03%	33.60%	41.36%
Panel B: Size, leverage, and flow variables			
Ln(NAV)	20.80	20.63	20.55
Ln(GAV)	21.08	21.13	21.02
Ln(Leverage)	0.28	0.50	0.44
NetReturn	1.94%	1.68%	1.61%
NetFlow	1.15%	1.38%	1.64%
Panel C: Investment strategy variables			
Credit	13.32	10.47	5.63
Equity	33.61	45.22	32.56
EventDriven	18.42	12.52	4.21
InvestOtherFunds	1.24	1.12	0.95
Macro	1.97	6.76	8.55
ManagedFutures	0.13	1.00	1.22
RelativeValue	10.90	9.51	14.41
Other	20.40	13.39	32.44
HHI	0.69	0.76	0.84
Panel D: Other variables			
Ln(AdvNAV)	22.72	22.61	23.06
DiscRestrict	0.68	0.83	0.68
IndepAdmin	0.68	0.72	0.57
#Brokers	2.80	3.22	1.83
Top5Owner	56.39	58.10	65.24
AdvOwner	13.31	13.95	12.49

Table 3: Determinants of liquidity mismatches and its components

The table reports the results from pooled regressions of hedge fund liquidity mismatches. The dependent variable in Columns (1) and (2) is the fund's liquidity mismatch (*Mismatch*) measured at the end of the quarter. In Columns (3) and (4) the dependent variable is the quarter-end illiquidity of the fund's assets (*AssetIlliq*) and liabilities and equity (*FinInvIlliq*). Independent variables are measured contemporaneously with the dependent variable and (except for dummies) standardized to have a zero mean and unit variance. All regressions include (not tabulated) an intercept, *Credit*, *Equity*, *EventDriven*, *InvestOtherFunds*, *Macro*, *ManagedFutures*, *RelativeValue*, and *Other*. Quarter dummies are included in (1). *t*-statistics are reported in parentheses. Standard errors account for heteroskedasticity and fund-level clustering. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Mismatch		*AssetIlliq*	*LiabEqIlliq*
	(1)	(2)	(3)	(4)
Ln(NAV)	-9.84***	-9.80***	-16.39***	-6.51*
	(-2.81)	(-2.81)	(-5.10)	(-1.75)
Ln(Leverage)	16.24***	16.23***	-6.46***	-23.00***
	(7.31)	(7.31)	(-3.38)	(-9.76)
HHI	1.61	1.64	0.89	-1.34
	(0.38)	(0.39)	(0.25)	(-0.27)
Ln(AdvNAV)	6.09**	6.08**	11.79***	5.46*
	(2.36)	(2.36)	(4.75)	(1.94)
DiscRestrict	28.06***	28.05***	-88.46***	-117.15***
	(3.48)	(3.47)	(-10.97)	(-12.06)
IndepAdmin	-26.31**	-26.08**	-70.09***	-42.72***
	(-2.55)	(-2.53)	(-6.44)	(-4.51)
#Brokers	-8.54***	-8.55***	-2.36	6.42***
	(-3.78)	(-3.79)	(-1.26)	(2.60)
Top5Owner	0.70	0.66	-18.03***	-18.67***
	(0.22)	(0.20)	(-6.46)	(-5.38)
AdvOwner	-4.65**	-4.59**	-4.19**	0.56
	(-2.05)	(-2.03)	(-2.05)	(0.21)
VIX		3.11***	2.16***	-0.90
		(4.51)	(3.71)	(-1.27)
Quarter dummies?	Yes	No	No	No
Strategy controls?	Yes	Yes	Yes	Yes
Observations	6,944	6,944	6,944	6,944
R-squared	0.110	0.109	0.513	0.486

Table 4: Does portfolio illiquidity impact investor and financing illiquidity?
Columns (1) and (2) show coefficients from two-stage least squares (2SLS) estimation of instrumental variable regressions of two endogenous variables, *FinIlliq* and *InvIlliq*. Columns (3) and (4) show coefficients from ordinary least squares (OLS) regressions in which the dependent variable is *FinIlliq* and *InvIlliq*, respectively. Strategy variables – *Credit*, *Equity*, *EventDriven*, *InvestOtherFunds*, *Macro*, *ManagedFutures*, *RelativeValue*, and *Other* – and an intercept are included in all models (not tabulated). All variables are defined in the Appendix and standardized to have zero mean and unit variance. *t*-statistics are reported in parentheses. Standard errors account for heteroskedasticity and fund-level clustering. *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

	IV	IV	OLS	OLS
	FinIlliq	*InvIlliq*	*FinIlliq*	*InvIlliq*
	(1)	(2)	(3)	(4)
PortIlliq	0.0758	0.5650***	0.3544***	0.4618***
	(0.86)	(5.16)	(7.82)	(14.80)
Ln(NAV)	0.0266	0.1113*	0.0640***	0.0657**
	(0.95)	(1.92)	(2.63)	(2.35)
Ln(AdvNAV)	0.0350	-0.0593**	0.0021	-0.0519**
	(1.25)	(-2.26)	(0.09)	(-2.23)
IndepAdmin	-0.5580***	-0.1920	-0.6369***	0.0040
	(-4.16)	(-0.84)	(-4.82)	(0.05)
HHI	0.1649***	-0.0115	0.1613***	-0.0694
	(4.04)	(-0.15)	(4.10)	(-1.65)
#Brokers	-0.0434		0.0015	
	(-1.51)		(0.06)	
Ln(NAV)^2	-0.0483***		-0.0403***	
	(-3.43)		(-2.98)	
InvIlliq	0.4753***			
	(3.65)			
Top5Owner		-0.0749**		-0.0838***
		(-2.26)		(-3.06)
AdvOwner		0.0500*		0.0378
		(1.72)		(1.58)
DiscRestrict		-0.6342***		-0.5282***
		(-4.30)		(-6.00)
FinIlliq		-0.3449		
		(-0.98)		
Level of clustering	Fund	Fund	Fund	Fund
Strategy controls?	Yes	Yes	Yes	Yes
Observations	6,944	6,944	6,944	6,944
R-squared	0.293	0.332	0.309	0.478

Table 5: Do managers use cash and unused borrowing capacity as liquidity buffers? Regressions of quarterly cash holdings (*CashRatio*) and unused borrowing capacity (*UnuBrwRatio*). Independent variables (except dummies) are standardized to have a zero mean and unit variance, and measured contemporaneously with the dependent variable. All models include (not tabulated) an intercept, strategy variables. Models (1) and (3) also include quarter dummies. The dependent variable is either the ratio of unencumbered cash to net assets ((1) and (2)) or the ratio of unused borrowing to total available borrowing ((3) and (4)) All variables are defined in the Appendix. *t*-statistics are in parentheses. Standard errors account for heteroskedasticity and fund-level clustering. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	CashRatio		*UnuBrwRatio*	
	(1)	(2)	(3)	(4)
InvIlliq	-0.0283***	-0.0286***	0.0013	0.0005
	(-4.01)	(-4.04)	(0.11)	(0.04)
FinIlliq	-0.0019	-0.0017	-0.0627***	-0.0624***
	(-0.39)	(-0.35)	(-6.49)	(-6.44)
PortIlliq	-0.0062	-0.0063	0.0259*	0.0257*
	(-1.02)	(-1.03)	(1.94)	(1.93)
Ln(NAV)	0.0029	0.0028	-0.0208*	-0.0211*
	(0.40)	(0.39)	(-1.77)	(-1.79)
Ln(Leverage)	0.0351***	0.0350***	-0.1194***	-0.1196***
	(4.63)	(4.62)	(-12.57)	(-12.58)
HHI	-0.0274***	-0.0273***	0.0125	0.0126
	(-2.68)	(-2.67)	(0.78)	(0.79)
Ln(AdvNAV)	0.0313***	0.0311***	-0.0450***	-0.0452***
	(4.81)	(4.77)	(-4.63)	(-4.66)
DiscRestrict	0.0040	0.0037	-0.1114***	-0.1126***
	(0.31)	(0.29)	(-4.14)	(-4.16)
IndepAdmin	0.0476***	0.0484***	-0.1070***	-0.1053***
	(3.52)	(3.57)	(-3.49)	(-3.44)
#Brokers	0.0057	0.0058	-0.0038	-0.0035
	(0.90)	(0.93)	(-0.45)	(-0.42)
Top5Owner	0.0090	0.0088	-0.0212*	-0.0220**
	(1.51)	(1.47)	(-1.91)	(-1.98)
AdvOwner	0.0119*	0.0121*	-0.0165**	-0.0161*
	(1.71)	(1.73)	(-2.00)	(-1.96)
VIX		0.0033*		-0.0024
		(1.96)		(-0.85)
Observations	6,944	6,944	6,944	6,944
R-squared	0.259	0.257	0.295	0.293
Other controls?	Yes	Yes	Yes	Yes

Table 6: Are changes in cash holdings sensitive to net flows?

The table reports estimates from pooled, contemporaneous regressions of quarterly changes in hedge funds' unencumbered cash. Panel A presents results for the full sample of funds. The dependent variable is either the change in unencumbered cash divided by prior quarter's net asset value (Δ*Cash* / Lag *NAV* , Columns (1)-(3)) or the change in unencumbered cash ratio (*ΔCashRatio* , Models (4)-(6)). Panel B presents *ΔCashRatio* regressions for fund subsamples based on whether the sorting variable is above (High) or below (Low) the sample median (Columns (1)-(6)). Columns (7) and (8) present results for subsamples of funds with below-median investor illiquidity (*InvIlliq*), depending on whether the funds use discretionary liquidity restrictions or not (*DiscRestrict*). All regressions include an intercept, quarter dummies, and fund strategy variables (not tabulated to save space). All independent variables (defined in the Appendix) are measured contemporaneously with the dependent variable. Panel C presents *ΔCashRatio* regressions for the full sample with *NetFlow* decomposed into expected ($NetFlow^{E}$) and unexpected ($NetFlow^{U}$) flows. Expected net flows are based on a predictive model of net flows based on prior quarter flows, returns, and investor illiquidity. Parameters of the predictive model are estimated from a pooled one-time estimation (Pooled, (1)-(2)) or estimated each quarter using an expanding window (Recursive, (3)-(4)). *t*-statistics are reported in parentheses. Standard errors account for heteroskedasticity and fund-level clustering. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Full sample results

	Dependent variable: Δ*Cash* / Lag *NAV*			Dependent variable: Δ*CashRatio*		
	(1)	(2)	(3)	(4)	(5)	(6)
NetFlow	0.1796***			-0.0221***		
	(15.81)			(-2.63)		
(a) max(*NetFlow*,0)		0.1691***	0.1682***		-0.0009	-0.0015
		(11.36)	(11.31)		(-0.10)	(-0.16)
(b) min(*NetFlow*,0)		0.2005***	0.2139***		-0.0640***	-0.0629***
		(9.93)	(11.01)		(-3.21)	(-3.15)
(c) max(*NetReturn*,0)			0.2329***			0.0190
			(5.54)			(0.53)
(d) min(*NetReturn*,0)			0.1563***			-0.0934**
			(3.56)			(-2.51)
Observations	9,325	9,325	9,325	9,325	9,325	9,325
R-squared	0.099	0.099	0.110	0.012	0.015	0.016
Additional controls?	Yes	Yes	Yes	Yes	Yes	Yes
p-value for F test: (a)=(b)		0.2345	0.075		0.0064	0.0079
p-value for F test: (c)=(d)			0.2342			0.055

Panel B: Δ*CashRatio* regressions for fund subsamples

	Sorting variable							
	VIX		Lag *InvIlliq*		Lag *Ln(AdvNAV)**		Lag *DiscRestrict**	
	Low	High	Low	High	Low	High	0	1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(a) *max(NetFlow,0)*	-0.0023	-0.0080	-0.0096	0.0074	-0.0243	0.0171	0.0033	-0.0109
	(-0.21)	(-0.40)	(-0.74)	(0.57)	(-1.51)	(0.76)	(0.10)	(-0.80)
(b) *min(NetFlow,0)*	0.0079	-0.1100***	-0.0824***	-0.0351	-0.1141***	-0.0367	0.0483	-0.1070***
	(0.28)	(-4.15)	(-3.23)	(-1.12)	(-3.30)	(-1.02)	(1.09)	(-3.86)
(c) *max(NetReturn,0)*	-0.0060	0.0477	-0.0054	0.0628	-0.0464	0.0423	-0.3206***	0.0412
	(-0.14)	(0.87)	(-0.10)	(1.35)	(-0.59)	(0.70)	(-3.16)	(0.75)
(d) *min(NetReturn,0)*	-0.3364***	-0.0449	-0.0274	-0.1782***	0.0224	-0.0995	0.3496***	-0.0939*
	(-4.66)	(-1.09)	(-0.57)	(-2.95)	(0.31)	(-1.52)	(2.67)	(-1.96)
Observations	4,684	4,641	5,037	4,270	2,666	2,371	614	4,423
R-squared	0.011	0.027	0.019	0.021	0.034	0.013	0.064	0.026
Controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value: Low(a)=High(a)	(0.849)		(0.349)		(0.151)		(0.684)	
p-value: Low(b)=High(b)	(0.002)		(0.261)		(0.100)		(0.001)	
p-value: Low(c)=High(c)	(0.235)		(0.251)		(0.200)		(0.016)	
p-value: Low(d)=High(d)	(0.003)		(0.112)		(0.338)		(0.005)	

* Excludes funds with above-the-median Lag *InvIlliq*.

Panel C: Δ*CashRatio* regressions with expected vs. unexpected net flows

	(1)	(2)	(3)	(4)
max(*NetFlow*^{E},0)	-0.1122***	-0.1034***	-0.0928***	-0.0796***
	(-3.90)	(-3.56)	(-3.54)	(-3.00)
max(*NetFlow*^{U} ,0)	0.0191	0.0206	0.0186	0.0199
	(1.36)	(1.47)	(1.28)	(1.37)
min(*NetFlow*^{E},0)	0.0896**	0.0897**	0.0782*	0.0653
	(2.03)	(2.02)	(1.89)	(1.56)
min(*NetFlow*^{U} ,0)	-0.0592**	-0.0501*	-0.0646**	-0.0537**
	(-2.26)	(-1.94)	(-2.37)	(-2.00)
max(*NetReturn*,0)	0.0510	0.0696*	0.0415	0.0521
	(1.55)	(1.90)	(1.16)	(1.32)
min(*NetReturn*,0)	-0.1179***	-0.0718*	-0.1199***	-0.0765*
	(-3.18)	(-1.72)	(-3.18)	(-1.80)
Observations	7,552	7,552	6,874	6,874
R-squared	0.007	0.016	0.007	0.016
Additional controls?	No	Yes	No	Yes
Estimation of expected net flows	Pooled	Pooled	Recursive	Recursive

Table 7: Are changes in cash buffers predictive of fund distress?

The table reports the results from regressions of distress-related variables on lagged changes in hedge funds' cash ratios. The first three columns show the OLS coefficients where the dependent variable is *NetFlow* ((1)-(3)) or *NetReturn* ((4)-(5)). Final two columns show the marginal effects of Probit regressions where the dependent variable is a dummy variable that equals one if *NetReturn* is less than zero during quarter q (Column (6)), and a dummy variable that equals one if the fund stops filing Form PF (Column (7)) after quarter q (i.e., defunct). Independent variables are lagged one quarter. All regressions include an intercept, quarter dummies and fund strategy variables (not tabulated to save space). *t*-statistics are reported in parentheses. Standard errors account for heteroskedasticity and fund-level clustering. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	NetFlow			*NetReturn*		Return<0?	Defunct?
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔCashRatio	-0.1153***	-0.0883***		-0.0017			
	(-3.71)	(-2.71)		(-0.23)			
max(ΔCashRatio,0)			-0.0979**		-0.0008	0.0865	0.0511***
			(-1.96)		(-0.06)	(0.77)	(3.39)
min(ΔCashRatio,0)			-0.0772		-0.0027	0.1302	-0.0337*
			(-1.51)		(-0.23)	(1.07)	(-1.76)
max(NetFlow,0)		0.2831***	0.2838***	0.0025	0.0024	0.0473	-0.0166*
		(10.62)	(10.51)	(0.55)	(0.54)	(1.07)	(-1.69)
min(NetFlow,0)		0.4182***	0.4165***	-0.0257**	-0.0255**	-0.0012	-0.0464***
		(9.15)	(8.96)	(-2.34)	(-2.29)	(-0.02)	(-4.55)
max(NetReturn,0)		-0.0837	-0.0838	0.2485***	0.2485***	-0.1502	-0.0644*
		(-0.98)	(-0.98)	(6.34)	(6.34)	(-0.78)	(-1.69)
min(NetReturn,0)		0.2242**	0.2239**	0.1047**	0.1047**	-2.4094***	-0.1289***
		(2.20)	(2.19)	(2.53)	(2.53)	(-8.19)	(-3.23)
Ln(NAV)	-0.0023	-0.0039*	-0.0040*	-0.0007	-0.0007	0.0024	-0.0025***
	(-0.75)	(-1.80)	(-1.82)	(-1.41)	(-1.41)	(0.47)	(-3.54)
Ln(AdvNAV)	0.0012	0.0007	0.0007	0.0006	0.0006	-0.0030	-0.0026***
	(0.65)	(0.48)	(0.47)	(1.42)	(1.41)	(-0.63)	(-3.24)
Observations	8,027	8,027	8,027	8,027	8,027	8,027	7,059
R-squared	0.020	0.134	0.134	0.229	0.229	0.1583	0.1401
Additional controls?	yes	yes	yes	yes	yes	yes	yes

Table 8: Do fund flows and returns explain quarterly changes in unused borrowing capacity?

The table reports the coefficients from pooled, contemporaneous regressions of quarterly changes in hedge funds' unused borrowing capacity. Panel A presents the results for the full sample of funds in which the dependent variable is either the change in unused borrowing divided by prior quarter's total available (i.e., used plus unused) borrowing (*ΔUnuBrw* / Lag *TotBrwAvail*, Columns (1)-(3)) or the change in unused borrowing ratio (*ΔUnuBrwRatio* , Models (4)-(6)). Panel B presents the *ΔUnuBrwRatio* regression results for fund subsamples based on whether the sorting variable is above (High) or below (Low) the sample median. All independent variables (defined in the Appendix) are measured contemporaneously with the dependent variable. All regressions include an intercept, quarter dummies, and fund strategy variables (not tabulated to save space). *t*-statistics are reported in parentheses. Standard errors account for heteroskedasticity and fund-level clustering. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Full sample results

	Dependent variable: *ΔUnuBrw* / Lag *TotBrwAvail*			Dependent variable: *ΔUnuBrwRatio*		
	(1)	(2)	(3)	(4)	(5)	(6)
NetFlow	0.5949***			0.0032		
	(6.78)			(0.17)		
(a) *max(NetFlow,0)*		0.7307***	0.7297***		-0.0124	-0.0137
		(5.54)	(5.52)		(-0.50)	(-0.54)
(b) *min(NetFlow,0)*		0.3047***	0.3256***		0.0367	0.0420
		(3.72)	(4.14)		(1.11)	(1.28)
(c) *max(NetReturn,0)*			0.5648***			0.1037
			(3.04)			(1.59)
(d) *min(NetReturn,0)*			0.3391*			-0.1655**
			(1.69)			(-2.24)
Observations	6,999	6,999	6,999	6,999	6,999	6,999
R-squared	0.047	0.049	0.051	0.015	0.016	0.016
Additional controls?	yes	yes	yes	yes	yes	yes
p-value for F test: (a)=(b)		0.0148	0.0198		0.2653	0.2052
p-value for F test: (c)=(d)			0.4327			0.0156

Panel B: *ΔUnuBrwRatio* regressions for fund subsample

	Sorting variable							
	VIX		Lag *FinIlliq*		Lag *Ln(AdvNAV)*		Lag *Leverage*	
	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(a) *max(NetFlow,0)*	-0.0269	0.0077	-0.0262	0.0101	-0.0037	-0.0197	-0.0331	0.0088
	(-0.75)	(0.25)	(-0.78)	(0.29)	(-0.10)	(-0.60)	(-0.89)	(0.28)
(b) *min(NetFlow,0)*	0.1090*	-0.0069	0.0390	0.0590	0.0336	0.0565	0.1101**	-0.0240
	(1.84)	(-0.17)	(0.85)	(1.18)	(0.60)	(1.43)	(2.28)	(-0.52)
(c) *max(NetReturn,0)*	0.1034	0.0748	-0.0752	0.2227***	0.0943	0.1189	0.1845	0.0664
	(0.96)	(0.93)	(-0.73)	(2.92)	(1.19)	(1.10)	(1.58)	(0.95)
(d) *min(NetReturn,0)*	0.0564	-0.2216***	-0.0960	-0.2597**	-0.3399***	-0.0398	-0.0360	-0.2842***
	(0.27)	(-2.82)	(-0.96)	(-2.55)	(-2.88)	(-0.42)	(-0.33)	(-3.01)
Observations	3,517	3,482	3,857	3,109	3,502	3,497	3,498	3,497
R-squared	0.015	0.021	0.022	0.015	0.015	0.024	0.022	0.020
Controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value: Low(a)=High(a)	(0.459)		(0.496)		(0.768)		(0.328)	
p-value: Low(b)=High(b)	(0.113)		(0.838)		(0.759)		(0.081)	
p-value: Low(c)=High(c)	(0.952)		(0.062)		(0.626)		(0.718)	
p-value: Low(d)=High(d)	(0.139)		(0.495)		(0.159)		(0.195)	

Table 9: Are changes in margin buffers predictive of fund distress?

The table reports the results from regressions of distress-related variables on lagged changes in hedge funds' unused borrowing capacity (*UnuBrwRatio*). First four columns show the OLS coefficients where the dependent variable is *NetFlow* ((1)-(2)) or *NetReturn* ((3)-(4)). Final two columns show the marginal effects of Probit regressions where the dependent variable is a dummy variable that equals one if *NetReturn* is less than zero during quarter q (Column (5)), and a dummy variable that equals one if the fund stops filing Form PF (Column (6)) after quarter q (i.e., defunct). Independent variables are lagged one quarter. All regressions include an intercept, quarter dummies and fund strategy variables (not tabulated to save space). t-statistics are reported in parentheses. Standard errors account for heteroskedasticity and fund-level clustering. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	NetFlow		*NetReturn*		Return<0?	Defunct?
	(1)	(2)	(3)	(4)	(5)	(6)
ΔUnuBrwRatio	0.0020		-0.0049			
	(0.12)		(-1.55)			
max(ΔUnuBrwRatio,0)		0.0036		-0.0065	0.1271**	0.0148**
		(0.13)		(-1.34)	(2.37)	(2.06)
min(ΔUnuBrwRatio,0)		0.0003		-0.0031	-0.0302	0.0008
		(0.02)		(-0.66)	(-0.54)	(0.08)
max(NetFlow,0)	0.2865***	0.2863***	0.0043	0.0045	0.0159	-0.0157
	(10.72)	(10.71)	(0.94)	(0.98)	(0.36)	(-1.52)
min(NetFlow,0)	0.4246***	0.4247***	-0.0242**	-0.0243**	0.0207	-0.0517***
	(9.37)	(9.35)	(-2.13)	(-2.15)	(0.27)	(-4.90)
max(NetReturn,0)	-0.0915	-0.0917	0.2496***	0.2498***	-0.1425	-0.0781*
	(-1.06)	(-1.06)	(6.28)	(6.28)	(-0.73)	(-1.94)
min(NetReturn,0)	0.2142**	0.2144**	0.1033**	0.1030**	-2.4343***	-0.1312***
	(2.09)	(2.10)	(2.46)	(2.45)	(-8.15)	(-3.22)
Ln(NAV)	-0.0043*	-0.0043*	-0.0007	-0.0007	0.0025	-0.0026***
	(-1.91)	(-1.91)	(-1.50)	(-1.51)	(0.48)	(-3.55)
Ln(AdvNAV)	0.0007	0.0007	0.0007	0.0007	-0.0034	-0.0028***
	(0.47)	(0.47)	(1.55)	(1.54)	(-0.70)	(-3.34)
Observations	7,775	7,775	7,775	7,775	7,775	6,840
R-squared	0.133	0.133	0.232	0.232	0.1596	0.1290
Quarter fixed effects?	yes	yes	yes	yes	yes	yes