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Hedge Fund Liquidity Management: Insights for Fund Performance (March 2022)

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HEDGE FUND LIQUIDITY MANAGEMENT: INSIGHTS FOR FUND PERFORMANCE

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ABSTRACT

Using Form PF filings over 2013–2017, we find that hedge funds maintain higher levels of cash holdings and available borrowing ("liquidity buffers") when they hold more illiquid assets, have shorter-term commitments from investors and creditors, and when market volatility is greater. Funds with low abnormal buffers – liquidity buffers below the level predicted by fund attributes – outperform their benchmarks. Stocks with greater ownership by managers with abnormally low buffers subsequently outperform other stocks, especially around earnings announcements. We conclude that managers with better investment opportunities utilize more of their capital and have lower liquidity buffers than their peers.

JEL Classification: G11; G23
Keywords: Liquidity buffer, hedge funds, fund performance, cash, borrowing.

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1. Introduction[1]

The 2008 financial crisis and turbulent market conditions of March 2020 highlight the importance of sound liquidity risk management to guarantee the viability of financial institutions during severe market downturns. Larger cash positions enable managers to meet funding shocks without having to engage in fire sales of its non-cash assets. Likewise, credit lines and other forms of available borrowing can provide a type of liquidity insurance that allows funds to avoid the costs of transacting in underlying securities markets, particularly when these become impaired. However, maintaining a larger liquidity buffer in normal times could entail significant opportunity costs for asset managers if doing so means foregoing profitable investment opportunities that require a more active use of fund capital and available borrowing. Such opportunity costs would be most onerous for managers with the greatest capacity for informed trading. In this paper, we take a fresh look at detecting skill in the hedge fund marketplace and propose a new predictor of fund performance based on a fund's liquidity buffer. We posit that managers with better investment opportunities will utilize more of the fund's capital and, hence, have lower liquidity buffers than their peers.

Our two main research questions are as follows. First, does a hedge fund manager's liquidity buffer – defined as a fund' unencumbered cash plus its unused borrowing capacity – vary across funds in a way that is consistent with liquidity risk management (e.g., choosing higher buffers when holdings are more illiquid or when investors are allowed to redeem their shares on a shorter notice)? Second, do managers that maintain *abnormally* low buffers – buffers below the level predicted by fund attributes – exhibit superior performance and a

[1] 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.

greater capacity for informed trading? It is possible that an abnormally low buffer may reflect a fund manager's choice to exploit especially good investment opportunities by drawing down liquidity buffers to finance positions in undervalued securities.

Answers to these questions in a hedge fund setting are uniquely informative as hedge fund managers face few regulatory constraints on their illiquid asset holdings or borrowing. Our analysis uses information extracted from the quarterly filings of Form PF that are submitted confidentially by hedge fund managers to the SEC over 2013-2017.[2] These disclosures provide detailed information about several fund characteristics that are relevant to our analysis, including the level of unencumbered cash holdings, available borrowing (e.g., excess margins and lines of credit), and portfolio returns. We find that hedge funds maintain relatively large liquidity buffers of 41%, on average, which is the sum of cash holdings of 18% and available borrowing capacity of 23% as a percentage of net asset value (NAV). These estimates contrast sharply with those from the mutual fund literature. The average cash holdings of mutual funds range between 4-8% (Chernenko and Sunderam, 2016) and borrowing capacity is severely limited by virtue of regulation under the Investment Company Act. The fact that hedge funds typically maintain large liquidity buffers is broadly consistent with the conventional wisdom that cash and available borrowing provide a useful hedge against liquidity risk and that, compared to mutual funds, hedge funds face greater exposure to illiquid assets.

We then turn to our first research question and examine how liquidity buffers vary

[2] Other studies of Form PF filings include Aragon et al. (2017; 2021), Barth et al. (2020), Barth and Monin (2019) and Kruttli, Monin, and Watugala (2017; 2021; 2022). A more complete 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.

across funds. For example, funds with shorter-term commitments from fund investors are more exposed to investor redemptions. For such funds, we would expect higher levels of unencumbered cash so that managers can quickly meet a large wave of redemptions without having to liquidate the fund's non-cash assets. Likewise, we would expect funds with a greater exposure to illiquid assets in the fund's portfolio maintain higher buffers to hedge against funding shocks from investors and creditors. Consistent with these predictions, we find that a one standard deviation drop in portfolio liquidity is associated with a higher buffer of 15.21 percentage points, which is about 40% of one standard deviation of buffer. Funds also maintain higher buffers when they are more exposed to investor redemptions (investor liquidity) and margin calls from their prime brokers (financing liquidity). We estimate 7.38% and 4.60% higher buffers per one standard deviation increases in investor and financing liquidity, respectively. Market conditions also matter: funds maintain higher liquidity buffers during periods of higher market volatility as measured by the CBOE Volatility Index (VIX). These results support a central prediction of theories that funds' cash and available borrowing provide a hedge against future financing constraints.[3]

Next, we turn to our second research question and test whether *abnormal* liquidity buffers – liquidity buffers above the level predicted by fund attributes – are related to funds' investment opportunities. Fig. 1 shows our main result: hedge funds with low abnormal buffers significantly outperform other funds. Specifically, funds with the lowest abnormal buffers earn positive and significant monthly net-of-fees risk-adjusted alphas of 0.28%, as compared to just -0.02% for funds with the highest abnormal buffers. The difference, 0.30%

[3] See, e.g., Boot, Thakor, and Udell (1987) and Holmstrom and Tirole (1998), Kashyap, Rajan, and Stein (2002), and Gatev and Strahan (2006). For a review of this literature see Almeida et al. (2014).

per month, is significant (t-statistic = 2.90). We also use multiple regressions to confirm that the negative buffer-performance relation is not just picking up other known predictors of hedge fund performance. Overall, our evidence supports the idea that managers respond to successful investment signals by actively deploying the funds' liquid capital and, hence, have abnormally lower buffers; in other words, abnormally low buffers signify greater investment opportunities.

Our post-crisis sample period covers a period of relatively low volatility and rising equity market valuations. Thus, a potential concern is that the outperformance of hedge funds with low abnormal buffers is not due to a greater ability to detect investment opportunities, but instead reflects merely luck due to having a greater exposure to risky securities during a bull market period. We address this concern in several ways. First, the performance we document is market-adjusted and goes above and beyond a fund's exposure to several market benchmarks, including a broad equity market index and option-based strategies. Second, our focus on *abnormal* liquidity buffers weakens the direct link between a fund's raw, unadjusted buffer and its factor exposures; e.g., many funds with low abnormal buffers have relatively high amount of cash holdings. As we show (Table 2), differences in factor exposures between funds in the highest and lowest abnormal buffer groups are insignificant for six out of the seven Fung and Hsieh (2004) factors. Third, the risk-adjusted returns of our low-minus-high buffer spread portfolio have a slight *positive* correlation with VIX, suggesting that low buffer funds tend to fare better, not worse, in more volatile markets.

To further exclude the possibility that higher returns among funds with lower abnormal buffers are simply being driven by lower "cash drag" on performance, we more directly measure the performance of stocks held in fund managers' portfolios using their disclosures contained in quarterly filings of Form 13F. We find that stocks held by managers with low abnormal buffers experience higher future stock returns. For example, a one standard deviation increase in low-buffer ownership predicts higher market-adjusted stock returns of 0.24% per month. An increase in ownership by low-buffer managers also predicts higher stock returns around earnings announcements. Thus, the equity positions of hedge fund managers with low abnormal buffers reflect information about future cash flow news. We further show that the predictability of low-buffer stock ownership for future stock returns is stronger among the subsample of equity-oriented managers and, therefore, managers for which stock positions contained in Form 13F are more representative of their overall portfolio. In sum, the analysis of stock holdings corroborates our story that abnormally low buffers reflect greater investment opportunities and, thus, are predictive of greater fund performance.

Our findings contribute to research showing that investment skill among mutual fund managers is related to measures of active portfolio management, such as a fund's portfolio turnover (Pastor, Stambaugh and Taylor, 2017) and the share of a fund's holdings that deviate from its benchmark index holdings (Cremers and Petajisto, 2009).[4] We follow this logic to the hedge fund setting and use a fund's abnormal liquidity buffer as a measure of (in)active portfolio management. Our evidence supports the basic idea that a manager with greater profit opportunities will utilize more of the fund's capital to finance positions in securities markets and, hence, have a lower liquidity buffer than what would be predicted by fund attributes. In contrast, a manager without such opportunities keeps more of the fund's capital parked as cash or available borrowing and, hence, maintain a higher buffer.

[4] See, also, Titman and Tiu (2011), Sun, Wang, and Zheng (2012), Jagannthan, Malakhov, and Novikov (2010), Duanmu, Malakhov, and McCumber (2018), Bali, Brown, and Caglayan (2011, 2012, and 2014). Kacperczyk, Sialm, and Zheng (2005, 2006), Alexander, Cici, and Gibson (2006), and Chen, Jegadeesh, and Wermers (2000).

Simutin (2014) finds that larger abnormal cash holdings predict better performance among mutual funds, but extremely high levels of cash predict worse performance. He concludes that abnormal cash allows funds to avoid costly fire sales and to capitalize on investment opportunities that may arise in the future, but too much cash is detrimental to performance. We build on this research and present the first analysis of liquidity buffers as a predictor of performance in hedge funds. Since hedge fund managers make significant use of leverage to finance their trading positions, we are careful to account for both cash holdings and available borrowing to build our measure of liquidity buffers. Our finding of a negative relation between abnormal buffers and future performance supports the view that managers with investment opportunities actively use their liquid capital rather than keeping it on hand as dry powder.[5]

Prior work shows that greater cash holdings by mutual funds can reduce the damage from redemptions by spreading flow-triggered trades over a longer period, and that funds hold more cash when they have illiquid portfolios. Consistent with this evidence, we show that hedge funds maintain greater cash holdings when they face a greater liquidity risk in the form of portfolio illiquidity and short-term financing commitments from investors. provide insurance against liquidity risk. Furthermore, given that hedge funds make significant use of leverage, we also consider a fund's available borrowing as an additional component of a fund's total liquidity buffer. We find that available borrowing constitutes over half of a hedge fund's total liquidity buffer, on average, and funds maintain greater available borrowing when

[5] Other papers on cash and mutual funds include Chordia (1996), Yan (2006), Chernenko and Sunderam (2016). Several papers highlight the role of cash in corporate liquidity management (e.g., Opler et al., 1999; Almeida, Campello, and Weisbach, 2004; Faulkender and Wang, 2006; Bates, Kahle, and Stulz, 2009; and Falato, Kadyrzhanova, and Sim, 2015).

they face shorter commitments from their prime brokers and creditors. This supports existing theories that credit lines and other forms of available borrowing provide insurance against liquidity risk.[6] To our knowledge, our paper is the first to provide empirical support for these theories in the hedge fund setting where leverage and liquidity management play important roles in fund operations.[7]

Finally, our results have implications for financial regulation as it pertains to financial stability and systemic risk. As we show, hedge fund managers maintain higher liquidity buffers when they have shorter-term financial commitments from investors and creditors, and when they hold more illiquid assets. This suggests that fund managers tend to align their cash holdings and unused borrowing with an aim to prevent asset fire sales resulting from funding shocks. Second, abnormally low buffers can reflect perceived profit opportunities by the fund manager. Thus, constraints on a fund's liquid capital aimed at improving fund's resilience (e.g., minimum cash holdings and available borrowing) could adversely impact price efficiency, since they would have more effect on managers with a capacity for informed trading and impair their ability to finance positions in undervalued securities.[8]

2. Data and summary statistics

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[6] Empirically, Chen, Goldstein, and Jiang (2010) find greater cash holdings among mutual funds with greater asset illiquidity, while Agarwal, Aragon, and Shi (2019) find greater cash holding among funds of hedge funds with greater mismatch between assets and investor illiquidity. Jiang, Li, and Wang (2021) show that cash holdings are used strategically by corporate bond funds to dynamically manage their liquidity.

[7] In contemporaneous work, Kruttli, Monin, and Watugala (2017) find (as we do) that hedge funds maintain higher levels of cash holdings when they allow investors to redeem their shares more frequently. However, they do not examine a fund's available borrowing as a component of a hedge fund's overall liquidity buffer, nor do they examine the predictive power of liquidity buffers for fund performance.

[8] Generally, hedge funds have played a positive role in price discovery (Cao, Chen, Goetzmann, and Liang 2018) and improved stock market efficiency (Cao, Liang, Lo, and Petrasek 2018).

In this section, we describe the main databases used in our analysis and then explain and summarize the sample constructed.

2.1. Form PF filings

The main data come from quarterly filings of Form PF. 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.[9] 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, cash holdings, and available borrowing capacity. Our analysis focuses on the subsample of private funds that report their fund type as "Hedge Fund" and answer Section 2b of Form PF.[10] Our final sample contains 10,666 quarterly filings over 2013Q1-2017Q2 made by 1,268 funds of 440 advisers.[11]

Section 2b of Form PF provides fund-level information that is central to our analysis. Unencumbered cash is reported in Question 30 and represents cash equivalent assets that have not been pledged as margin with the fund's counterparties. It is the portion of the fund's liquid assets that are unencumbered by counterparty obligations and available to be freely deployed to meet investor redemptions. Available borrowing is the difference between total

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[9] We use the terms "adviser" and "manager" interchangeably. 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."

[10] 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).

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

available borrowing (i.e., used plus unused) and used borrowing. Total 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 undrawn, committed and uncommitted lines of credit as well as any term financing)." Used borrowing is the sum of the responses to the subcategories of Question 43, which relate to the dollar amounts of the fund's unsecured and secured borrowings.[12] Unused borrowing includes short-term credit facilities that can be used to meet investor redemptions, and any free credit balance in the fund's margin account. Such "excess margin" provides a buffer against margin calls from the fund's creditors.[13] We define a fund's liquidity buffer as its unencumbered cash plus available borrowing.

Section 2b of Form PF also provides information for other variables used in our analysis. Question 32 asks each fund to report the percentage of its 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, 181-365, and 365 or more. We define *Portfolio liquidity* as the percentage of assets that can be liquidated in 90 days or less; 69% of a fund's non-cash assets are liquid under this classification. Questions 50 and 46(b) ask analogous questions regarding the duration of a hedge fund's investor capital and borrowing. Thus, we define *Investor liquidity* as the percentage of investor capital that is contractually committed to the

[12] If responses to Question 43 are missing, we use the response to Question 12. We also drop observations with negative values of unused borrowing, which we attribute to reporting error.

[13] 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, reduce its equity down to $50, and increase its debit balance to $50. Alternatively, if the margin requirement is only 25% the fund could withdraw cash up to $50, reduce its equity to $25, and increase 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.

fund for 90 days or less after accounting for redemption restrictions like lock-up periods, imposed gates, redemption frequency, and notice periods, and define *Financing liquidity* as the percentage of a fund's total available (i.e., used and unused) borrowing that has been contractually committed to the fund for 90 days or less (Question 46(b)).

We also obtain monthly returns, net asset values (*NAV*), and gross asset values (*GAV*) for each fund. Monthly returns are reported net of fees (*Net return*). We compute quarterly net flows (*Net flow*) in the usual way as the percentage change in *NAV* minus net of fees returns. *Leverage* is defined as the ratio of *GAV* and *NAV*. In our analysis of Form 13F filings, we classify advisers as "equity-oriented" if they allocate at least 50% of their assets towards equity strategies (Question 20). Finally, to control for the ownership concentration of a fund's investors we define *Top5Owner* as the percentage of a fund's equity owned by the top 5% of its owners (Question 15).

2.2. Other data sources

We obtain the stock positions of hedge fund managers in our sample from the Thomson Reuters 13F Database. This database contains the quarterly filings of Form 13F and are reported at the level of the hedge fund manager.[14] We identify 13F filings for our sample by manually matching the manager names in our Form PF sample with those in Thomson Reuters. We only include filings with at least five stock holdings, holdings that are common equity securities (share code 10 or 11), and stocks that trade on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), or NASDAQ (exchange code 1, 2, or 3). The

[14] All advisers who exercise investment discretion over accounts holding at least $100 million in Section 13(f) securities are required to file Form 13F. Section 13(f) securities consist mainly of common stock but also include American Depository Receipts (ADRs), exchange traded funds (ETFs) and other trusts, convertible bonds, and equity call and put options. See Section 13(f) of the Exchange Act of 1934 for more details. Only long positions in these securities are reportable in Form 13F.

final sample contains 2,618 quarterly filings of Form 13F over 2013Q1-2017Q2 made by 307 advisers.

We obtain monthly observations of the CBOE Volatility Index (VIX) from DataStream, historical stock returns and stock characteristics from the Center for Research in Security Prices (CRSP) and Compustat, and benchmark returns for the Fung and Hsieh (2004) model.[15] Finally, for our analysis of stock returns around earnings announcements, we obtain earnings announcement dates from IBES Summary History Files. All variables used in our analysis are defined in the Appendix.

2.3. Summary statistics

Panel A of Table 1 presents summary information of Form PF variables for the final sample of hedge funds. On average, cash and available borrowing total 18% and 23%, respectively, of a fund's net asset value (*NAV*). Combined, hedge funds maintain an average liquidity buffer (*Buffer*) of 41%, which is larger than mutual funds. For example, equity mutual funds have an average cash ratio of only 8% (Chernenko and Sunderam, 2016) and face restrictions on borrowing from the Investment Company Act of 1940. The sample mean of *Available borrowing*, 23%, is similar in magnitude to the average unused margin loan capacity of broker-dealer customers as reported to the New York Stock Exchange.[16] The fact that these two numbers are close makes sense since hedge funds' available borrowing reflects available lines of credit and/or free credit balance in margin accounts, and most hedge funds

[15]Fung-Hsieh benchmarks are available here: http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls. The benchmarks correspond to the U.S. equity market, the return to small market capitalization stocks, credit and term structure spreads, and three option-based, trend-following factors as in (Fung and Hsieh, 2001).

[16] To compare, we divided 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). 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).

are broker-dealer customers.

Panel A of Table 1 shows that 69% of a fund's non-cash assets (*Portfolio liquidity*) can be liquidated within 90 days without fire sale discounting, and 45% of a fund's investor capital (*Investor liquidity*) can be redeemed within 90 days. In contrast, mutual funds face restrictions on the amount of portfolio illiquidity and have much greater investor liquidity as investors may redeem their shares daily. Strikingly, the 25th percentile of *Financing liquidity* is 100%, indicating that a typical hedge fund's financing from creditors is short-term as it is committed for less than 90 days.[17] The median of *NAV* is \$1.07 billion and larger than the median size of hedge funds reporting to commercial databases (Agarwal, Daniel, and Naik, 2011; Aragon and Nanda, 2017). Thus, our sample contains larger funds compared to these prior studies.[18] Although our sample excludes many small funds, it captures the majority of assets under management of U.S. hedge funds. We estimate that our sample represents assets of \$2.525 trillion $(= \$1.99133 \text{ billion} \times 1{,}268 \text{ funds})$, or, about 84% of the \$3 trillion hedge fund industry at the start of 2017.[19] *Leverage* has a sample mean of 1.82, which is similar to Jiang's (2018) estimate of 1.92 for hedge fund leverage obtained from Form ADV filings over 2011-2013, and Ang, Gorovyy, and van Inwegen's (2011) estimate of 2.13 for hedge fund leverage. Average quarterly returns (1.50%) and net flows (0.20%) are positive,

[17] 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 do 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.

[18] 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.

[19] Source: Hedge Fund Research, "Hedge Fund Industry Capital Surpasses Historic \$3 Trillion Dollar Milestone," published on 1/20/2017.

but there is considerable variation as the standard deviation of returns and flows are 6.5% and 13.8%, respectively. Equity strategies represent 42.13% of a hedge fund's assets, on average, suggesting that our 13F analysis of stock holdings captures a significant portion of a hedge fund's total (i.e., equity plus non-equity) portfolio. Finally, the median of *Top5Owner* is 57%, indicating that a typical fund's largest five investors account for a majority of its NAV.

The remaining panels of Table 1 summarize variables from our analysis of stock holdings disclosed in Form 13F filings. Most of these variables are computed at either the adviser-quarter or stock-quarter level since 13F filings and earnings announcements are measured at a quarterly frequency. For example, from Panel B we see that the median adviser holds around 31 stock positions ($= e^{3.43}$) with a dollar value of \$1.39 billion ($= e^{21.05}$). We also see that the typical adviser has aggregate hedge fund NAV of \$2.7 billion ($= e^{7.90} \times 1{,}000{,}000$), indicating that stock holdings in Form 13F typically represent a significant fraction of a hedge fund's total assets. At the stock level, Panel C shows that hedge funds own 6% of a stock's market capitalization, on average, which is similar to estimates reported in prior studies of hedge fund stock ownership (e.g., Cao et al., 2018).

2.4. External validation: Comparing Form PF and 13F variables.

Before proceeding to our main analysis, we use portfolio disclosures contained in Form 13F filings as an external validation check of the Form PF data and verify the relation between the characteristics of stocks held (i.e., in Form 13F data) and the characteristics of the adviser's overall portfolio as reported in Form PF. Specifically, we compute pairwise correlations between Form PF liquidity variables (aggregated to the adviser level each quarter) and measures of market liquidity of stock holdings reported in Form 13F (ownership-weighted average across all stock holdings in each 13F filing). Reassuringly, we find that hedge funds holding more liquid assets according to Form PF are associated with more liquid (i.e., less illiquid) stock holdings according to Form 13F, as measured by stocks with low bid-ask spreads, low Amihud (2002) illiquidity measures, and large stock market capitalizations. Thus, a fund manager's subjective assessment of portfolio liquidity reported in Form PF bears a strong relation with objective measures of stock market liquidity.

3. Hedge fund liquidity buffers

In this section we study hedge fund liquidity management practices by analyzing the determinants of funds' liquidity buffers. We also define our key variable – *Abnormal buffer* – used in the subsequent analysis of the paper.

3.1. Buffer determinants

We model a hedge fund's liquidity buffer using the following pooled regression:

$$Buffer_{iq} = b_0 + b_1 Portfolio\ Liquidity_{i,q} + b_2 Investor\ liquidity_{i,q} + b_3 Financing\ liquidity_{i,q} + b_4\, VIX_{i,q} + Controls + e_{iq} \qquad (1)$$

The unit of observation is fund-quarter and standard errors are clustered at the fund-level. The first four variables on the right-hand side of Eq. (1) are motivated by prior theories of liquidity management. The basic idea is that a fund manager's choice of buffer reflects a tradeoff between 1) the benefits of cash and available borrowing as a hedge against future financial distress and 2) the opportunity costs associated with low expected returns from holding cash and available borrowing.[20] Ceteris paribus, we expect greater buffers among funds with shorter-term capital commitments from investors and creditors. The reason is that, in the event of financial distress, such funds could experience investor redemptions and

[20] Cash can mitigate the need to liquidate assets to meet payments in the future (Chordia, 1996; Opler et al., 1999; and Zeng, 2017) and allow firms to avoid costly external finance (Froot, Scharfstein and Stein, 1993). Disadvantage of cash is the opportunity cost (i.e., "liquidity premium") and the possibility "free-cash flow" problems. Lines of credit allow firms to obtain funds when financing needs arise (Boot, Thakor, and Udell, 1987; Holmstrom and Tirole, 1998, Martin and Santomero, 1997, and Sufi, 2009).

margin calls, leading to a costly liquidation of fund assets. A finding that b_2 and b_3 are larger than zero would support this prediction. On the other hand, if the fund is holding relatively liquid non-cash assets, then the potential costs of distressed selling are lower. Thus, we would expect a negative relation between buffers and portfolio liquidity and, hence, $b_1 < 0$. Finally, during periods of market stress, there is a greater potential for large drawdowns and, hence, liquidity needs inside the fund. During such periods, therefore, we would expect fund managers to hold larger buffers (i.e., $b_4 > 0$).

Eq. (1) also includes several control variables that could drive variation in *Buffer*, including contemporaneous (i.e., quarter *q*) observations of *Leverage*, log(*NAV*), log(*AdvHFNAV*), log(*GNE*), *Top5Owner*, and lagged (i.e., quarter *q*-1) observations of *Net flow* and *Net return*. We allow for sign asymmetries in flows and returns since it is possible that negative values of returns and flows are signals of future distress and, hence, managers are more inclined to hold larger buffers in those situations (Zeng, 2017; Agarwal, Aragon, and Shi, 2019). Finally, we control for a fund's investment style by including variables that represent a fund's allocation to certain investment strategies, including equity, macro, relative value, event driven, credit, managed futures, and investment in other funds.

The regression results are reported in Table 2. The first column strongly shows that liquidity buffers are lower among funds with more liquid assets. For example, a one standard deviation increase in *Portfolio liquidity* is associated with an 8.39% drop in *Buffer* (*t*-statistic = -7.53). In addition, funds maintain larger buffers when they have shorter-term capital commitments from investors and creditors. A one standard deviation in *Investor liquidity* and *Financing liquidity* is associated with a higher *Buffer* of 7.92% and 5.59%, respectively. Both estimates are significant at the 1% level. The *R*-squared is 7.6%, indicating that a fund's exposure to liquidity risk explains a large portion of variation in liquidity buffers. Column

(3) shows that hedge fund buffers are larger during periods of higher market volatility; however, while significant (*t*-statistic = 3.22), the coefficient estimate of *VIX* is an order of magnitude smaller than those on the other three liquidity variables.

Column (5) of Table 2 presents the results for estimating the full model of Eq. (1), including all liquidity variables, *VIX*, and all control variables. Besides confirming our findings from Columns (1) and (3), this "kitchen sink" model delivers additional insights. First, buffers are larger among more levered funds, smaller funds and smaller advisers, and funds with greater investor ownership concentration.[21] Buffers are also larger among funds with negative returns and net flows during the prior quarter; however, the significance is weak (*t*-statistic = -1.96). Overall, these results provide additional support for liquidity management motives of buffers, to the degree that liquidity risk is greater among funds with greater leverage, less capital, more concentrated investor ownership, and recently poor performance and flows.[22]

3.2. Abnormal buffers

Liquidity buffers measure the amount of available "passive" capital that is not yet part of an active trading strategy. As we show above, a significant portion of *Buffer* can be explained by liquidity management motives; however, we focus the remaining analysis on buffers that cannot be predicted by fund attributes – i.e., its abnormal buffer.

We define *Abnormal buffer* as the residuals from the full specification in Eq. (1) (i.e.,

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[21] Kruttli, Monin, and Watugala (2017) find greater cash holdings among hedge funds with greater investor concentration.

[22] We tried alternative specifications of Eq. (1) that also include measures of a fund's operational risk (e.g., the omega score of Brown, Goetzmann, Liang, and Schwarz, 2008, 2009), liquidity risk (Pastor and Stambaugh, 2003), and downside return risk (e.g., tail risk, value-at-risk of Liang and Park, 2007, 2010) as explanatory variables for liquidity buffer. Since none were significant when added to our kitchen sink specification of Column (5) of Table 2, we exclude them from Table 2 and our analysis of abnormal buffers below.

Column (5) of Table 2). However, unlike the one-time pooled regression estimates reported in Table 5, we estimate *Abnormal buffer* following a backward-looking, recursive strategy. Specifically, at the end of each quarter q, we estimate Eq. (1) using an expanding window that includes all available fund-quarter observations from the start of our sample through quarter q. We define a fund's abnormal buffer in quarter q as its estimated residual in quarter q. For example, the earliest quarter in which we can estimate abnormal buffers is 2013Q3, since our sample period starts in 2013Q1, Eq. (1) requires lagged values of quarterly flows, and flows require two consecutive quarterly observations of NAV (i.e., 2013Q1 and 2013Q2). Thus, abnormal buffers in 2013Q3 are based on estimating Eq. (1) using a cross-sectional regression of observations in 2013Q3 only. In the following quarter, 2013Q4, abnormal buffers are based on estimating Eq. (1) using a pooled regression of observations in the expanded sample combining 2013Q3 and 2013Q4, and so on. A recursive approach avoids forward-looking information, so that any evidence that abnormal buffers predict returns could potentially be of economic value to investors.

Before turning to our analysis of abnormal buffers and future performance, we run a simple check to support our main story. If a low abnormal buffer reflects a capacity for informed trading, then we would expect *Abnormal buffer* for a fund to persist over time, to the degree that such investment skill endures over the life of a fund. We sort funds into deciles based on their *Abnormal buffer* and track whether, say, funds with bottom-decile buffers remain in or drift from the bottom decile over subsequent quarters. We find that the *Abnormal buffer* of an individual fund is persistent over time. Decile rankings do not change much from year to year: the bottom decile ranking rises from 1 to 2.21 and the top decile falls from 10 to 8.90. Even over three years, bottom decile rank rises only to 3.28 from 1 while the top decile rank falls to 7.98 from 10. Hence, *Abnormal buffer* is a good predictor of *Abnormal* *buffer* next quarter, next year, and thereafter.

4. Abnormal liquidity buffers and investment opportunities

We now test whether hedge funds' abnormal liquidity buffers contain predictive power for fund performance and the performance of stocks that fund advisers hold.

4.1. Portfolio sorts

We investigate the monthly returns of portfolios of individual hedge funds while allowing for time variation in abnormal buffers. Specifically, we form 10 portfolios of hedge funds every quarter (with equal number of funds in each portfolio) using expanding window estimates of *Abnormal buffer* (i.e., the residuals in Eq. (1)). Since Eq. (1) is re-estimated every quarter, funds are kept in the portfolio for the three months following each quarter. As noted earlier, we estimate Eq. (1) residuals using a backward-looking approach that only uses information through quarter q. The results are robust to using a one-time estimation of Eq. (1) residuals using the entire sample; however, since the one-time approach is forward-looking, the returns are not investable in real-time. Portfolio formation therefore begins at the end of 2013Q3 with real-time tracking returns starting in October, November, and December of 2013. This portfolio approach makes it easy to compare abnormal buffers with the risks captured by the Fung-Hsieh factors. Such a comparison can be done by simply regressing the monthly *Abnormal buffer* portfolio returns on the seven hedge fund factors. The intercept of this regression is the Fung-Hsieh alpha.

Fig.1 plots the alpha of each *Abnormal buffer* decile (in dashed bars) along with the respective *t*-statistics (in circles). The figure shows that the lowest abnormal buffer portfolio has an average monthly alpha of 0.28% (*t*-statistic = 2.34) and the highest abnormal buffer portfolio has an average monthly alpha of -0.02% (*t*-statistic = -0.19). The difference, 0.30%, is significant (*t*-statistic = 2.90). The rest of the portfolio alphas generally decrease with abnormal buffer. The performance of the portfolio spread (solid bar) suggests that low abnormal buffer funds significantly outperform high abnormal buffer funds in the future, consistent with the interpretation that hedge fund managers maintain lower abnormal buffers when they have greater investment opportunities.[23]

An important consideration is whether low-buffer funds are simply lucky at timing the post-crisis bull equity market that covers our sample period. Note, however, that our alpha estimates are risk-adjusted returns that subtract off any additional premium related to exposures to the Fung and Hsieh (2004) factors, including a broad equity market index. Furthermore, Panel A of Table 3 compares factor exposures (betas) of the long and short legs of the spread portfolio. Aside from exposure to the returns from trend-following strategies in the bond market trend (PTFSBD), the exposures of the spread portfolio have no significant relation to the Fung-Hsieh factors. This helps to further reassure that the spread portfolio is not simply picking up an expected return premium to holding, say, equity or commodity price risk.

Panel B of Table 3 shows the results from sorting funds based on their raw liquidity buffers (i.e., *Buffer*), rather than sorting on *Abnormal buffer*. This would be of interest, for example, if investors find it easier to gauge a fund's raw buffer rather the level of a fund's buffer below that predicted based on a fund's other attributes. Again, we find a positive and significant spread in monthly returns between funds with the lowest and highest *Buffer* (coef.

[23] Our preferred model of benchmarking hedge fund returns is the Fung and Hsieh (2004) seven factor model; however, we also tried the following alternative models to benchmark hedge fund returns: 1) a simple market model using the S&P 500 Index return, 2) a lagged market model including the S&P 500 Index return and three monthly lags of the S&P 500 Index return, and 3) an expanded nine-factor Fung and Hsieh (2004) model that includes the original seven factors plus an emerging markets index and Pastor and Stambaugh's (2003) liquidity risk factor. These alternative models yield similar results to those tabulated using the Fung and Hsieh (2004) seven factor model.

= 0.28%; *t*-statistic = 3.18). Note that, in contrast to *Abnormal buffer*, funds in the lowest decile portfolio based on *Buffer* have considerably greater risk exposure to equity market risk (SNPMRF) than funds in the highest decile (0.2742 vs. 0.2020; *t*-statistic = 2.63). This is not surprising since funds with a large *Buffer* maintain large cash holdings and available borrowing and, therefore, tend to have less risk exposure. Thus, in comparison to *Abnormal buffer*, spread portfolios based on *Buffer* entail more factor risk exposure. Finally, Panels C and D show similar results on the ability of raw and abnormal buffers to predict fund performance for funds managed by advisers that file Form 13F. This subsample provides a closer comparison to the results from our later analysis of the performance of hedge funds' stock holdings report in Form 13F filings.

4.2. Cross-sectional regressions

One disadvantage of the portfolio-based approach is that it is difficult to simultaneously control for other characteristics that affect fund performance. However, as regression residuals to Eq. (1), abnormal buffers are orthogonal to several fund characteristics that are known to impact hedge fund returns, like fund size, share restrictions, and lagged returns. Nevertheless, to distinguish our main findings from competing explanations, we estimate Fama and Macbeth (1973) cross-sectional regressions on monthly hedge fund returns. Specifically, we first run cross-sectional regressions for each month. Then, we report the time series averages of the coefficient estimates and use the time series standard errors of the average slopes to draw inferences.

Specifically, we estimate the following month-by-month Fama and Macbeth cross-sectional regressions:

$$Net\ return_{iqm} - RF_{qm} = a + b Abnormal\ buffer_{i,q-1} + \text{Controls} + e_{iqm}, \quad (2)$$

where the dependent variable is fund *i*'s net return during month *m* of quarter *q* (*m*=1,2,3), in excess of the one-month Treasury Bill rate (RF). The key independent variable is *Abnormal buffer* measured at the end of the prior quarter. A finding that $b < 0$ would indicate that greater abnormal buffers predict lower hedge fund returns and, therefore, support our earlier findings from the portfolio sorts. Control variables are measured at the end of the prior quarter and include quarterly net returns and net flows, investment strategy variables, *Portfolio liquidity*, *Investor liquidity*, *Financing liquidity*, *Top5Owner*, log(*Leverage*), log(*NAV*), and log(*AdvHFNAV*).

The results are reported in Columns (1)-(3) of Table 4. The coefficient on *Abnormal buffer* is negative and significant across all specifications, and ranges between -0.0273 and -0.0414. For example, a coefficient of -0.0333 in Column (2) indicates that a one standard deviation decrease in *Abnormal buffer* is associated with an increase in monthly excess returns of 1.10% (= 3.33% × 0.33). Again, we reach similar findings for the subsample of 13F funds (Column (3)). Consistent with prior literature, several other variables predict hedge fund returns, including past returns and funding liquidity.[24] Overall, the results in Table 4 support the portfolio-based evidence that abnormal buffers predict fund returns; we now know that this finding is unlikely to be driven by other known predictors of fund performance.

4.3. Pooled regressions

The above results show that abnormal buffers predict hedge fund returns after controlling for several fund characteristics, but do not control for differences in expected

[24] See, e.g., Liang (1999), Aragon (2007), Agarwal, Daniel, and Naik (2009), Jagannathan, Malakhov, and Novikov (2010), Aragon, Liang, and Park (2013), Sadka (2010), Teo (2011), Aragon, Martin, and Shi (2019), and Barth and Monin (2019). We also tried other control variables, including a fund's adjusted R-squared with respect to the seven-factor model of Fung and Hsieh (2004) (Titman and Tiu, 2011), a fund's strategy distinctiveness index (Sun, Wang, and Zheng, 2012), a measure of a manager's personal investment in the fund from Form ADV filings (Gupta and Sachdeva, 2019), and alternative definitions of *Portfolio liquidity*, *Investor liquidity*, and *Financing liquidity*; however, our qualitative results on the coefficient on *Abnormal buffer* remain the same.

return premiums related to factor risk. However, the evidence in Panel A of Table 3 show that exposures to the Fung-Hsieh factors are very similar among funds with the lowest and highest abnormal buffers. Thus, prima facie, it is unlikely that the predictive power of abnormal buffer for future returns is due to differences in factor exposures. To be sure, we account for differences in factor exposures using the pooled regression model:

$$Net\ return_{iqm} - RF_{qm} = a + b Abnormal\ buffer_{i,q-1} + \text{Controls} + \sum_{k=1}^{7} d_{ki,q-1} F_{km} + e_{im}, \quad (3a)$$

$$d_{ki,q-1} = d_{k0} + d_{ki} Abnormal\ buffer_{i,q-1}, \quad (3b)$$

where F_{km} is the monthly realization of the k'th Fung-Hsieh factor (k=1,…,7) and $d_{ki,q-1}$ is fund i's exposure to the k'th factor at the end of the prior quarter q-1. By allowing factor exposures to depend linearly on abnormal buffers in Eq. (3b), we follow prior studies that address potential misspecification in models relating returns with asset attributes, where variation in the attribute proxies for variation in the asset's exposure to factor risk (Ferson and Harvey, 1997, 1999).

The pooled regression results are reported in Columns (4)-(6) of Table 4. Standard errors are clustered at the month level. Consistent with the evidence from Fama-Macbeth regressions, we find a negative and significant coefficient on *Abnormal buffer* (i.e., $b < 0$). For example, from Column (5) we estimate that a one standard deviation decrease in *Abnormal buffer* predicts 0.88% higher excess returns (t-statistic = -2.33). The results are similar in Column (6) for the subsample of 13F hedge funds. Taken together, the results strongly show that low abnormal buffers predict higher hedge fund returns, and that this finding is not subsumed by other fund characteristics or a greater exposure to factor risk. While the evidence supports the view that low abnormal buffers reflect a greater capacity for informed trading, it does not directly look at hedge fund manager trades. We now turn to this topic in our analysis of stock holdings contained in public filings of Form 13F.

5. Abnormal liquidity buffers and stock trading performance

If hedge fund managers with low abnormal buffers are those with greater profit-making opportunities, then their stock holdings should contain information about stock fundamentals that is not already reflected in prices. We address this in two ways. First, given a manager's stock holdings as of quarter q, we test whether stocks that are held by managers with low abnormal buffers have higher stock returns over quarter q+1. Second, we test whether such low abnormal buffer ownership predicts greater earnings news by the stock, as measured by cumulative stock returns around the earnings announcement date. To implement these tests, we aggregate the abnormal buffers and other characteristics of all hedge funds run by the same adviser. This is because stock holdings are reported at the adviser level (i.e., aggregated across a manager's individual hedge funds). We compute adviser-level NAV as the total NAV summed across an adviser's hedge funds. All other adviser-level variables (e.g., abnormal buffer, leverage) are computed as NAV-weighted averages across funds.

5.1. The predictive power of holdings for quarterly stock returns

We first estimate pooled regressions of the following form:

$$Adjusted\ stock\ return_{iqm} = a + b_1 Low\ buffer\ HF\ ownership_{i,q-1} + b_2 High\ buffer\ HF\ \ ownership_{i,q-1}$$
$$+\text{Controls} + e_{im} \quad (4a)$$

The unit of observation is stock-month. The dependent variable is stock *i*'s benchmark-adjusted return during month *m* of quarter *q* (*m*=1,2,3). Adjusted returns are computed by subtracting from raw stock returns either the CRSP value-weighted stock index return (market-adjusted) or, following Daniel et al., (1997), the return on a stock index comprised of stocks with similar market capitalization, book to market ratio, and past stock returns

(DGTW-adjusted).

The key independent variables in Eq. (4a) are the percentages of the stock's market capitalization held by managers with low abnormal liquidity buffers (*Low buffer HF ownership*) and high abnormal liquidity buffers (*High buffer HF ownership*). Low and high buffer managers are those with abnormal liquidity buffers below and above the median across all managers during the quarter, respectively. Thus, if low abnormal buffers are indicative of informed trading, then stocks with greater ownership by low buffer managers should outperform (i.e., $b_1 > 0$), while stocks with greater ownership by high buffer managers should not (i.e., $b_2 = 0$). Finally, we include month dummies and several control variables (not tabulated) to account for differences in stock characteristics, including lagged quarterly observations of the logarithm of the stocks' market capitalization, return volatility, Amihud (2002) illiquidity variable, bid-ask spread, turnover, the stock's return over the prior year, and the average leverage of the stock's hedge fund owners. All right-hand-side variables are measured at the end of quarter q-1. Standard errors are clustered at the stock level.

The results are reported in Panel A of Table 5. Stocks with greater ownership by managers with low buffers significantly outperform other stocks. For example, Column (1) shows that a one standard deviation increase in *Low buffer HF ownership* is associated with a 0.21% per month ($= 0.0417 \times 0.05$) increase in market-adjusted stock returns. A similar finding is shown for DGTW-adjusted returns in Column (4). We also see that *High buffer HF ownership* has no significant relation to future stock returns. Thus, the evidence is consistent with informed stock trading by managers with low liquidity buffers, but not with high liquidity buffers. This helps explain our findings in Section 4 that low abnormal buffers predict a hedge fund's overall portfolio performance.

Hedge fund managers trade across several asset markets, not just equity markets.

Thus, we would expect our stock-level evidence from Form 13F filings to be concentrated mainly among managers that focus more of their investments in equity markets. This is exactly what we find. As shown in Column (2) of Panel A of Table 5, the coefficient on *Low buffer HF ownership* is negative and significant for the subsample of equity-focused managers (coef. = 0.0485; *t*-statistic = 3.67); in contrast, Column (3) shows that the coefficient is insignificant for managers that are not equity-focused (coef. = 0.0024; *t*-statistic = 0.14). These results are robust to the method of adjusting stock returns. Thus, the predictability of abnormal buffer ownership for future stock returns is driven precisely by the subset of managers that focus their investment strategies on equity markets.

Finally, we run an alternative test of the predictive power of low-buffer hedge fund stock ownership by estimating the following pooled regression:

$$Adjusted\ stock\ return_{iqm} = a + c_1 Average\ buffer\ of\ HF\ owners_{i,q-1} + c_2 HF\ ownership + \text{Controls} + e_{im} \quad (4b)$$

All variables are the same as in Eq. (4b), except we swap out *Low buffer HF ownership* and *High buffer HF ownership* and swap in *Average buffer of HF owners* and *HF ownership*, where *Average buffer of HF owners* is the ownership-weighted average abnormal buffer of all hedge funds that hold the stock. The reason is that *Average buffer of HF owners* provides a different measure (compared to *Low buffer HF ownership*) of the extent of stock ownership held by managers with low liquidity buffers. Also, similar to our control for *High buffer HF ownership* in Eq. (4a), we include *HF Ownership* to isolate the effects of our key variable from a generic hedge fund ownership effect. Our main point of interest is whether stocks held by hedge funds with low abnormal buffers outperform (i.e., $c_1 < 0$).

The results are reported in Panel B of Table 5. Consistent with our findings in Panel A, stocks held by hedge funds with low buffers significantly outperform other stocks. For example, Column (1) shows that a one standard deviation drop in *Average buffer of HF owners* is associated with a 9 basis points per month $(= -0.0058 \times 0.15)$ increase in market-adjusted stock returns. We also find a negative coefficient on *Average buffer of HF owners* using DGTW-adjusted returns in Column (4); however, the coefficient is not significant (*t*-statistic = –1.20). We also see that hedge fund ownership is a positive predictor of stock returns, which is consistent with existing results from hedge fund stock trading (Brunnermeier and Nagel, 2004; Aragon and Martin, 2012). Finally, in comparing Columns (2) and (3), we again find stronger results for the subsample of equity-focused managers, and that these results are robust to the method of adjusting stock returns.

5.2. The predictive power of holdings for earnings announcement returns

The evidence in Table 5 shows that that stocks that low-buffer hedge fund managers hold outperform other stocks. In this section, we run a complementary analysis in which we analyze how stocks perform at subsequent corporate earnings announcements. As noted by Baker et al., (2010), analyzing the earnings announcement returns of holdings may have more power to detect successful trading activities since it exploits specific events in which concentrated information about a firm's earning prospects is publicly disclosed.

We measure quarterly earnings announcement returns using cumulative adjusted stock returns over the period covering one day prior to three days after the day of the firm's earnings announcement day during quarter *q*. Adjusted returns are computed as the stock's raw return minus either the CRSP value-weighted stock market index (*Market-adjusted CAR*) or the return on the stock's DGTW-matched portfolio (*DGTW-adjusted CAR*). We exclude observations in which the duration between the announcement date and the consensus forecast data exceeds 90 days or is less than 15 days, and observation where the announcement date precedes the IBES Statistical Period.

Following our Table 5 analysis of quarterly stock returns, we estimate two pooled regression models:

$$Adjusted\ CAR_{iq} = a + b_1 Low\ buffer\ HF\ ownership_{i,q-1} + b_2 High\ buffer\ HF\ ownership_{i,q-1} + \text{Controls} + e_{im} \quad (5a)$$

$$Adjusted\ CAR_{iq} = a + c_1 Average\ buffer\ of\ HF\ owners_{i,q-1} + c_2 HF\ ownership + \text{Controls} + e_{im} \quad (5b)$$

The main difference from the Table 5 analysis is that the unit of observation is stock-quarter (since earnings announcements occur once per quarter), and the dependent variable is either the *Market-adjusted CAR* or *DGTW-adjusted CAR* of stock *i* during quarter *q*. Our key predictions are the same: if low abnormal buffers are indicative of informed trading, then stocks with greater ownership by low buffer managers should outperform around earnings announcements (i.e., $b_1 > 0$), while stocks with greater ownership by high buffer managers should not (i.e., $b_2 = 0$). Likewise, in Eq. (5b), we are interested in testing whether stocks held by hedge funds with low abnormal buffers outperform around earnings announcements (i.e., $c_1 < 0$). Finally, we include quarter dummies and the same control variables as in Table 5 (not tabulated) Standard errors are clustered at the stock level.

The results are reported in Table 6. Stocks with greater ownership by managers with low buffers significantly outperform other stocks. For example, Column (1) of Panel A shows that a one standard deviation increase in *Low buffer HF ownership* is associated with a 0.33% per quarter ($= 0.0659 \times 0.05$) increase in market-adjusted stock returns. In contrast, *High buffer HF ownership* has no significant relation to future stock returns. In addition, the predictability of *Low buffer HF ownership* is only significant for equity-focused managers versus non-equity-focused managers (Column (2) vs. (3)). A similar set of results are reported in Columns (4)-(6) for DGTW-adjusted returns and in Panel B where earnings-related CARs are regressed on the average abnormal buffer of a stock's hedge fund owners.

Overall, the evidence in Table 6 complements our earlier findings on the predictability of stock holdings for future stock returns. This evidence is strongest precisely among the subset of managers that focus on equity strategies and, therefore, managers for which stock holdings are more representative of their overall portfolio.

5.3. Portfolio-level results: Do advisers with lower buffers outperform?

An alternative approach to testing the predictability of abnormal buffers for future stock returns is to track the performance of hedge fund advisers' stock portfolios. For each adviser and quarter, we compute one-quarter-ahead returns on the adviser's stock portfolio. We then run the following pooled regression:

$$Adjusted\ portfolio\ return_{i,q} = a + b AbnormalBuffer_{iq-1} + \text{Controls} + e_{i,q+1} \quad (6)$$

where the dependent variable is adviser i's adjusted portfolio return during q corresponding to stocks held at the end of quarter q-1. All right-hand side variables are measured at the end of quarter q-1. The key independent variable is the adviser's abnormal buffer. The finding, $b < 0$, would indicate that advisers with lower abnormal buffers are associated with outperformance in their stock portfolios. As control variables we include quarter dummies, adviser leverage, and natural logarithms of the adviser's *NAV* (summed *NAV* across the adviser's funds), dollar value of stock holdings, and number of stock holdings. We also include several variables (not tabulated) that control for the aggregate characteristics of stocks held, including the stock's return over the prior 12 months, quarterly return volatility, bid-ask spread, Amihud's (2002) illiquidity measure, turnover, and the natural logarithm of stock market capitalization. Standard errors are clustered at the adviser level.

The results are reported in Table 7 and show that abnormal buffers are negative predictors for future stock portfolio returns. For example, the coefficient on *Abnormal buffer* is -0.0070 (t-statistic = -2.14) and -0.0055 (t-statistic = -1.86) for market-adjusted and

DGTW-adjusted returns, respectively. The results are especially significant among equity-oriented managers: a one standard deviation decrease in abnormal buffer is associated with higher market-adjusted quarterly returns on their stock portfolios of 0.38% ($= -0.0116 \times 0.33$). In contrast, we find no significant relation between buffers and returns for managers that are not focused on equity strategies. To further put the magnitudes of our results into perspective, note that the numbers in Tables 5-7 are effects on *unlevered* returns and, therefore, understate the contribution of stock performance to an adviser's actual portfolio returns, which reflect leverage. For example, a 0.38% quarterly return could translate into a 2:1 levered return of 0.76% per quarter. Taken together, the above results indicate that the stock holdings of advisers with low abnormal buffers contain information about stock fundamentals that are not already reflected into stock prices.

6. Conclusions

We examine the quarterly filings of Form PF over 2013-2017 to shed light on the liquidity management practices of hedge fund managers, and the implications of these practices for fund performance. We find that funds maintain higher liquidity buffers when they hold less liquid assets and when they have shorter-term financing commitments from their investors and creditors. In addition, abnormal buffers – i.e., cash and available borrowing that cannot be explained by funding needs or other characteristics – are predictive of fund performance. Funds with low abnormal buffers outperform their peers by 3% to 4% per year on a risk-adjusted basis, while stocks held by managers with low abnormal buffers earn higher risk-adjusted returns over the following quarter, especially around corporate earnings announcements.

Our findings have important implications for investors and policymakers. First, our evidence shows that hedge fund managers adopt a more conservative approach to their liquidity buffers when they face greater funding liquidity risk. Second, our evidence linking a fund's abnormal liquidity buffer with its investment opportunities suggests that potential constraints on hedge funds' liquidity buffer would be most disruptive to the trading activities of managers with a capacity for informed trading, since these managers make greater-than-normal use of liquid capital to finance positions in undervalued securities. Such disruptions to trading activity could prevent information from being impounded into prices and, hence, reduce market efficiency. Our results highlight the potential policy trade-offs between systemic risk-oriented policies requiring larger liquidity buffers to improve funds' resilience and the impairment of regular price discovery in financial markets.

References

Agarwal, V., Daniel, N.D. and Naik, N.Y., 2009. Role of managerial incentives and discretion in hedge fund performance. *Journal of Finance* 64, 2221-2256.

Agarwal, V., Daniel, N.D. and Naik, N.Y., 2011. Do hedge funds manage their reported returns? *Review of Financial Studies* 24, 3281-3320.

Agarwal, V., Aragon, G.O., and Shi, Z., 2019. Liquidity transformation and financial fragility: Evidence from funds of hedge funds, *Journal of Financial and Quantitative Analysis* 54, 1-27.

Alexander, G.J., Cici, G. and Gibson, S., 2006. Does motivation matter when assessing trade performance? An analysis of mutual funds. *Review of Financial Studies* 20, 125-150.

Almeida, H., Campello, M., and Weisbach, M.S., 2004. The cash flow sensitivity of cash, *Journal of Finance* 59, 1777-1804.

Almeida, H., Campello, M., Cunha, I., and Weisbach, M.S., 2014. Corporate liquidity management: A conceptual framework and survey, *Annual Review of Financial Economics* 6, 135-162.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets* 5, 31-56.

Ang, A., Gorovyy, S., and Van Inwegen, G.B., 2011. Hedge fund leverage, *Journal of Financial Economics* 102, 102-126.

Aragon, G.O., 2007. Share restrictions and asset pricing: Evidence from the hedge fund industry. *Journal of Financial Economics* 83, 33-58.

Aragon, G.O., Ergun, T., Getmansky, M., and Girardi, G., 2017. Hedge funds: Portfolio, investor, and financing liquidity, White Paper, U.S. Securities and Exchange Commission, Washington D.C.

Aragon, G.O., Ergun, T., Getmansky, M., and Girardi, G., 2021. Measuring hedge fund liquidity mismatch, *Journal of Alternative Investments* 24, 26-42.

Aragon, G., Liang, B. and Park, H., 2013. Onshore and offshore hedge funds: are they twins?. *Management Science* 60, 74-91.

Aragon, G.O. and Martin, J.S., 2012. A unique view of hedge fund derivatives usage: Safeguard or speculation?. *Journal of Financial Economics* 105, 436-456.

Aragon, G.O., Martin, J.S. and Shi, Z., 2019. Who benefits in a crisis? Evidence from hedge fund stock and option holdings. *Journal of Financial Economics* 131, 345-361.

Aragon, G.O., and Nanda, V.K., 2017. Strategic delays and clustering in hedge fund reported returns, *Journal of Financial and Quantitative Analysis* 52, 1-35.

Baker, M., Litov, L.P., Wachter, J.A. and Wurgler, J., 2010. Can mutual fund manager pick stocks? Evidence from their trades prior to earnings announcements. *Journal of Financial and Quantitative Analysis* 45, 1111-1131.

Bali, T.G., Brown, S.J. and Caglayan, M.O., 2011. Do hedge funds' exposures to risk factors predict their future returns?. *Journal of Financial Economics* 101, 36-68.

Bali, T.G., Brown, S.J. and Caglayan, M.O., 2012. Systematic risk and the cross section of hedge fund returns. *Journal of Financial Economics* 106, 114-131.

Bali, T.G., Brown, S.J. and Caglayan, M.O., 2014. Macroeconomic risk and hedge fund returns. *Journal of Financial Economics* 114, 1-19.

Barth, D., and Monin, P., 2019. Illiquidity in intermediary portfolios: Evidence from large hedge funds, Working Paper, Office of Financial Research.

Barth, D., Joenvaara, J., Kauppila, M., and Wermers, R., 2020. The hedge fund industry is bigger (and has performed better) than you think. Working Paper, Office of Financial Research.

Bates, T.W., Kahle, K.M. and Stulz, R.M., 2009. Why do US firms hold so much more cash than they used to? *Journal of Finance* 64, 1985-2021.

Boot, A., Thakor, A.V., and Udell, G.F., 1987. Competition, risk neutrality and loan commitments, *Journal of Banking & Finance* 11, 449-471.

Brown, S., Goetzmann, W., Liang, B. and Schwarz, C., 2008. Mandatory disclosure and operational risk: Evidence from hedge fund registration. *Journal of Finance* 63, 2785-2815.

Brown, S., Goetzmann, W., Liang, B. and Schwarz, C., 2009. Estimating operational risk for hedge funds: The ω-score. *Financial Analysts Journal* 65, 43-53.

Brunnermeier, M.K., and Nagel, S., 2004. Hedge funds and the technology bubble. *Journal of Finance* 59, 2013-2040.

Cao, C., Chen, Y., Goetzmann, W.N. and Liang, B., 2018. Hedge funds and stock price formation. Financial Analysts Journal 74, 54-68.

Cao, C., Liang, B., Lo, A.W., and Petrasek, L., 2018. Hedge fund holdings and stock market efficiency, *Review of Asset Pricing Studies* 8, 77-116.

Chen, Q., Goldstein, I. and Jiang, W., 2010. Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics* 97, 239-262.

Chen, H.L., Jegadeesh, N. and Wermers, R., 2000. The value of active mutual fund management: An examination of the stockholdings and trades of fund managers. *Journal of Financial and quantitative Analysis* 35, 343-368.

Chernenko, S. and Sunderam, A., 2016. Liquidity transformation in asset management: Evidence from the cash holdings of mutual funds, Working Paper, National Bureau of Economic Research.

Chordia, T., 1996. The structure of mutual fund charges, *Journal of Financial Economics* 41, 3-39.

Cremers, K.M. and Petajisto, A., 2009. How active is your fund manager? A new measure that predicts performance. *Review of Financial Studies* 22, 3329-3365.

Daniel, K., Grinblatt, M., Titman, S. and Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance*, 52, 1035-1058.

Duanmu, J., Malakhov, A. and McCumber, W.R., 2018. Beta Active Hedge Fund Management. *Journal of Financial and Quantitative Analysis* 53, 2525-2558.

Falato, A., Kadyrzhanova, D., and Sim, J., 2015. Rising intangible capital, shrinking debt capacity, and the corporate savings glut, Working Paper, Federal Reserve Board.

Fama, E.F. and MacBeth, J.D., 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy* 81, 607-636.

Faulkender, M., and Wang, R., 2006. Corporate financial policy and the value of cash, *Journal of Finance* 61, 1957-1990.

Ferson, W.E. and Harvey, C.R., 1997. Fundamental determinants of national equity market returns: A perspective on conditional asset pricing. *Journal of Banking and Finance* 21, 1625-1665.

Ferson, W.E. and Harvey, C.R., 1999. Conditioning variables and the cross section of stock returns. *Journal of Finance* 54, 1325-1360.

Fortune, P., 2000, Margin requirements, margin loans, and margin rates: Practice and principles. *New England Economic Review*, 19-44.

Froot, K. A., Scharfstein, D.S., and Stein, J.C., 1993. Risk management: Coordinating corporate investment and financing policies, *Journal of Finance* 48, 1629-1658.

Fung, W. and Hsieh, D.A., 2001. The risk in hedge fund strategies: Theory and evidence from trend followers. *Review of Financial Studies* 14, 313-341.

Fung, W. and Hsieh, D.A., 2004. Hedge fund benchmarks: A risk-based approach. *Financial Analysts Journal* 60, 65-80.

Gatev, E., and Strahan, P.E., 2006. Banks' advantage in hedging liquidity risk: Theory and evidence from the commercial paper market, *Journal of Finance* 61, 867-892.

Gupta, A. and Sachdeva, K., 2019. Skin or Skim? Inside Investment and Hedge Fund Performance. Working Paper, New York University.

Holmström, B., and Tirole, J., 1998. Private and public supply of liquidity, *Journal of Political Economy* 106, 1-40.

Jagannathan, R., Malakhov, A. and Novikov, D., 2010. Do hot hands exist among hedge fund managers? An empirical evaluation. *Journal of Finance* 65, 217-255.

Jiang, W., 2018. Leveraged speculators and asset prices. Available at SSRN 2525986.

Jiang, H., Li, D. and Wang, A., 2021. Dynamic liquidity management by corporate bond mutual funds. *Journal of Financial and Quantitative Analysis* 56, 1622-1652.

Kacperczyk, M., Sialm, C. and Zheng, L., 2005. On the industry concentration of actively managed equity mutual funds. *Journal of Finance* 60, 1983-2011.

Kacperczyk, M., Sialm, C. and Zheng, L., 2006. Unobserved actions of mutual funds. *Review of Financial Studies* 21, 2379-2416.

Kashyap, A.K., Rajan, R., and Stein, J.C., 2002. Banks as liquidity providers: An explanation for the coexistence of lending and deposit-taking, *Journal of Finance* 57, 33-73.

Kruttli, M.S., Monin, P. and Watugala, S.W., 2017. Investor concentration, flows, and cash holdings: Evidence from hedge funds, Working Paper, Cornell University.

Kruttli, M.S., Monin, P. and Watugala, S.W., 2021. LTCM redux? Hedge fund Treasury trading and funding fragility during the COVID-19 crisis, Working Paper, Federal Reserve Board.

Kruttli, M.S., Monin, P. and Watugala, S.W., 2021. The Life of the Counterparty: Shock Propagation in Hedge Fund-Prime Broker Credit Networks, forthcoming at *Journal of Financial Economics*.

Liang, B., 1999. On the performance of hedge funds. *Financial Analysts Journal* 55, 72-85.

Liang, B. and Park, H., 2007. Risk measures for hedge funds: a cross-sectional approach. European financial management 13, 333-370.

Liang, B. and Park, H., 2010. Predicting hedge fund failure: A comparison of risk measures. Journal of Financial and Quantitative analysis 45, 199-222.

Martin, J.S., and Santomero, A.M., 1997. Investment opportunities and corporate demand for lines of credit, *Journal of Banking and Finance* 21, 1331-1350.

Opler, T., Pinkowitz, L., Stulz, R., and Williamson, R., 1999. The determinants and implications of corporate cash holdings, *Journal of Financial Economics* 52, 3-46.

Pástor, L., and Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. *Journal of Political Economy* 111, 642-685.

Pástor, L., Stambaugh, R.F. and Taylor, L.A., 2017. Do funds make more when they trade more?. *Journal of Finance* 72, 1483-1528.

Sadka, R., 2010. Liquidity risk and the cross-section of hedge-fund returns. *Journal of Financial Economics* 98, 54-71.

Simutin, M., 2014. Cash holdings and mutual fund performance. *Review of Finance* 18, 1425-1464.

Sufi, A., 2009. Bank lines of credit in corporate finance: An empirical analysis. *Review of Financial Studies* 22, 1057-1088.

Sun, Z., Wang, A. and Zheng, L., 2012. The road less traveled: Strategy distinctiveness and hedge fund performance. *Review of Financial Studies* 25, 96-143.

Teo, M., 2011. The liquidity risk of liquid hedge funds. *Journal of Financial Economics* 100, 24-44.

Titman, S. and Tiu, C., 2011. Do the best hedge funds hedge? *Review of Financial Studies* 24, 123-168.

Yan, X., 2006. The determinants and implications of mutual fund cash holdings: Theory and evidence. *Financial Management* 35, 67-91.

Zeng, Y., 2017. A dynamic theory of mutual fund runs and liquidity management, Working Paper, University of Washington.

Appendix: Variable definitions

Variable	Description and data source
Abnormal buffer	Estimated residuals from pooled least squares regression of hedge fund liquidity buffer (see Eq. (1)) using the full specification corresponding to results in Column (5) of Table 2. Residuals in quarter q are estimated recursively using an expanding estimation window using all available data as of quarter q-1. Data are from Form PF and Datastream.
Average buffer of HF owners	Ownership-weighted average abnormal buffer of all hedge funds that hold the stock. Weights are based on quarter-end stock ownership. Data are from Form PF and 13F.
Available borrowing	Total borrowing available minus used borrowing, divided by NAV. Total borrowing available is from Form PF, Q46 (a). Used borrowing equals actual used borrowing and is from Form PF, Q43 or, if missing, then Q12. NAV is from Form PF, Q9.
Buffer	*Cash* plus *Available borrowing*.
Cash	Unencumbered cash divided by NAV. Form PF, Q33.
DGTW-adjusted CAR	Cumulative adjusted stock return over the period covering one day prior to three days after the day of the firm's earnings announcement day during quarter q+1. Adjusted returns are computed as the stock's raw return minus the return on the stock's DGTW-matched portfolio. Data are from Form 13F, IBES, and CRSP.
DGTW-adjusted portfolio return	Quarter q+1 return of stocks held at the end of quarter q. Returns are computed for each manager and quarter as weighted averages of stock returns in excess of the DGTW benchmarks. Data are from Form 13F, CRSP, and Compustat.
Equity	Percentage of fund's NAV following Equity strategy. Form PF, Q20.
Financing liquidity	Percentage of borrowing with a commitment period of 90 days or less.
HF ownership	Total stock ownership of all hedge fund managers. Ownership is measured at quarter-end. Data are from 13F filings.
High buffer HF ownership	Total stock ownership of hedge fund managers with above-median abnormal liquidity buffers. Ownership is measured at quarter-end. Data are from 13F filings.
Investor liquidity	Percentage of investor capital with a commitment period of 90 days or less.
Leverage	Fund leverage: GAV/NAV, where GAV is fund gross asset value. Form PF, Q8 and Q9.
Log(*AdvHFNAV*)	Natural logarithm of adviser HFs AUM.
Log(*GNE*)	Natural logarithm of fund gross notional exposure.
Log(*leverage*)	Natural logarithm of leverage.
Log(*NAV*)	Natural logarithm of fund NAV.
Log(*Number of stocks held*)	Natural logarithm of number of disclosed stock positions in Form 13F.

Log(*Value of stocks held*)	Natural logarithm of dollar value of disclosed stock positions in Form 13F.
Low buffer HF ownership	Total stock ownership of hedge fund managers with below-median abnormal liquidity buffers. Ownership is measured at quarter-end. Data are from 13F filings.
Market-adjusted CAR	Cumulative adjusted stock return over the period covering one day prior to three days after the day of the firm's earnings announcement day during quarter q+1. Adjusted returns are computed as the stock's raw return minus the CRSP value-weighted stock market index. Data are from Form 13F, IBES, and CRSP.
Market-adjusted portfolio return	Quarter q+1 return of stocks held at the end of quarter q. Returns are computed for each manager and quarter as weighted averages of stock returns in excess of the CRSP value-weighted stock market index. Data are from Form 13F and CRSP.
NAV	Net asset value ($ millions). Form PF, Q9.
Net flow	Quarterly net flows computed as [*NAV*(q)-*NAV*(q-1)*(1+*Net return*(q))]/*NAV*(q-1).
Net return	Quarterly net-of-fees returns computed as the product of (one plus) the monthly returns within the quarter, minus one.
Portfolio liquidity	Percentage of non-cash assets that need 90 days or less to be liquidated.
Prior 2 to 12 month return	Prior 2 to 12 month return of stock underlying disclosed position in Form 13F.
Top5Owner	Percentage of fund's equity own by top 5% owners. Form PF, Q15.
VIX	Level of CBOE Volatility Index. From Datastream.

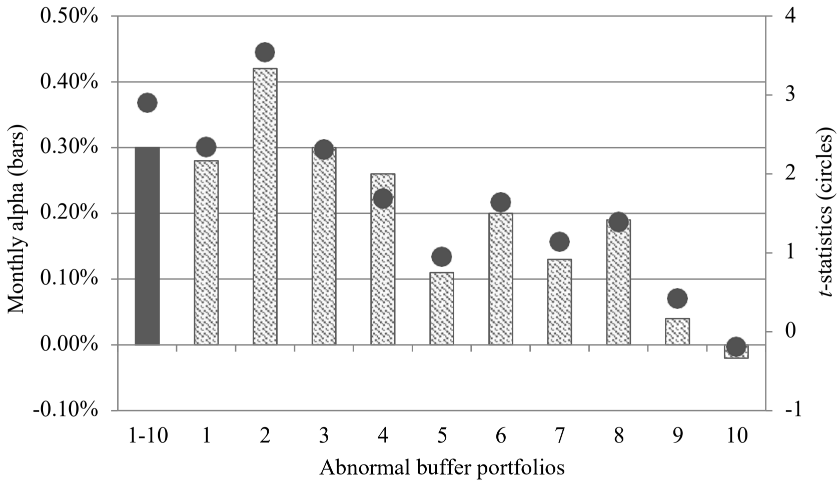

Figure 1: Monthly alphas of hedge fund portfolios. Fung and Hsieh (2004) alphas of hedge fund portfolios. Hedge funds are sorted quarterly into 10 portfolios according to *Abnormal buffer* (defined in Appendix) at the end of each quarter q-1. Monthly portfolio returns are computed as equally weighted net-of-fees fund returns during the following three months of quarter q. Each of the ten series of monthly portfolio returns is regressed on the Fung and Hsieh (2004) seven factors, which include benchmark returns corresponding to the U.S. equity market, the spread between small and big market capitalization stocks, credit spread, term structure spread, and three trend-following strategies. The intercept of each regression is the monthly Fung-Hsieh alpha. The analysis includes the hedge fund universe on Form PF for the period October 2013-June 2017. The dashed bars represent monthly Fung-Hsieh alphas. The circles present the respective t-statistics of the alphas. The figure also displays the alpha of the low-minus-high abnormal buffer spread portfolio (1-10, solid bar).

Table 1: Characteristics of the hedge fund sample over 2013Q2-2017Q3. This table reports summary statistics. All variables are defined in the Appendix.

Variable	N	mn	sd	p25	p50	p75
Panel A: Form PF variables (fund-quarter)						
Buffer	10,666	0.41	0.38	0.15	0.33	0.57
Cash	10,666	0.18	0.22	0.01	0.09	0.26
Available borrowing	10,666	0.23	0.32	0.00	0.11	0.38
Abnormal buffer	10,666	-0.01	0.33	-0.21	-0.05	0.14
Portfolio liquidity	10,666	0.69	0.31	0.51	0.79	0.95
Investor liquidity	10,666	0.45	0.45	0.00	0.25	1.00
Financing liquidity	10,666	0.87	0.29	1.00	1.00	1.00
Log(leverage)	10,666	0.45	0.48	0.09	0.32	0.62
Log(NAV)	10,666	6.87	1.37	6.24	6.97	7.72
Log(AdvHFNAV)	10,666	22.83	1.40	21.70	22.87	23.99
Log(GNE)	10,666	7.92	1.74	6.97	7.94	8.99
Equity	10,666	42.13	46.11	0.00	12.00	100.00
Top5Owner	10,666	60.88	27.62	37.00	57.00	90.00
Net flow	10,666	0.002	0.138	-0.042	-0.001	0.026
Net return	10,666	0.015	0.065	-0.007	0.016	0.038
VIX	10,666	15.56	3.32	13.29	15.29	18.21
NAV ($ millions)	10,666	1991.33	2657.57	514.74	1065.71	2244.75
Leverage	10,666	1.82	1.52	1.09	1.37	1.85

Panel B: Form 13F variables (adviser-quarter)						
Abnormal buffer	2,618	-0.01	0.29	-0.17	-0.03	0.13
Log(NAV)	2,618	8.06	1.11	7.27	7.90	8.84
Log(Value of stocks held)	2,618	21.11	1.52	20.26	21.05	21.97
Log(Number of stocks held)	2,618	3.84	1.48	2.77	3.43	4.60
Leverage	2,618	1.85	1.10	1.29	1.51	1.90
Market-adjusted portfolio return	2,618	0.00	0.06	-0.02	0.00	0.03
DGTW-adjusted portfolio return	2,618	0.00	0.05	-0.02	0.00	0.02
Panel C: Form Stock-level variables (stock-month)						
Average buffer of HF owners	136,012	-0.08	0.15	-0.15	-0.07	-0.01
Low buffer HF ownership	136,012	0.04	0.05	0.01	0.02	0.05
High buffer HF ownership	136,012	0.03	0.04	0.00	0.01	0.03
HF ownership	136,012	0.06	0.07	0.02	0.05	0.09
Market-adjusted portfolio return	136,012	0.00	0.14	-0.05	0.00	0.05
DGTW-adjusted portfolio return	136,012	0.00	0.13	-0.05	0.00	0.05
Panel D: Stock-level variables (stock-quarter)						
Market-adjusted CAR	38,518	0.00	0.11	-0.04	0.00	0.04
DGTW-adjusted CAR	38,518	0.00	0.11	-0.04	0.00	0.04

Table 2: Determinants of hedge fund liquidity buffers. Regressions of quarterly liquidity buffers (cash plus available borrowing). All variables are defined in the Appendix and standardized to have a zero mean and unit variance. *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.

	Dependent variable: $Buffer_{i,q}$				
	(1)	(2)	(3)	(4)	(5)
$Portfolio\ liquidity_{i,q}$	-0.0839***				-0.1521***
	(-7.53)				(-12.87)
$Investor\ liquidity_{i,q}$	0.0792***				0.0738***
	(8.63)				(7.59)
$Financing\ liquidity_{i,q}$	0.0559***				0.0460***
	(5.36)				(4.92)
$Leverage_{i,q}$		0.0240*			0.0392***
		(1.70)			(2.99)
Log(NAV)$_{i,q}$		-0.1341***			-0.0809***
		(-4.96)			(-2.88)
Log($AdvHFNAV$)$_{i,q}$		-0.0368***			-0.0661***
		(-3.79)			(-6.47)
Log(GNE)$_{i,q}$		0.1311***			0.1072***
		(4.47)			(3.63)
$Top5Owner_{i,q}$			0.0315***		0.0279***
			(3.74)		(2.85)
VIX_q			0.0093***		0.0053**
			(3.22)		(2.03)
$Max(Net\ flow,0)_{i,q-1}$				-0.0014	-0.0085**
				(-0.33)	(-2.24)
$Min(Net\ flow,0)_{i,q-1}$				-0.0181***	-0.0087
				(-3.11)	(-1.60)
$Max(Net\ return,0)_{i,q-1}$				-0.0048	-0.0098*
				(-0.71)	(-1.84)
$Min(Net\ return,0)_{i,q-1}$				-0.0225***	-0.0095*
				(-3.70)	(-1.96)
Intercept	0.4155***	0.3927***	0.3591***	0.4091***	0.3256***
	(42.16)	(43.01)	(14.43)	(42.82)	(14.19)
Style controls?	No	No	Yes	No	Yes
N	10,666	10,666	10,666	10,666	10,666
R-squared	0.076	0.058	0.062	0.005	0.212

Table 3: Sorts on liquidity buffer

Hedge funds are sorted into deciles based on their liquidity buffer at the end of every quarter. Alpha is estimated using monthly net-of-fees portfolio returns relative to the Fung and Hsieh (2004) seven-factor model. Portfolio returns are equally-weighted. The Fung and Hsieh (2004) seven factors are Standard and Poor's 500 return minus the risk free rate (SNPMRF), Russel 2000 index minus Standard and Poor's 500 index returns (SCMLC), Barclays U.S. Treasury 7-10 Year index minus the risk free rate (BD10RET), Barclays Baa U.S. Corporate USD index minus Barclays Aaa U.S. Corporate index returns (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodities PTFS (PTFSCOM), where PTFS is primitive trend following strategy. *t*-statistics are reported in parentheses. The evaluation period is from October 2013 to June 2017. Results are reported separately for abnormal buffer (Panels A and C) and raw buffer (Panels B and D), and for the subsample of funds that file Form 13F (Panels C and D). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Excess return	Alpha	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM
				Panel A: *Abnormal buffer*, full sample					
Q1	0.0059***	0.0028**	0.2314***	0.0255	0.0027	0.2142	-0.0264**	0.0115	-0.0033
	(3.54)	(2.34)	(5.48)	(0.61)	(0.02)	(1.68)	(-2.18)	(1.39)	(-0.38)
Q10	0.0020	-0.0002	0.2207***	0.0167	0.0532	0.1488	0.0007	0.0009	0.0002
	(1.34)	(-0.19)	(4.14)	(0.36)	(0.47)	(0.99)	(0.06)	(0.13)	(0.02)
Q1 − Q10	0.0039***	0.0030***	0.0107	0.0088	-0.0505	0.0654	-0.0272**	0.0106	-0.0036
	(3.90)	(2.90)	(0.36)	(0.29)	(-0.45)	(0.46)	(-2.48)	(1.50)	(-0.48)
				Panel B: *Buffer*, full sample					
Q1	0.0059***	0.0028***	0.2742***	0.0442	0.0995	0.3240***	-0.0171	0.0077	0.0019
	(3.59)	(2.85)	(7.43)	(1.29)	(1.25)	(3.17)	(-1.62)	(1.15)	(0.28)
Q10	0.0017	-0.0000	0.2020***	-0.0083	0.1245	0.1957	0.0045	0.0056	0.0044
	(1.29)	(-0.04)	(4.07)	(-0.18)	(1.13)	(1.28)	(0.36)	(0.76)	(0.51)
Q1 − Q10	0.0042***	0.0028***	0.0722**	0.0525	-0.0250	0.1282	-0.0216**	0.0021	-0.0025
	(3.91)	(3.18)	(2.63)	(1.42)	(-0.29)	(0.93)	(-2.28)	(0.33)	(-0.44)

Panel C: *Abnormal buffer*, 13F sample									
Q1	0.0060***	0.0024*	0.2849***	0.0144	0.0593	0.2249	-0.0285**	0.0129	0.0019
	(3.21)	(1.97)	(5.49)	(0.32)	(0.45)	(1.46)	(-2.22)	(1.54)	(0.18)
Q10	0.0016	-0.0012	0.3206***	0.0712	0.1090	0.1082	0.0084	-0.0008	0.0003
	(0.88)	(-0.85)	(6.02)	(1.47)	(0.80)	(0.58)	(0.54)	(-0.09)	(0.02)
Q1 − Q10	0.0043***	0.0036**	-0.0357	-0.0567*	-0.0498	0.1168	-0.0369**	0.0137*	0.0016
	(3.32)	(2.56)	(-0.93)	(-1.75)	(-0.35)	(0.64)	(-2.56)	(1.71)	(0.16)
Panel D: *Buffer*, 13F sample									
Q1	0.0056***	0.0021	0.2823***	0.0774	0.0894	0.2652*	-0.0251*	0.0076	-0.0021
	(2.97)	(1.59)	(5.48)	(1.66)	(0.85)	(1.85)	(-1.71)	(0.83)	(-0.26)
Q10	0.0017	-0.0003	0.2450***	0.0141	0.1836	0.1285	0.0074	0.0069	0.0045
	(1.11)	(-0.21)	(4.73)	(0.28)	(1.28)	(0.62)	(0.51)	(0.80)	(0.48)
Q1 − Q10	0.0038***	0.0024**	0.0373	0.0632	-0.0942	0.1367	-0.0325***	0.0007	-0.0066
	(2.93)	(2.04)	(1.04)	(1.56)	(-0.81)	(0.92)	(-2.84)	(0.08)	(-0.92)

Table 4: Fama-Macbeth and pooled regressions of hedge fund performance

The table reports results from regressions of monthly hedge fund portfolio returns. The dependent variable is the net-of-fees return of hedge fund i during the m'th month of quarter q (m = 1,2,3) in excess of the risk-free rate. The key independent variable is the hedge fund's abnormal liquidity buffer (*Abnormal buffer*) at the end of quarter q-1. Additional controls are measured at the end of quarter q-1 and include *Leverage*, *Net return*, *Net flow*, *Top5Owner*, *Investor liquidity*, *Financing liquidity*, *Portfolio liquidity*, and natural logarithms of *NAV* and the aggregate hedge fund *NAV* of the fund's adviser. All variables are defined in the Appendix. Columns (1)-(3) report the average coefficient obtained from month-by-month, cross-sectional regressions in the spirit of Fama and Macbeth (1973). Columns (4)-(6) show estimated coefficients from pooled OLS regressions using the entire sample of monthly fund returns. Standard errors in pooled regressions are clustered at the month level. Columns (5) and (6) additionally include monthly observations of the seven factors of Fung and Hsieh (2004) and their interaction with *Abnormal buffer*. All regressions include strategy variables. Columns (1), (2), (4), and (5) present results for the full sample of hedge funds; Columns (3) and (6) present results for the subsample of hedge funds that file Form 13F. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: *Net return*$_{i,q,m}$ - Risk free rate$_{q,m}$					
	Fama Macbeth regressions			Pooled regressions		
	(1)	(2)	(3)	(4)	(5)	(6)
Abnormal buffer$_{i,q-1}$	-0.0414***	-0.0333***	-0.0273***	-0.0360***	-0.0267**	-0.0260**
	(-3.85)	(-3.11)	(-3.55)	(-3.79)	(-2.33)	(-2.64)
Log(*leverage*$_{i,q-1}$)	-	-0.0153	-0.0156	-	-0.0128	-0.0139
	-	(-1.05)	(-0.95)	-	(-0.79)	(-0.76)
Log(*NAV*$_{i,q-1}$)	-	0.0034	0.0055	-	0.0035	0.0007
	-	(0.22)	(0.53)	-	(0.23)	(0.07)
Log(*AdvHFNAV*$_{i,q-1}$)	-	0.0057	-0.0029	-	-0.0011	-0.0057
	-	(0.5)	(-0.23)	-	(-0.09)	(-0.41)
Net return$_{i,q-1}$	-	0.1552***	0.1671***	-	0.1518***	0.1667***
	-	(4.73)	(4.52)	-	(5.78)	(5.64)
Net flow$_{i,q-1}$	-	-0.0182*	-0.0167	-	-0.0085	-0.0099
	-	(-1.84)	(-1.6)	-	(-0.89)	(-1.03)
Top5Owner$_{i,q-1}$	-	-0.0009	-0.0027	-	0.0013	-0.0022
	-	(-0.1)	(-0.38)	-	(0.15)	(-0.29)
Investor liquidity$_{i,q-1}$	-	-0.0047	0.0056	-	-0.0007	0.0076
	-	(-0.53)	(0.64)	-	(-0.07)	(0.77)
Financing liquidity$_{i,q-1}$	-	-0.023***	-0.0292***	-	-0.0321***	-0.0409***
	-	(-2.8)	(-2.97)	-	(-3.90)	(-3.94)
Portfolio liquidity$_{i,q-1}$	-	-0.0202	-0.0118	-	-0.0228	-0.0148
	-	(-1.19)	(-0.7)	-	(-1.25)	(-0.82)
Observations	29,331	29,331	21,655	29,331	29,331	21,655
Adj. R-squared	0.004	0.170	0.187	0.115	0.106	0.129
Strategy controls?	Yes	Yes	Yes	Yes	Yes	Yes
Month dummies?	No	No	No	Yes	No	No
FH7 controls?	No	No	No	No	Yes	Yes
Sample	All funds	All funds	13F funds	All funds	All funds	13F funds

Table 5: Hedge fund ownership and future stock returns

The unit of observation is stock-month. Dependent variable is stock *i*'s adjusted return during month *m* of quarter *q* (*m*=1,2,3). Adjusted returns subtract either the aggregate equity market return (1-3) or the Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997) benchmark return (4-6). All independent variables are measured at the end of quarter *q*-1. In Panel A, the key independent variable is the stock ownership aggregated across all hedge fund owners with low liquidity buffers (*Low buffer HF ownership*). A hedge fund has a low buffer if its abnormal buffer is below the median abnormal buffer during the quarter. In Panel B, the key independent variable is the average abnormal buffer of the stock's hedge fund owners. *HF ownership* is the total number of shares held by all hedge fund managers dividedby shares outstanding. All other variables are defined in the Appendix. All regressions include month dummies and lagged quarterly observations of the logarithm of the stocks' market capitalization, return volatility, Amihud (2002) illiquidity variable, bid-ask spread, turnover, and the stock's return over the prior year. We also include the average leverage of the stock's hedge fund owners. Results arereported separately for the full sample, equity-oriented, and non-equity-oriented managers. Equity oriented managers have more than 50% of their aggregate net asset value invested in equity strategies. *t*-statistics are in parentheses. Standard errors account for heteroskedasticity and stock-level clustering. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Returns regressed on low versus high buffer ownership

	Market-adjusted returns$_{i,q,m}$			*DGTW-adjusted returns$_{i,q,m}$*		
	(1)	(2)	(3)	(4)	(5)	(6)
Low buffer HF ownership$_{i,q-1}$	0.0417***	0.0485***	0.0024	0.0363***	0.0404***	0.0051
	(3.46)	(3.67)	(0.14)	(3.17)	(3.19)	(0.28)
High buffer HF ownership$_{i,q-1}$	-0.0019	-0.0058	0.0045	-0.0004	-0.0010	0.0010
	(-0.17)	(-0.39)	(0.23)	(-0.03)	(-0.07)	(0.05)
Observations	136,012	128,683	130,537	136,012	128,683	130,537
R-squared	0.025	0.027	0.026	0.002	0.002	0.001
Month fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
Stock control variables?	Yes	Yes	Yes	Yes	Yes	Yes
Subsample	Full sample	Equity	Non-equity	Full sample	Equity	Non-equity

Panel B: Returns regressed on average buffer of hedge fund owners

	Market-adjusted returns$_{i,q,m}$			*DGTW-adjusted returns$_{i,q,m}$*		
	(1)	(2)	(3)	(4)	(5)	(6)
Average buffer of HF owners$_{i,q-1}$	-0.0058**	-0.0063***	0.0059	-0.0032	-0.0049**	0.0060
	(-2.22)	(-3.20)	(1.36)	(-1.20)	(-2.51)	(1.39)
HF ownership$_{i,q-1}$	0.0246***	0.0317***	0.0032	0.0218***	0.0276***	0.0031
	(3.18)	(3.15)	(0.27)	(2.89)	(2.86)	(0.27)
Observations	136,012	128,683	130,537	136,012	128,683	130,537
R-squared	0.024	0.026	0.026	0.002	0.002	0.001
Month fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
Stock control variables?	Yes	Yes	Yes	Yes	Yes	Yes
Subsample	Full sample	Equity	Non-equity	Full sample	Equity	Non-equity

Table 6. Hedge fund ownership and stock returns around earnings announcements. The unit of observation is stock-quarter. Dependent variable is stock *i*'s cumulative adjusted return (CAR) around its earnings announcement during quarter *q*. The event window covers one day before through three days after the announcement day [-1,+3]. Adjusted returns subtract either the aggregate equity market return (1-3) or the Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997) benchmark return (4-6). All independent variables are measured at the end of quarter *q*-1. In Panel A, the key independent variable is the stock ownership aggregated across all hedge fund owners with low liquidity buffers (*Low buffer HF ownership*). A hedge fund has a low buffer if its abnormal buffer is below the median abnormal buffer during the quarter. In Panel B, the key independent variable is the average abnormal buffer of the stock's hedge fund owners. *HFownership* is the total number of shares held by all hedge fund managers divided by shares outstanding. All other variables are definedin the Appendix. All regressions include month dummies and lagged quarterly observations of the logarithm of the stocks' market capitalization, return volatility, Amihud (2002) illiquidity variable, bid-ask spread, turnover, and the stock's return over the prior year. We also include the average leverage of the stock's hedge fund owners. Results are reported separately for the full sample, equity-oriented, and non-equity-oriented managers. Equity oriented managers have more than 50% of their aggregate net asset value invested in equity strategies. *t*-statistics are in parentheses. Standard errors account for heteroskedasticity and stock-level clustering. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Earnings-related CARs regressed on low versus high buffer ownership

	Market-adjusted $CARs_{i,q}$			*DGTW-adjusted* $CARs_{i,q}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Low buffer HF ownership$_{i,q-1}$	0.0659**	0.0748**	0.0221	0.0623**	0.0684*	0.0226
	(2.21)	(1.99)	(1.13)	(2.13)	(1.85)	(1.15)
High buffer HF ownership$_{i,q-1}$	0.0093	-0.0031	0.0355	0.0053	-0.0079	0.0260
	(0.53)	(-0.13)	(1.33)	(0.30)	(-0.37)	(0.92)
Observations	38,518	37,220	38,006	38,518	37,220	38,006
R-squared	0.004	0.004	0.003	0.002	0.002	0.002
Month fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
Stock control variables?	Yes	Yes	Yes	Yes	Yes	Yes
Subsample	Full sample	Equity	Non-equity	Full sample	Equity	Non-equity

Panel B: Earnings-related CARs regressed on average buffer of hedge fund owners

	Market-adjusted $CARs_{i,q}$			*DGTW-adjusted* $CARs_{i,q}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Average buffer of HF owners$_{i,q-1}$	-0.0102**	-0.0049*	-0.0027	-0.0101***	-0.0050*	-0.0016
	(-2.53)	(-1.65)	(-0.42)	(-2.58)	(-1.75)	(-0.25)
HF ownership$_{i,q-1}$	0.0435***	0.0488**	0.0278*	0.0398**	0.0429*	0.0240
	(2.73)	(2.11)	(1.84)	(2.53)	(1.90)	(1.53)
Observations	38,518	37,220	38,006	38,518	37,220	38,006
R-squared	0.004	0.004	0.003	0.002	0.002	0.002
Month fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
Stock control variables?	Yes	Yes	Yes	Yes	Yes	Yes
Subsample	Full sample	Equity	Non-equity	Full sample	Equity	Non-equity

Table 7: Quarterly returns of managers' stock portfolios.
The unit of observation is manager-quarter. The dependent variable is the quarterly adjusted return of adviser *i*'s stock portfolio during quarter *q*. Adjusted returns subtract either the aggregate equity market return (1-3) or the Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997) benchmark return (4-6). All independent variables are measured at the end of quarter q-1. The key independent variable is the manager's abnormal buffer. Additional control variables include the adviser's leverage and the natural logarithms of aggregate hedge fund *NAV*, dollar value of stock holdings, and number of stocks held. All regressions include quarter dummies and portfolio-weighted, quarterly observations of stock portfolio control variables, including quarterly return volatility, Amihud (2002) illiquidity measure, bid-ask spread, turnover, prior year's stock return, and the natural logarithm of stock market capitalization. Results are reported separately for the full sample, equity-oriented managers, and non-equity-oriented managers. Equity oriented managers have more than 50% of their aggregate net asset value invested in equity strategies. Standard errors are clustered by managers; t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Market-adjusted portfolio return$_{i,q}$			*DGTW-adjusted portfolio return$_{i,q}$*		
	(1)	(2)	(3)	(4)	(5)	(6)
Abnormal buffer$_{i,q-1}$	-0.0070**	-0.0116***	0.0024	-0.0055*	-0.0104***	0.0057
	(-2.14)	(-3.07)	(0.43)	(-1.86)	(-3.04)	(1.19)
Log(NAV$_{i,q-1}$)	-0.0029**	-0.0030*	-0.0006	-0.0026**	-0.0026	-0.0006
	(-2.04)	(-1.69)	(-0.36)	(-2.02)	(-1.47)	(-0.41)
Log(Value of stocks held$_{i,q-1}$)	0.0026**	0.0027	-0.0000	0.0023**	0.0025	-0.0001
	(2.38)	(1.42)	(-0.01)	(2.46)	(1.33)	(-0.08)
Log(Number of stocks held$_{i,q-1}$)	-0.0001	-0.0003	0.0010	0.0001	-0.0003	0.0014
	(-0.09)	(-0.22)	(0.79)	(0.11)	(-0.22)	(1.28)
Leverage$_{i,q-1}$	-0.0012	-0.0005	-0.0010	-0.0010	-0.0004	-0.0010
	(-1.46)	(-0.34)	(-0.93)	(-1.48)	(-0.29)	(-1.11)
Portfolio control variables?	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,618	1,604	1,014	2,618	1,604	1,014
R-squared	0.138	0.180	0.125	0.089	0.120	0.089
Subsample	Full sample	Equity	Non-equity	Full sample	Equity	Non-equity

NOTES