Systemic Risk Channels of Nonbank Financial Entities: Evidence from Hedge Funds and Mutual Funds

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Abstract

Using a sample of hedge funds and mutual funds, I examine two channels through which nonbank financial entities can contribute to systemic risk: the service channel when funds act as liquidity suppliers and the asset liquidation channel when funds act as liquidity demanders. Consistent with the latter channel being more important, I find that contributions to systemic risk increase significantly when hedge funds demand liquidity. This result holds for individual funds and on the fund strategy-level. Conversely, no such effect exists for mutual funds. A decomposition of systemic risk reveals that the higher level of systemic risk for liquidity-demanding hedge funds can be explained by a higher degree of interconnectedness. Providing further evidence for the asset liquidation channel, I document that systemic risk is considerably larger when hedge funds demand liquidity in times of low funding liquidity and during stock market boom and bust phases. Complementary to that, the systemic risk of liquidity-supplying hedge funds is significantly lower in periods of low funding liquidity.

JEL classification: G23, G28

Key words: Systemic Risk, Hedge Funds, Mutual Funds, Liquidity

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1 Introduction

The top 500 asset managers intermediated \$76 trillion of assets, equivalent to 40% of global financial assets, (International Monetary Fund, 2015) in 2013. In general, institutional investors are central to financial markets and play a key role in ensuring market efficiency and providing liquidity. Apart from that, investment funds increasingly engage in activities traditionally executed by banks.[1] The mounting importance of investment funds is, however, a double-edged sword: If they contribute to the stability of the system in normal times, are they also a source of instability when markets become distressed?

Ever since the collapse of LTCM in 1998, this question has received considerable attention.[2] Recent empirical work suggests that equity funds (Hau and Lai, 2017), corporate bond funds (Manconi, Massa and Yasuda, 2012), and hedge funds (Adams, Füss and Gropp, 2014) played a role in the propagation of the financial crisis. On the other hand, Fricke and Fricke (2017) show that systemic risk among mutual funds is limited. As for the authorities, the Financial Stability Oversight Council (FSOC) published guidances to assess the systemic risk of nonbank financial entities (FSOC, 2012; FSOC, 2019). However, not a single nonbank financial entity is designated as systemically important as of today. It thus remains unclear if and how these entities matter for the emergence and transmission of systemic risk.

The contribution of this paper is to examine two channels through which nonbank financial entity, in particular investment funds, can contribute to systemic risk: the service channel and the asset liquidation channel. According to the first channel, entities which provide a critical service to other market participants contribute to systemic risk because of the vacuum that arises when they become unwilling or unable to provide this service. According to the second channel, systemic risk arises if asset sales of one or more entities trigger a fall in prices, which leads to further trading disruptions in key markets or funding problem for other participants. The goal of the paper is to evaluate the relative importance of these two channels for the

[1] Credit provision by investment funds to non-financial firms increased by 50% from 2010 to 2015, while the overall amount of credit only increased by 6% in these years (Doyle, Hermans, Molitor and Weistroffer, 2016).

[2] Brown, Kacperczyk, Ljungqvist, Lynch, Pedersen and Richardson (2009); Shelby (2017); Garbaravicius and Dierick (2005); Chan, Getmansky, Haas and Lo (2006); King and Maier (2009); Lo (2008); Kaal and Krause (2017); Kambhu, Schuermann and Stiroh (2007); Dixon, Clancy and Kumar (2012)

systemic risk of investment funds. As stated by Danielsson and Zigrand (2015), focusing on the channels instead of the individual entities can be an important step towards a better understanding of how asset managers contribute to systemic risk. The recent shift of the FSOC from a characteristics-based (FSOC, 2012) to an activities-based (FSOC, 2019) assessment of systemic risk highlights this point of view.

The present study is based on two subgroups of nonbank financial entities: hedge funds from the Thomson Reuters Lipper Fund database and mutual funds from the CRSP mutual fund database from January 1994 to December 2018. While much of the public debate has focused on hedge funds, it is at first sight not perfectly clear why their contribution to systemic risk should be higher relative to mutual funds. On the one hand, the use of leverage, the lack of transparency, and the interconnectedness of the hedge fund sector (Adams et al., 2014) support a more prominent role of hedge funds for systemic risk. On the other hand, mutual funds are, on average, much larger in terms of assets under management, which can be crucial for the systemic risk of an institution. Adding to this debate, I compare the systemic risk of hedge funds and mutual funds in a first step. Taking into account the different size of mutual funds and hedge funds when calculating the systemic risk measure, I observe that the systemic risk of mutual funds is indeed higher. However, in line with the public focus on hedge funds, I also show that hedge funds have higher systemic risk contributions when compared to mutual funds of the same size or when controlling for the effect of fund size on systemic risk.

Next, I turn to the main question of the paper: What is the channel through which investment funds contribute to systemic risk? To answer this question, I exploit the fact that the service channel and the asset liquidation channel yield opposite predictions with regard to the systemic risk of liquidity-demanding and liquidity-supplying funds. For the service channel, funds which act as liquidity suppliers should have higher systemic risk because they provide a critical function to others. Their unwillingness or inability to provide this liquidity service can pose a threat to the stability of the system if no one else is there to fill the gap. Such a situation can, for example, arise in times of low funding liquidity (Cötelioglu, Franzoni and Plazzi, 2019) when the propensity to supply liquidity is generally low (Nagel, 2012).

For the asset liquidation channel, in turn, funds which demand liquidity should have higher systemic risk. Here, systemic risk arises when funds sell their holdings as prices go down, i.e. when they consume liquidity. This can lead to further price declines, a dry-up of liquidity, and more asset sales (Brunnermeier and Pedersen, 2009), ultimately destabilizing the market.

Guided by these observations, I proceed as follows: First, I classify funds as liquidity suppliers (LS) and liquidity demanders (LD) based on the the approach of Jylhä, Rinne and Suominen (2014). Then, I relate this classification to each fund's $\Delta CoVaR$, as a measure for its contribution to systemic risk, to quantify the impact of the two channels outlined above. Consistent with the asset liquidation channel being more important, I find that on the fund level, contributions to systemic risk are significantly higher when a hedge fund demands liquidity. In addition to this, an analysis based on aggregating systemic risk for different hedge fund styles reveals that systemic risk also rises when the fraction of liquidity demanders within a given style increases. Conversely, no such effect exists for liquidity suppliers or mutual funds.

To further understand how institutional investors contribute to systemic risk, I continue my analysis by interacting fund characteristics with the LS and LD classification. The results suggest that contributions to systemic risk are even higher, relative to the baseline effect, when larger hedge funds or hedge funds which face outflows demand liquidity. One explanation for this finding is that in such a situation, the concurrent decline of market and funding liquidity could lead to a liquidity spiral (Brunnermeier and Pedersen, 2009) which transmits the initial shock to others and amplifies systemic risk.

In the next step, I decompose the systemic risk measure to understand what exactly drives my main result. To do so, I follow Brunnermeier, Dong and Palia (2019) and break down the ΔCoVaR into interconnectedness, tail risk, and exposure to macroeconomic and finance factors. The subsequent analysis shows that the higher systemic risk of hedge funds, especially when they demand liquidity, can be attributed to a higher degree of interconnectedness. This is in line with the work of Adams et al. (2014), who find that hedge funds play a major role in the transmission of shocks due to their linkages with banks and brokers.

According to the asset liquidation channel, assets sales of liquidity-demanding funds can lead to a deterioration of market liquidity and turn into liquidity spirals when funding liquidity is low. Based on this notion and the observation that systemic risk is likely to materialize when markets are distressed, I hypothesize that the relation between liquidity-demanding funds and systemic risk is stronger in periods of poor funding liquidity. Consistent with this, I show that contributions to systemic risk for liquidity-demanding funds increase dis-proportionally in times of a high VIX or TED spread. Moreover, systemic risk of liquidity-supplying hedge funds is significantly lower in periods of a high VIX or when dealer repo volume is low, which corrobrates the evidence on the asset liquidation channel of systemic risk.

Finally, motivated by the study of Brunnermeier, Rother and Schnabel (2019), I turn to the question whether the occurence of asset price boom and bust phases alters the systemic risk of the nonbank financial sector. As Brunnermeier and Nagel (2004) show, hedge funds significantly contributed to the emergence of the dotcom bubble. Adding to this, I find that systemic risk contributions of hedge funds in general increase in boom and bust periods. More importantly, I show that the systemic risk of hedge funds which demand liquidity is significantly higher during bubble episodes. This suggests that the asset liquidation channel of systemic risk plays a larger role in boom and bust phases of a stock market bubble relative to non-bubble periods.

The contribution of this paper to the literature is twofold. First, it extends existing work on systemic risk to another type of financial institution, namely asset managers. Traditionally, the literature focuses on banks as the prime example of systemically relevant institutions (e.g. Laeven, Ratnovski and Tong, 2016; López-Espinosa, Rubia, Valderrama and Antón, 2013, Brunnermeier et al., 2019, Brunnermeier et al., 2019). Nevertheless, the growing importance of nonbank financial entities for today's financial markets suggests a role for these institutions when it comes to systemic risk. With regard to hedge funds, prior studies on this topic often focus on certain elements of systemic risk like contagion across hedge funds (Boyson, Stahel and Stulz, 2010; Dudley and Nimalendran, 2011) or connectedness of hedge funds (Billio, Getmansky, Lo and Pelizzon, 2012). However, apart from two papers which relate systemic risk to hedge fund returns (Hwang, Xu, In and Kim, 2017) and look at the determinants of systemic risk of hedge funds (Joenväärä, 2011), there is little empirical evidence on how exactly investment funds contribute to systemic risk. This study tries to fill this gap by empirically disentangling and comparing two different channels of systemic risk for two different types of nonbank financial institutions.

Second, the asset liquidation channel is closely related to the literature on fire sales which shows that forced, flow-driven selling can negatively impact asset prices. In Coval and Stafford (2007), asset sales of mutual funds which face large outflows create price pressure in the sold securities. Mitchell, Pedersen and Pulvino (2007) document a similar effect for convertible bond markets around the collapse of LTCM and after convertible hedge funds faced large withdrawals in 2005. My finding that liquidity-demanding hedge funds have higher systemic risk adds another layer to this literature. It suggests that (forced) asset sales do not only have a negative effect on the asset being sold but might also be relevant from a broader stability perspective when taking systemic risk externalities into account. In this regard, my study is also related to Fricke and Fricke (2017), who use a stress test model to quantify systemic impact of mutual fund fire sales, and Girardi, Hanley, Nikolova, Pelizzon and Getmansky Sherman (2018), who examine portfolio similarity and common sales of insurance companies.

The remainder of the paper is structured as follows. In Section 2, I discuss the FOSC's framework to assess the systemic risk of non-bank financial entities and derive my main hypotheses. Section 3 describes the data as well as the methodology to measure systemic risk and to classify funds into liquidity suppliers and demanders. Section 4 contains the main result. In Section 5, I examine systemic risk in times of low funding liquidity. Section 6 analyzes systemic risk during the occurence of stock market bubbles. Section 7 discusses some robustness tests, and Section 8 concludes.

2 Systemic Risk Framework and Hypotheses

As part of the Dodd-Frank act, the FSOC developed a three-stage process in 2012 for assessing the systemic risk of nonbank financial entities. According to the procedure outlined in the first interpretive guidance, all entities with at least $50 billion in total consolidated assets are evaluated along the following six categories to determine whether an entity is systemically important: size, liquidity risk, substitutability, interconnectedness, leverage, and regulatory scrutiny (FSOC, 2012). While the six-category framework helps to understand how the characteristics of mutual funds and hedge funds relate to systemic risk, it has been subject to some criticism: As Shelby (2017) argues, imposing a threshold of $50 billion for determining the systemic risk of nonbanks fails to capture the possibility that a large number of smaller entities that are interconnected with other market participants can become systemic as a herd. Moreover, the regulatory burden that comes along with the designation of an entity as systemically important can be a competitive disadvantage. As a result, the entity could potentially litigate the designation, as was the case for MetLife in 2018.[3]

Acknowledging these shortcomings, the FSOC revised the guidance in 2019. In the new guidance (FSOC, 2019), the entity-specific approach based on the six-category framework was replaced by a broader activities-based assessment of systemic risk. More specifically, the FSOC highlights the importance of three channels through which nonbank financial entities can contribute to systemic risk.

Service Channel: This channel focuses on entities which provide critical functions to the financial system that other market participants rely upon. One example is the liquidity provision of investment funds to equity markets (Jylhä et al., 2014; Rinne and Suominen, 2016) and less liquid asset markets (Agarwal, Fung, Loon and Naik, 2011). Here, systemic risk arises when liquidity suppliers become unwilling or unable to provide the critical service and no substitute is readily available. With regard to the liquidity provision of hedge funds, this is exactly what happens in times of low funding liquidity (Cötelioglu et al., 2019), or in crisis episodes (Anand, Irvine, Puckett and Venkataraman, 2013). Hedge funds withdraw from liquidity provision and no one else fills the gap because the propensity to provide liquidity is generally low in such periods (e.g. Nagel, 2012). Importantly, the resulting vacuum can pose a threat to the market stability, as indicated by lower liquidity and resiliency of stocks which

[3]https://www.regulationtomorrow.com/us/metlife-sifi-lawsuit-dismissed-fsoc-designation-process-may-change/

are more exposed to liquidity-supplying hedge funds (Aragon and Strahan, 2012; Cötelioglu et al., 2019). In summary, liquidity provision, being one example for a critical service, can be associated with systemic risk. This leads to my first hypothesis:

Hypothesis 1a: According to the service channel, funds which supply liquidity have higher systemic risk

Hypothesis 1b: According to the service channel, funds which demand liquidity have lower contributions to systemic risk

Note that the systemic risk of liquidity-supplying funds arises because they provide a critical service to the market and tend to withdraw when no readily substitute is available. Conversely, liquidity-demanding funds do not fulfill such a critical function. Hence, they should contribute less to systemic risk according to the service channel.

Asset Liquidation Channel: In the second case, systemic risk arises if asset sales of one or more entities trigger a fall in prices, causing further trading disruptions in key markets or funding problem for other participants (FSOC, 2019). Such a feedback loop can be found in the theoretical model of Brunnermeier and Pedersen (2005) or in Pedersen (2009), who show that investors can either rationally "run for the exit" or because they face margin calls and are forced to deleverage as in Brunnermeier and Pedersen (2009). Ben-David, Franzoni and Moussawi (2012) provide empirical evidence for such large-scale asset sales. They show that hedge funds liquidated up to 30% of their equity portfolio in a falling markets as a response to deleveraging and investor redemptions. Similarly, Ben-Rephael (2017) documents that mutual funds reduce their illiquid stock holdings in times of high market uncertainty, thereby magnifying price declines and flight-to-liquidity episodes. The common theme of these studies is that funds who engage in such asset sales and create systemic risk essentially demand immediacy and consume liquidity. Therefore, my second hypothesis is as follows:

Hypothesis 2a: According to the asset liquidation channel, funds which demand liquidity have higher contributions to systemic risk

Hypothesis 2b: According to the asset liquidation channel, funds which supply liquidity *have lower contributions to systemic risk*

While liquidity-demanding funds create systemic risk through asset sales and price pressure, funds who supply liquidity in these situations (e.g. Aragon, Martin and Shi, 2019) have the potential to cushion the price decline. Hence, they can limit the negative externality arising from this channel and should contribute less to systemic risk.

Credit Channel: The last channel identified by the FSOC is related to situations in which counterparties have an exposure to a nonbank financial entity that is significant enough to materially impair the respective counterparty (FSOC, 2019). I do not examine this channel for two reasons: First, an analysis would require detailed data on counterparty exposure, which is not readily available. Second, as Dixon et al. (2012) highlight, the impact of the credit channel became much smaller following the collapse of LTCM. In the aftermath, regulatory authorities put a lot of emphasis on better counterparty risk management as well as adequate margin and collateral requirements with the goal to limit the impact of the credit channel (Kambhu et al., 2007). In line with having achieved this, a recent report from the Bank of England documents that none of the surveyed prime brokers had an aggregate potential exposure to hedge funds exceeding 7% of its Tier 1 capital (Kenny and Mallaburn, 2017).

3 Data and Methodology

For this study, I collect data on investment funds from two different sources. Data on hedge funds is from the Thomson Reuters Lipper Fund Database. It includes information on assets under management, fund returns, as well as a number of fund characteristics like the fund inception date, fund strategy, fund currency, fund management company, and management fees. For hedge funds with a reporting currency other than USD, I convert fund returns and total net assets to USD using end-of-month exchange rates. Following the literature, I restrict the sample to funds who report net returns on a monthly basis. Additionally, I require a fund to have at least 36 consecutive months of valid return observations over the sample period. To avoid survivorship bias, the sample period starts in January 1994 since data on defunct funds is often not available prior to 1994 (see for example Fung and Hsieh, 2001). The sample period ends in December 2018.

Aggarwal and Jorion (2010) note that the same fund can appear multiple times because a typical hedge fund has on- and off-shore funds as well as funds which report returns in different currencies. I filter out such duplicates using a correlation-based algorithm. For funds with the same management company, I compute the pairwise return correlation for each fund pair, if they have at least 10 months of return observation in common. If the correlation exceeds 99%, I keep the fund with the longer return series. If both have equally long return series, I keep the fund with higher average assets under management. If both have the same average fund size, I keep the fund with USD as the reporting currency. This filtering procedure leaves me with 4,083 unique hedge funds, of which 1,424 are alive.[4]

For the mutual fund data, I use the CRSP mutual fund database. Following Amihud and Goyenko (2013) I combine the information from different share classes using the MFLINKS table available on WRDS. Futhermore, I delete all observations before the fund's starting year as reported in CRSP to address the incubation bias. Analogous to the hedge fund sample, I only keep funds with at least 36 consecutive return observations over the sample period. I sort the remaining funds into one of the following four categories based on their Lipper classification: Domestic Equity, International Equity, Fixed Income, and Mixed Assets.[5] Finally, I drop sector funds, money market fund, index funds, and funds without a strategy classification. In total, the mutual fund sample includes 7,212 funds of which 4,168 are alive.

Table 1 provides summary statistics on a fund-level, with hedge funds in Panel A and mutual funds in Panel B. The average fund size is 113.35 million USD for hedge funds and 799.78 million USD for mutual funds. While mutual funds are considerably larger, both size distributions are heavily skewed. To limit the influence of small funds, I restrict the sample to funds with an average fund size of at least USD 10 million for the subsequent analysis.

[4]Although the number of funds is smaller in comparison to the Lipper TASS database, the sample still makes up a considerable subset of the hedge fund universe. Moreover, a comparison of descriptive statistics with existing studies on hedge funds (e.g. Hwang et al., 2017) indicates that the sample is representative.

[5]The document which describes Lipper's classification methodology can be accessed under https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/lipper-us-fund-classification-methodology.pdf

Average monthly fund flows are higher for mutual funds with 0.80% as compared to 0.68% for hedge funds. The average age of mutual funds is roughly 200 months. Hedge funds have a shorter lifetime with only 111 months. Concerning fund performance, the return of mutual funds over the sample period is sligthly better with an average of 0.51% per month relative to 0.40% for hedge funds. As a measure of a fund's asset portfolio liquidity, I employ the return smoothing coefficient θ_0 developed by Getmansky, Lo and Makarov (2004). Not surprisingly, it is lower for hedge funds with a value of 0.95 (1.11 for mutual funds), reflecting the fact that hedge funds commonly invest in rather illiquid assets. Finally, the average management fee for hedge funds (1.45%) is also higher when compared to the fee of mutual funds (0.66%).

3.1 Systemic Risk Measure

There are numerous ways to measure systemic risk.[6] Two of the most prominent measures are the Conditional Value at Risk (ΔCoVaR) of Adrian and Brunnermeier (2016) and the marginal expected shortfall (MES) of Acharya, Philippon and Richardson (2017). As argued by Brunnermeier et al. (2019), both measures take opposite perspective. ΔCoVaR quantifies the contribution of institution i to the overall level of systemic risk by computing the additional Value at Risk of the financial system when institution i moves from its median to a distressed state. MES, in turn, measures how an individual institution is affected when the system is in distress. Since the goal of my analysis is to examine how mutual funds and hedge funds contribute to systemic risk, I take ΔCoVaR as the main measure of systemic risk in what follows. In robustness tests, I also examine the marginal expected shortfall as an alternative of systemic risk. The calculation of ΔCoVaR proceeds in three step: In a first step, I compute the sensitivity of the financial system to distress originating from institution i using the following quantile regression:

$$R_{q,t}^{system|i} = \hat{\alpha}_q^{system|i} + \hat{\beta}_q^{system|i} M_{t-1} + \hat{\gamma}_q^{system|i} R_t^i + \epsilon^{system|i} \tag{1}$$

Here, $R_{q,t}^{system|i}$ is the system return in month t as given by the value-weighted average

[6] See Bisias, Flood, Lo and Valavanis (2012) for a survey of systemic risk analytics.

return of all financial institutions in CRSP with a SIC code between 6000 and 6799.[7]. R_t^i is the return of the i-th fund. M_{t-1} is a vector of state variables containing the following macroeconomic and financial variables: the VIX, the TED spread (LIBOR rate minus 3-month treasury bill rate), the change in the slope of the yield curve (10-year treasury rate minus 3-month treasury bill rate), the change in the credit spread (Moody's BAA corporate bond yield rate minus 10-year treasury rate), and the monthly return on the MSCI Global Index. Data on the economic indicators is obtained from FRED. Return data for the MSCI index is obtained from Datastream.

The second step consists of estimating individual VaRs for each institution, conditional on the set of lagged state variables. More specifically, I estimate the following quantile regression:

$$\widehat{VaR}_{q,t}^{i} = \hat{R}_t^i = \hat{\alpha}_q^i + \hat{\beta}_q^i M_{t-1} \tag{2}$$

Equation (3) gives the predicted conditional value at risk for institution i. For estimating the distressed state, I choose a stress level of $q = 1\%$.[8]. For estimating the conditional value at risk in an institutions median state, I set q=50%. Finally, the systemic risk measure ΔCoVaR for each institution i is given as:

$$\Delta CoVaR_{q,t}^{i} = \hat{\gamma}_q \cdot (\widehat{VaR}_{q,t}^{i} - \widehat{VaR}_{50,t}^{i}) \tag{3}$$

I multiply the resulting systemic risk measure by -1 such that higher ΔCoVaR values indicate higher systemic risk contributions.

Adrian and Brunnermeier (2016) note that the ΔCoVaR captures both direct linkages through spillovers from one institution to the financial system and indirect linkages through common exposure effect. The last point is related to the idea that the financial system can be impaired when an institution becomes systemic as part of a herd. Investment fund often exhibit such herding behavior because they rely on similar strategies and signals (Beggs,

[7] Including hedge funds and mutual funds for the calculation of the value-weighted return of the financial system does not change the results

[8] Results are robust to different levels of stress, with q ranging from 1% to 5%

Brogaard and Hill-Kleespie, 2019, Brown, Howard and Lundblad, 2019). Thus, the ability of the systemic risk measure to capture both types of linkages is rather beneficial here.

Looking at the average ΔCoVaR in Table 1 gives a first hint with regard to the systemic risk contribution of each fund type. The mean value is slightly higher for hedge funds with 359 basis points as compared to mutual funds with 316 basis points. The difference of the median values is considerably larger. To further illustrate the systemic risk of either fund type, I plot the average ΔCoVaR for hedge funds (blue line) and mutual funds (red line) over time in Figure 1. Not surprisingly, both time series move in a highly correlated fashion. The largest spikes for either fund type are associated with the breakdown of LTCM in September 1998, the bankruptcy of Lehman Brothers in September 2008, and the collapse of MF Global, a large derivatives broker, in October 2011. Figure 1 also indicates that the average systemic risk of the hedge fund sector seems to be larger relative to the mutual fund sector. However, ΔCoVaR as such does not take into account the different size of hedge funds and mutual funds because it represents the systemic risk per dollar invested. Put differently, it only yields a fair comparison if two funds have the same size. As can be seen in Table 1, mutual funds are more than seven times as large as hedge funds. Therefore, a comparison of the systemic risk of hedge funds and mutual funds should account for the larger size of mutual funds. Hence, I compute a size-adjusted systemic risk measure, $\Delta\text{CoVaR}^{Size}$, by multiplying each fund's ΔCoVaR with its assets under management. Then, I normalize the result with the cross-sectional average of assets under management each month to account for the fact that average assets under management grow substantially over the sample period. Figure 2 depicts the evolution of $\Delta\text{CoVaR}^{Size}$ over time. The size-adjusted measure clearly demonstrates that the average systemic risk oassociated with the mutual fund sector is higher as compared to the systemic risk of the hedge fund sector. Apart from this, two more facts emerge from Figure 2: First, the difference in systemic risk between hedge funds and mutual funds is rather small in the period leading into the financial crisis. Second, the size-adjusted systemic risk of hedge funds seems to be especially low in the more recent period.

3.2 Fund Classification: Liquidity Supplier and Liquidity Demander

Hypotheses 2 and 3 relate systemic risk to funds which supply liquidity and funds which demand liquidity. Therefore, I need to classify the funds accordingly. To do so, I follow the procedure outlined in Jylhä et al. (2014): The basic idea is to classify each fund based on its exposure to a strategy which mimics the returns for liquidity provision. To construct such a strategy, I collect CRSP data on daily returns for all ordinary common shares of companies incorporated in the US and listed on the NYSE and AMEX. Next, I conduct daily cross-sectional regressions to estimate short-term return reversal patterns:

$$R_{i,t+5} = \alpha_t + \sum_{\tau=0}^{19} \beta_{t,\tau} R_i t - \tau + \beta_{t,C} C_{i,t} + \epsilon_{i,t} \tag{4}$$

Here, $R_{i,t+5}$ is a stock's excess returns over the next week, $R_{i,t}$ are each of the stock's past 20 days' excess return and $C_{i,t}$ is a vector of controls including the product of the stocks's excess past monthly return with the past month's trading volume and with the logarithm of the stock's market capitalization at time t, respectively. Excess returns are calculated by industry-adjustment of raw returns using the 48 Fama-French industries. Based on the coefficients, I calculate expected 5-day returns for each stock. Then, I form a portfolio with long positions in stocks with positive 5-day expected returns and short positions in stocks with negative 5-day expected returns and hold the portfolio for the next 5 days after the formation. Analogous to Jylhä et al. (2014), I exclude penny stocks and stocks in the lowest decile of market capitalization prior to the portfolio formation,. Moreover, I exclude stocks with the highest and lowest 1% short-term expected return each day and require a stock to have positive trading volume when opening the position on day t. The return for liquidity provision is calculated by averaging the returns of all open positions on day t. In untabulated results, I document that such a strategy yields an average monthly return of 0.74% over the sample period with a positive return in 70% of all months.

For the classification of investment funds as liquidity suppliers (LS) and liquidity demanders (LD), I then measure each fund's exposure to liquidity provision (β^{LP}). To do so, I regress fund returns on the returns to liquidity provision, controlling for the Pástor and

Stambaugh (2003) liquidity factor and the seven hedge fund risk factors of Fung and Hsieh (2001).[9] To capture time-variation in the propensity to supply or demand liquidity, I conduct the regression on a 36-month rolling window basis. As in Jylhä et al. (2014), I repeat the exercise but compute returns to liquidity provision with a lag of 1, 2, 3, and 4 days between the calculation of expected 5-day returns and portfolio formation. This time gap reflects the fact that it takes time for hedge funds to build up or liquidate positions (Duffie, 2010). In the end, I classify a fund as a liquidity supplier (liquidity demander) if any of the coefficients associated with the returns to liquidity provision, based on different timing assumptions, is positive (negative) and significant at the 5% level.

The last two rows of each panel in Table 1 report the fraction of months for which a fund is a liquidity supplier or a liquidity demander. On average, a hedge fund acts as a liquidity supplier for 16% of its lifetime and as a liquidity demander for 10% of its lifetime. This is in line with the the findings of Jylhä et al. (2014) who document that hedge funds typically supply liquidity but can also demand liquidity, especially in crisis times. In Panel B, one can see that mutual funds are on average classified as liquidity demanders in 14% of all months while they supply liquidity in only 7% of months in their lifetime. This asymmetry is consistent with the evidence found in Rinne and Suominen (2016), who show that mutual funds are more often liquidity demanders than suppliers.

4 Main Results

To analyze how hedge funds and mutual funds contribute to systemic risk, I conduct a multivariate regression which relates the systemic risk measure to a number of fund characteristics and the two dummy variables for funds as liquidity suppliers and liquidity demanders:

$$\Delta CoVaR^{Size}_{1\%_{i,t}} = \alpha_j + \alpha_t + \beta_1 LS_{i,t-1} + \beta_2 LD_{i,t-1} + \boldsymbol{\gamma C_{i,t-1}} + \epsilon_{i,t} \tag{5}$$

[9]The risk factors include the trend factors for bonds, commodities, and currencies downloaded from David Hsieh's website (https://faculty.fuqua.duke.edu/ dah7/HFRFData.htm) Additionally, I compute an equity market factor (S&P 500 return), a size factor (Russell 2000 minus S&P 500), a bond market factor (Barclays US Aggregate), and a credit factor (Barclays US Corporate BAA minus Barclays US Corporate AAA.

The dependent variable is the size-adjusted ΔCoVaR^{Size}. I include time fixed effects (α_t) and strategy fixed effects (α_j), which are based on the Lipper Fund classification scheme. LS and LD are dummy variables equal to one if a fund is classified as a liquidity supplier or a liquidity demander based on the procedure outlined in Section 3.2. The main coefficients of interest are β_1 and β_2. If funds contribute to systemic risk through the service channel, I expect a positive sign for β_1 meaning that liquidity suppliers have higher systemic risk (Hypothesis 1a), and a negative sign for β_2 (Hypothesis 1b). For the asset liqudiation channel, the opposite holds: the contribution to systemic risk should be higher for liquidity-demanding funds, i.e. $\beta_2 > 0$ (Hypothesis 2a) and lower for liquidity-supplying funds, i.e. $\beta_1 < 0$ (Hypothesis 2b).

I additionally control for several fund characteristics which can be related to the FSOC's six-category framework outlined in the first interpretive guidance (FSOC, 2012). I include the logarithm of assets under management to control for the *size* category of systemic risk. Intuitively, the systemic risk of larger entities should be higher. Moreover, I include fund return and fund flows (measured as the change in assets under management from $t-1$ to t adjusted for the fund return over the same period), as well as θ_0, a measure of a fund's asset portfolio liquidity based on the return smoothing model of Getmansky et al. (2004).[10] These three variables are related to a fund's *liquidity risk*. In the context of systemic risk, liquidity risk captures the fact that bad-performing investment funds often face outflows and can be subject to investor runs and fire-sale behavior (Liu and Mello, 2011) because they use short-term redeemable funding and invest it into illiquid assets.[11] Therefore, I expect bad-performing funds, funds which face outflows, and funds with more illquid assets to have higher systemic risk. I also include a fund's age, which one could relate to the *interconnectedness* category of systemic risk under the assumption that more established funds have more linkages to others. Finally, I add the fund management fee as a proxy for skilled managers who tend to avoid systematic risk exposure (Titman and Tiu, 2010), and the standard deviation of fund

[10]Specifically, I apply a MA(2) model to a fund's reported returns and take the smoothing parameter θ_0 as a measure for a fund's asset liquidity. Larger values indicate more liquid investments.

[11]Arguably, this problem might be more severe for mutual funds because they offer daily liquidity to their investors, while redemption frequencies of hedge funds are typically lower. However, Chen, Goldstein and Jiang (2010) document that such strategic complementarities among investors are more severe for funds with illiquid assets, which would be more typical for hedge funds (also see Agarwal, Aragon and Shi, 2018; Teo, 2011).

returns as a measure of standalone risk. As for the liquidity-supplier and liquidity-demander classification, I estimate θ_0 and the return standard deviation based on a rolling window of 36 months. For the regressions, all time-varying control variables are lagged by one month. Furthermore, I de-mean all continuous variables for the ease of interpretation.

Table 2 displays the regression results. The first three columns are based on the pooled sample of hedge funds and mutual funds. Columns 4 to 6 and Columns 7 to 9 show results for the subsample of hedge funds and mutual funds, respectively. In the pooled sample, I add an additional dummy variable to indicate whether the fund is a hedge fund or not. The coefficient on the hedge fund dummy in Column 1 shows that once I control for the effect of size on systemic risk, the systemic risk of a hedge fund is 241.96 basis points higher compared to a mutual fund, with the effect being statistically different from zero.[12]

For hedge funds (Column 3 and 4), systemic risk increases when a fund is a liquidity demander, with the effect being significant at the 1% level. The significantly positive relation between LD and $\Delta\text{CoVaR}^{Size}$ is consistent with Hypothesis 2a and suggests that the asset liquidation channel seems to be more important for the systemic risk contributions of hedge funds. To get a rough estimate of the economic impact of this channel, I compute the additional systemic risk (in dollar terms) associated with a 10% increase in liquidity-demanding hedge funds. I argue that it is reasonable to look at a group of funds instead of a single fund here, since systemic risk is most likely to arise through the coordinated behavior of a large number of funds with similar strategies (see for example Khandani and Lo, 2011 or Beggs et al., 2019). The activities based approach now pursued by the FSOC reflects this line of reasoning as well. According to a recent report by Preqin, the total number of hedge funds at the end of 2018 amounted to 15,837.[13] If we consider a 10% increase in liquidity demanders at the average fund sample size of \$113 million, then the additional systemic risk through the asset liquidation channel amounts to approximately \$2 billion (= 15,837 x 0.1 x \$113mio x 112.80bps). In contrast, no statistically significant effect on systemic risk can be detected

[12]Note that the strategy fixed effects subsume the hedge fund dummy in Column 2 because there is no overlap between the Lipper Classification Codes for hedge funds and mutual funds.

[13]See https://docs.preqin.com/press/HFs-in-2018.pdf for more details.

when hedge funds act as liquidity suppliers although the negative sign of the coefficient is consistent with Hypothesis 2b. With regard to the control variables, I document higher systemic risk for larger and older funds, presumably because they become more interconnected over the course of the years. Furthermore, systemic risk increases when a hedge fund faces outflows and when its asset liqudity is lower. As Chen et al. (2010) show, strategic complementaries among investors rise with the illiquidity of fund holdings and make investor runs more likely. Hence, these funds have a higher liquidity risk.

In Columns 5 and 6, I repeat the analysis for mutual funds. The results indicate that systemic risk significantly increases for liquidity-supplying funds and decreases for liquidity-demanding funds, demonstrating that the pooled sample results for the LD dummy in Column 1 are driven by the mutual fund subsample. Although this pattern coincides with the predictions of the service channel and supports Hypothesis 1a and 1b, the results are not robust to an alternative calculation of the systemic risk measure as I will show in Section 7 and should therefore be taken with caution. With regard to the economic magnitude, I again consider a 10% increase in liquidity-supplying mutual funds. According to the Investment Company Factbook 2019,[14] the number of mutual funds was 9,599 at the end of 2018. At the average sample fund size of $800 million, a 10% increase in liquidity-supplying funds translates into additional systemic risk of roughly $1 billion (= 9,599 x 0.1 x $800mio x 14.25bps). The control variables show that systemic risk is higher for larger funds, funds which experience outflows or underperform, funds with a higher standalone risk, and funds with lower management fees.

All in all, the results thus far give a first impression on how nonbank financial entities can contribute to systemic risk through different channels. In line with the asset liquidation channel, hedge funds' systemic risk increases when they demand liquidity. For mutual funds the evidence is more consistent with the service channel: systemic risk is significantly higher when they supply liquidity and lower when they demand liquidity.

[14]See https://www.ici.org/pdf/2019_factbook.pdf for more details

4.1 Systemic Risk of Fund Strategies

To further analyze how hedge funds and mutual funds contribute to systemic risk, I repeat the analysis on the fund strategy level. The motivation for doing so is that systemic risk is most likely to arise when a number of funds with a similar strategy engage in coordinated behavior, as noted above. Hence, the channels of systemic risk should also be visible on the strategy level. For the aggregation of the systemic risk measure, I average the ΔCoVaR for each strategy in each month. Then, I multiply it by the total assets under management for the respective style and divide the result by the cross-sectional average of total assets under management across styles. *LS* and *LD* are defined as the fraction of liquidity-supplying and liquidity-demanding funds within each strategy. *Size* is total assets under management, *Flow* are aggregate in- and outflows to each strategy. *Theta*, *SD*, and *Return* are asset-weighted averages of the respective fund-level measures and added as additional controls. Table 3 presents the results for hedge funds (Column 1 and 2) and mutual funds (Column 3 and 4). Consistent with the fund-level results in Table 2, the systemic risk of a hedge fund strategy rises when the fraction of liquidity-demanding funds is higher, as indicated by the positive and statistically significant coefficients for *LD* in the first two columns. For mutual funds, in turn, the positive relationship between *LS* and systemic risk on the fund level does not carry over to the strategy level, as indicated by the insignificant coefficient on the fraction of liquidity suppliers, *LS*, in Columns 3 and 4 of Table 3.

4.2 Fund Characteristics and Channels of Systemic Risk

The analysis in Table 2 documents that the systemic risk of a hedge fund increases when the fund acts as a liquidity demander, supporting the asset liquidation rather than the service channel of systemic risk. The opposite seems to hold for mutual funds. In order to investigate these two channels in more depth, I interact the LS and LD dummy with the remaining fund characteristics. This exercise helps to understand whether certain fund characteristics play a peculiar role when systemic risk arises through either of the channels. Again, I split the sample into hedge funds and mutual funds and report results separately.

Table 4 displays the results. Focusing on hedge funds in Column 1, I first note that the inclusion of interactions does not alter the baseline effect, as indicated by the positive and highly significant coefficient for LD at 160.71. Moreover, interacting LD with fund size yields a positive coefficient, significantly different from zero. This means that larger funds which demand liquidity are associated with higher systemic risk. Presumably, this is because the scope of asset liquidations and thus, the potential to cause trading disruptions, grows with funds size. Also, the interaction of LD with fund flows yields a negative coefficient, significant at a 1% level. As such, the finding is consistent with the model of Brunnermeier and Pedersen (2009). When funds face outflows and need to liquidate assets to satisfy investor redemptions, they soak up market liquidity and put downwards pressure on prices. This can trigger more redemptions and margin calls for the fund itself but also for others, who use the same asset as collateral and now face a decline in the collateral value. The resulting liquidity spirals amplifies the initial funding shock and systemic risk increases.

With regard to liquidity-supplying funds, the interaction of LS with fund size and fund age yields a positive coefficient, both being significant at a 1% level. This suggests that larger hedge funds or hedge funds with a longer track record also seem to contribute to systemic risk when they supply liquidity, possibly because the impact of a sudden withdrawal from liquidity provision is stronger when the liquidity provider is larger or more established.

For mutual funds in Column 2, the coefficient for LS becomes significantly negative once the interaction terms are included. This suggests that the relation between liquidity-supplying mutual funds and systemic risk seems to be driven by certain fund types. In particular, systemic risk only increases significantly when larger funds, older funds, or funds with higher management fees provide liquidity.

4.3 Decomposing Systemic Risk

To understand what drives the higher systemic risk of hedge funds relative to mutual funds as well as the increase in systemic risk when hedge funds demand liquidity, I decompose the systemic risk measure as outlined in Brunnermeier et al. (2019). They show that ΔCoVaR consists of three parts:

$$\Delta CoVaR^i_{q,t} = \hat{\gamma}^{system|i}_q [(\hat{\alpha}^i_q - \hat{\alpha}^i_{50}) + (\hat{\beta}^i_q - \hat{\beta}^i_{50})M_{t-1}] \tag{6}$$

The first part, $\hat{\gamma}^{system|i}_q$ is related to the interconnectedness of a fund. In the context of asset managers, interconnectedness relates to the trading activity of mutual funds and hedge funds which can act as a conduit to transmit distress. Institutional investors can propagate shocks from financial to non-financial stocks (Hau and Lai, 2017), across asset classes (Manconi et al., 2012) and from domestic to emerging markets (Jotikasthira, Lundblad and Ramadorai, 2012).The second part, $(\hat{\alpha}^i_q - \hat{\alpha}^i_{50})$, captures a fund's idiosyncratic tail risk while the last part, $(\hat{\beta}^i_q - \hat{\beta}^i_{50})M_{t-1}$, captures tail risk driven by macroeconomic and finance risk factors. For investigating how the different components relate to hedge funds and mutual funds, I repeat the panel regressions specified in Equation (5). However, I now replace the dependent variable with either one of the three components of the $\Delta CoVaR$, evaluated at a stress level of 1%. I winsorize the components at the upper and lower 1% quantile to mitigate the influence of outliers. Again, I report results separately for the pooled sample, and the subsamples of hedge funds and mutual funds in Table 5. In Columns 1, 4, and 7 the dependent variable is *gamma* (interconnectedness). In Columns 2, 5, and 8 the dependent variable is *alpha* (idiosyncratic tail risk). In Columns 3, 6, and 9 the dependent variable is *beta* (systematic tail risk).

Focusing on the pooled sample, I first document that *gamma*, i.e. interconnectedness, is significantly higher for hedge funds (Column 1). The coefficient for the hedge fund dummy is statistically and economically significant with interconnectedness increasing by up to 65% (=0.33/0.51) for a hedge fund relative to a mutual fund. As such, this evidence is consistent with Adams et al. (2014), who show that hedge funds play a major role in the transmission of shocks through their linkages to banks or broker-dealers. These connections build up in normal times and materialize in times of distress.[15]

Columns 4 to 6 contain the results for the subsample of hedge funds. The main message is that the *gamma* of funds which are classified as liquidity demanders is significantly higher, as indicated by the positive coefficient for LD in Column 4. In economic terms, the interconnectedness of hedge funds which demand liquidity is 27% higher relative to the average interconnectedness for hedge funds at 0.6544. Hence, the interconnectedness of a hedge fund seems to be the major driver of the increase in systemic risk I observe for liquidity demanders. This link between the asset liquidation channel and interconnectedness can also be found in Adrian and Brunnermeier (2016). They argue that the ΔCoVaR captures direct and indirect spillovers, or common exposure effects, which arise when asset sales lead to losses for all market participants with similar exposure.

For mutual funds in Column 7 to 9, I focus on the coefficient for the LS dummy since the preceding section gave some evidence of higher contributions to systemic risk when mutual funds supply liquidity. One can observe that systemic risk of liquidity-supplying mutual funds is mostly driven by higher interconnectedness (Column 7) and higher systematic tail risk (Column 9). Exactly the opposite can be observed when a mutual fund acts as a liquidity demander. A caveat to these results is the economic magnitude of the coefficients for LS and LD. Despite the statistical significance, the additional effect of LS and LD on the three ΔCoVaR components relative to their unconditional means is small.

5 Systemic Risk and Market-Wide Distress

The notion of systemic risk is inherently tied to situations of market-wide distress. Therefore, the next section analyzes the systemic risk channels of nonbank financial entities in periods of distress. I use poor funding conditions to capture market-wide distress, because the level

[15] One example for such a hedge fund-specific link is the bilateral repo market. As Singh (2011) documents, hedge funds obtain short-term funding and are the main provider of collateral in this market, while mutual funds barely participate. Broker-dealers then use this collateral, in the form of re-hypothecation, to obtain short-term funding themselves. Consistent with a link between hedge funds and broker-dealers in this market, Gorton and Metrick (2015) attribute the run on repo to a large extent to hedge funds. Moreover, Infante (2019) theoretically shows that a run on repo can be driven by a collateral run of hedge funds.

of funding liquidity can influence both channels of systemic risk I examine. For the service channel, funding liquidity matters because the propensity to supply liquidity is generally lower when funding conditions are poor (see for example Nagel, 2012, Jylhä et al., 2014). In such a situation, readily available substitutes for liquidity providers are even scarcer. Thus, if systemic risk arises through the service channel, the following prediction should hold:

Hypothesis 3a: According to the service channel, the systemic risk of funds which supply liquidity is higher in times of low funding liquidity as compared to other times.

On the other hand, the level of funding liquidity can also be relevant for the asset liquidation channel. As pointed out by Brunnermeier and Pedersen (2009), selling assets in times of low funding liquidity can lead to liquidity spirals which make the effect of asset sales disproportionally larger than the initial shock. In such a scenario, the systemic risk associated with the asset sales of liquidity-demanding funds should be even higher. This observation can be summarized in the following prediction:

Hypothesis 3b: According to the asset liquidation channel, the systemic risk of funds which demand liquidity is higher in times of low funding liquidity as compared to other times.

To find out which channel of systemic risk matters in times of distress, I follow Cötelioglu et al. (2019) and use the VIX (tightness of margins) and the TED spread (cost of leverage) as proxies for funding liquidity. Moreover, I use the volume of dealer repos, as measured by the cumulative difference in short-term lending by U.S. primary dealers reported by the New York Federal Reserve, because repo agreements constitute an important source of funding for hedge funds (Singh, 2011). For all three funding proxies, I define an indicator variable to capture months of low funding liquidity: *High VIX* are months in which the VIX exceeds its 90th percentile value. *High TED Spread* is defined accordingly. *Low Repo Volume* are months in which the volume of dealer repos falls below its 10th percentile value. In defining the percentiles, I use values up to month t in order to avoid a look-ahead bias. Then, I interact the LD and LS dummy with each of the three indicator variables to capture the systemic risk of liquidity suppliers and liquidity demanders in periods of bad funding conditions.

Table 6 displays the results. Columns 1 to 3 contain results for the hedge fund sample, Columns 4 to 6 for the mutual funds When focusing on hedge funds, the first observation is that the coefficient for *LD* in Columns 1 to 3, now measuring systemic risk of liquidity demanders in times of normal funding liquidity, is smaller but stays both economically and statistically significant across all specifications. Additionally, the systemic risk of hedge funds is generally higher when funding conditions are bad, as evidenced by the large and highly statistically significant coefficients for all three indicator variables. More importantly and consistent with the asset liquidation channel and hypothesis 3b, I observe that the interaction terms *High VIX* x LD_{t-1} and *High TED Spread* x LD_{t-1} are both positive and significant at a 5% level. Moreover, the magnitude of the coefficients is more than three times as large as the baseline effect. This suggests that the systemic risk of funds which demands liquidity increases dis-proportionally when funding liquidity is scarce. Corrobrating this evidence, I further find that the systemic risk of liquidity-supplying hedge funds declines by 178 basis points when the VIX peaks and by 170 basis points when dealer repo volume plunges. Both effects are again highly statistically significant.

In summary, I document that low funding liquidity has a strong effect on hedge funds' systemic risk in general and on liquidity-demanding hedge funds' systemic risk in particular. Contrary to this, the level of funding liqudiity does not seem to play a major role for the systemic risk of mutual funds, as can be seen in Columns 4 to 6. More specifically, the systemic risk of mutual funds only seems to increase significantly, by about 50 basis points, in high VIX periods (Column 4). Furthermore, none of the interaction terms, except for *High TED Spread* x LD_{t-1} in Column 5, indicate any significant change in systemic risk contributions of liquidity-supplying or -demanding mutual funds when funding liquidity is scarce.

6 Systemic Risk and Asset Price Bubbles

Institutional investors play a central role for the emergence and subsequent burst of stock market bubbles, as documented by Brunnermeier and Nagel (2004) and Griffin, Harris, Shu and Topaloglu (2011). They ride the bubble instead of trading against it and, at least for the case of hedge funds, leave the market before the bubble bursts. Consistent with the view that such asset price boom and bust cycles often go hand in hand with systemic risk, Brunnermeier et al. (2019) provide evidence that the systemic risk of banks rises significantly during periods of stock market and real estate bubbles. Motivated by this observation, the next section examines whether systemic risk contributions of hedge funds and mutual funds increase during asset price boom and bust phases. Moreover, I investigate whether the service and the asset liquidation channel become more important for explaining systemic risk in times of stock market bubbles.

Empirically, the main challenge is to identify asset price bubbles. Following Brunnermeier et al. (2019), I apply the Backward Sup Augmented Dickey-Fuller (BSADF) approach proposed by Phillips, Shi and Yu (2015a, 2015b) to the MSCI Global Index from 1976 until 2017.[16] This approach is based on the fact that prices often exhibit explosive behavior when bubbles occur. It repeatedly applies augmented Dickey-Fuller tests to the data, iteratively varying the starting and ending fraction over which the test is calculated. The start of a bubble is the point at which the test statistic exceeds its critical value for the first time. The end is the point at which the test statistic falls below the critical value again. Critical values are based on Monte Carlo simulations with 2,000 repetitions. I require a minimum bubble length of six months and distinguish between boom and bust phases of a bubble, based on the peak of the price series. This procedure results in one binary variable to indicate the boom phase (*Boom*) and another one to indicate the bust phase of a bubble (*Bust*). I interact both dummies with the fund characteristics and the LD and LS dummy to investigate if any of the characteristics plays a more important role during bubble episodes.

The results are summarized in Table 7. For hedge funds in Column 1, the *Boom* and *Bust* dummy yield significantly positive coefficients, with the *Bust* dummy being twice as large as the *Boom* dummy. Hence, a hedge fund's contribution to systemic risk rises in both stages of a stock market bubble, but especially when the bubble bursts. With regard to the asset

[16]Compared to the study's sample period, I use and extended time period here in order to improve the properties of the BSADF test

liquidation channel of systemic risk, the coefficient for LD again quantifies the systemic risk of liquidity demanders in normal times. Although the magnitude of the coefficient is somewhat reduced when including the bubble dummies together with the interactions, it is still positive and significant. At the same time, the interactions of LD with the $Boom$ and the $Bust$ indicator both yield a significantly positive coefficient. The magnitude of both interaction terms relative to the baseline effect suggests that the systemic risk of liquidity-demanding hedge funds increases by more than eight times in stock market boom and bust periods. Thus, the additional effect on systemic risk when a fund demands liquidity in bubble episodes seems to be economically large. With regard to the remaining control variables, the relation between a fund's size and systemic risk is magnified in times of boom and bust periods, as can be observed from the positive and significant interaction terms of $Log(Size)$ with the $Boom$ and $Bust$ indicator.

For mutual funds in Column 2, the coefficients associated with $Boom$ is positive, yet insignificant. Interestingly, the significantly negative coefficient for $Bust$ even suggests that systemic risk of mutual funds decreases during a stock market bust phase. Furthermore, I observe a positive and significant interaction of LS with the $Bust$ indicator. This means that mutual funds which supply liquidity in bust phases have a higher systemic risk, possibly because no one else is willing to provide the service in these times.

Taken together, the preceding analysis highlights that hedge funds might play a special role in contributing to systemic risk in times of asset price booms and busts, as indicated by a general rise in systemic risk of this fund type. Furthermore, the large increase in the systemic risk of liquidity-demanding funds in both boom and bust phases suggests that their role might be related to the asset liquidation channel of systemic risk.

7 Robustness Tests

In this section, I conduct further tests to assess the robustness of my baseline result. First, I calculate two alternative measures of systemic risk: ΔCoVaR using historical estimates of a fund's Value at Risk and the marginal expected shortfall (MES). Second, I examine whether the main result is sensitive to the backfilling bias or the inclusion of additional fixed effects. Third, I use an alternative measure for a fund's propensity to provide liquidity.

7.1 Alternative Measures of Systemic Risk

In the first robustness check, I use an alternative calculation method for ΔCoVaR to show that the previous results are not driven by a particular choice of the estimation procedure for the systemic risk measure. In Section 3, I have estimated the conditional VaR of each fund based on the state variables and equation (3) to calculate ΔCoVaR. For the rolling ΔCoVaR, I compute the historical VaR for each fund based on its past returns using a 36-month rolling window. As noted by Brunnermeier et al. (2019), this makes the time variation in the rolling ΔCoVaR independent of the state variables while leaving the rest of the estimation procedure unchanged. A correlation of 0.7833 between the two ΔCoVaR measures suggests that they are closely related. As before, I compute a size-adjusted version of the rolling ΔCoVaR by multiplying each fund's rolling ΔCoVaR with its assets under management, normalizing the result with the cross-sectional average of assets under management in each month. Then, I re-run the panel regression specified in equation (5) separately for hedge funds and mutual funds and report results with rolling $\Delta\text{CoVaR}^{Size}$ in Table 8. In Column 1 and 2, liquidity-demanding hedge funds are still associated with higher contributions to systemic risk, as illustrated by the positive and significant coefficients on LD. Note that the same does not hold for mutual funds. Although the coefficients on LS in Columns 5 and 6 remain positive, they are no longer statistically significant. Hence, only for hedge funds, the main result is robust to the calculation of the systemic risk measure.

In the next test, I use the marginal expected shortfall (MES), proposed by Acharya et al. (2017), as an alternative measure of systemic risk. The MES is calculated as the average return of a fund during the 10% for which the returns of the financial system are worst. As before, I use a rolling window of 36 months to compute the measure.[17] An important aspect that one has to keep in mind when comparing ΔCoVaR with MES is that they relate to

[17] I use a 10% threshold instead of the 5% threshold in the original paper to have a larger number of observations for the calculation of MES in each rolling window

different concepts. As pointed out by Brunnermeier et al. (2019), ΔCoVaR quantifies the contribution of institution i to systemic risk while MES measures the impact of systemic risk on institution i. The fact that both measures have opposite perspectives on systemic risk becomes apparent when looking at the MES and ΔCoVaR of hedge funds and mutual funds in Table 1. The average MES of hedge funds is 278.58 basis points while the corresponding figure for mutual funds is 502.19 basis points. This is different to the average ΔCoVaR, which is larger for hedge funds. As an additional piece of evidence to highlight that ΔCoVaR and MES are distinct measures, I find that the correlation between the two is only 0.1888.

Table 9 displays the results for re-running the baseline specification with MES as the dependent variable. As before, I use a size-adjusted version of the systemic risk measure. The coefficients for LS and LD in Column 1 and 2 suggest that liquidity-supplying hedge funds are significantly less affected by systemic risk and liquidity-demanding hedge funds are somewhat more affected by systemic risk, although the effect becomes insignificant when including strategy fixed effects. One way to interpret this result is that although liquidity-demanding hedge funds *contribute to* systemic risk, they are not necessarily *affected by* it. Mutual funds, in turn, seem to have a significantly lower MES regardless of whether they supply or demand liquidity (Column 5 and 6).

7.2 Additional Robustness Tests

In Table 10 and 11, I conduct additional robustness checks for the subsample of hedge funds and mutual funds, respectively. Column 1 controls for the backfilling bias by deleting the first 12 months of observations for each fund. The main results remain unaffected. In Column 2, I add strategy-time fixed effects to control for unobserved time-varying factors on the strategy level. Again, the main results stay the same. Column 3 includes fund fixed effects to control for unobserved heterogeneity on the fund level which might be related to systemic risk. In line with the asset liquidation channel, Table 10 shows that liquidity-demanding hedge funds have higher systemic risk, while liquidity-supplying hedge funds have lower systemic risk after controlling for fund fixed effects.

Finally, I employ an alternative measure for the propensity to provide liquidity. Instead of the LS and LD dummies, I directly use β^{LP}, the exposure of each fund to the liquidity provision strategy, as a regressor. The results in Table 10, Column 4 show that systemic risk contributions of hedge funds decrease significantly for larger values of β^{LP}. In other words, funds with a negative exposure to liquidity provision, i.e. liquidity demanders, have higher systemic risk. For mutual funds, in turn, systemic risk is significantly but positively related to β^{LP}, as can be seen in Table 11, Column 4. All in all, these results are thus consistent with the main result and the asset liquidation channel of systemic risk for hedge funds.

8 Conclusion

In this paper, I examine two channels through which two types of non-bank financial entities can contribute to systemic risk. Consistent with an asset liquidation channel of systemic risk, I document that systemic risk of hedge funds is significantly higher when they demand liquidity. This result holds on the individual fund-level as well as on the fund strategy-level and supports the view that systemic risk arises when asset liquidations trigger price declines and disrupt trading or funding in other markets. Decomposing the systemic risk measure, I document that these results can be explained by higher interconnectedness of liquidity-demanding hedge funds. Moreover, I document that the systemic risk of liquidity-demanding hedge funds increases dis-proportionally in times of low funding liquidity. This reflects the idea of liquidity spirals, in which tight funding constraints and a decline in market liquidity can reinforce each other (Brunnermeier and Pedersen, 2009). Finally, I show that systemic-risk of liquidity-demanding hedge funds' increases during asset price boom and bust periods.

All in all, these results suggest that attempts to regulate the systemic risk of nonbank entities should pay special attention to limiting externalities caused by the asset liquidation channel. As discussed by Brown et al. (2009), two such possibilities could be to impose longer lock-up periods or to stagger redemptions across the year. With regard to the former, a recent report by the Bank of England (2017) points out that hedge funds have already lengthened lock-up periods since the crisis to mitigate the risk of disorderly asset liquidations due to an investor run. Another possibility to limit forced asset liquidations would be to reduce the incentives for investors to run. One way to achieve this are alternative pricing rules, such as swing- or dual-pricing. Jin, Kacperczyk, Kahraman and Suntheim (2019) document that such pricing rules distribute the costs associated with redemptions more evenly between existing and exiting investors and might protect funds from investor runs.

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Figure 1:
ΔCoVaR - Hedge Funds vs. Mutual Funds

This figure displays the evolution of the Conditional Value at Risk ($\Delta\text{CoVaR}_{1\%}$) for hedge funds and mutual funds over time. The calculation of the systemic risk measure is outlined in Section 3. The sample period is January 1994 to December 2018, at a monthly frequency. Horizontal dashed lines, from left to right, mark the following events: the breakdown of LTCM in September 1998; the bankruptcy of Lehman in September 2008; the collapse of MF Global in October 2011.

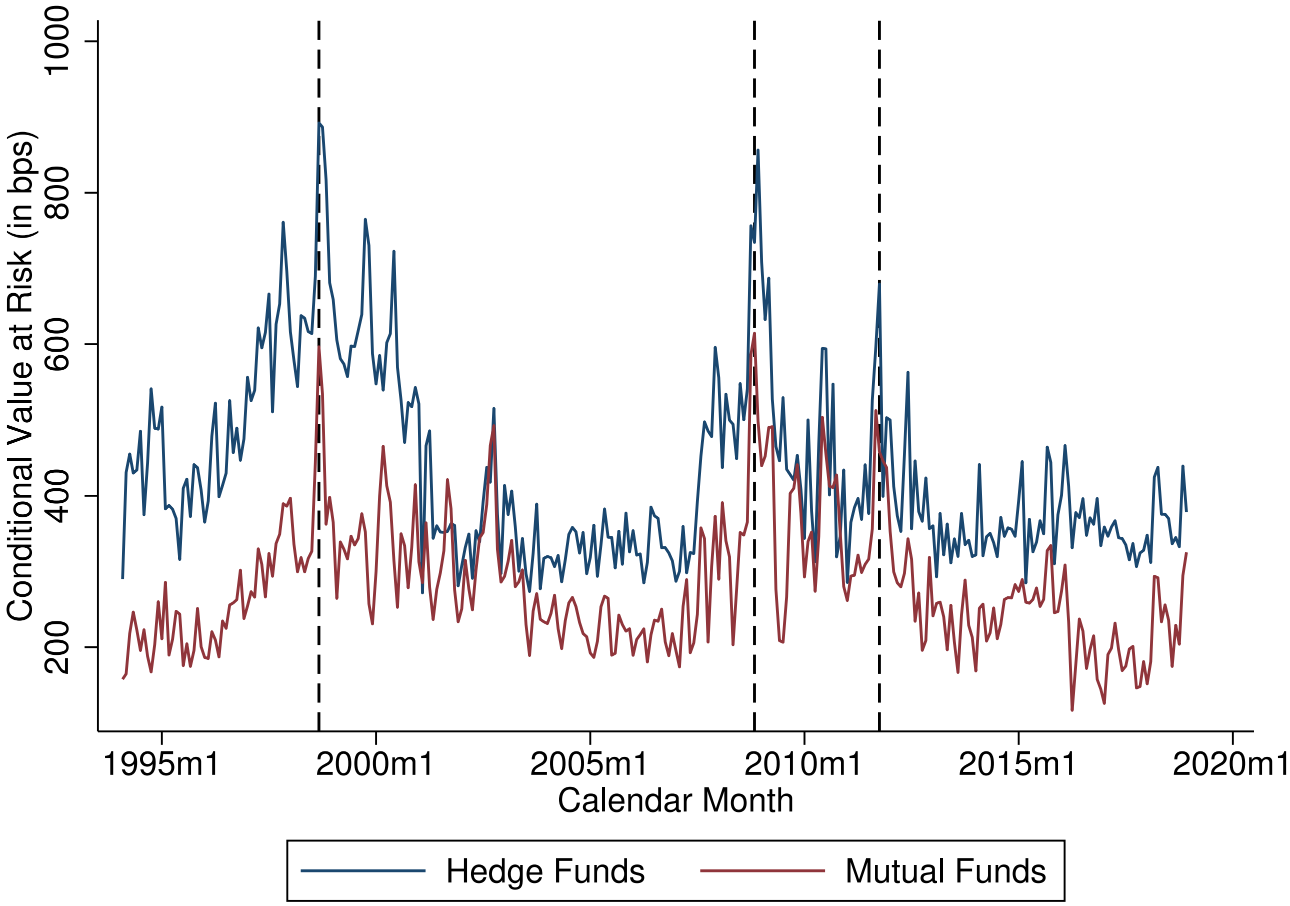

Figure 2:
Size-Adjusted ΔCoVaR - Hedge Funds vs. Mutual Funds

This figure displays the evolution of the size-adjusted Conditional Value at Risk ($\Delta\text{CoVaR}^{Size}_{1\%}$) for hedge funds and mutual funds over time. The calculation of the systemic risk measure is outlined in Section 3. For the size adjustment, each fund's ΔCoVaR is multiplied by the fund's assets under management and divided by the cross-sectional average of assets under management across all funds in each month. The sample period is January 1994 to December 2018, at a monthly frequency. Horizontal dashed lines, from left to right, mark the following events: the breakdown of LTCM in September 1998; the bankruptcy of Lehman in September 2008; the collapse of MF Global in October 2011.

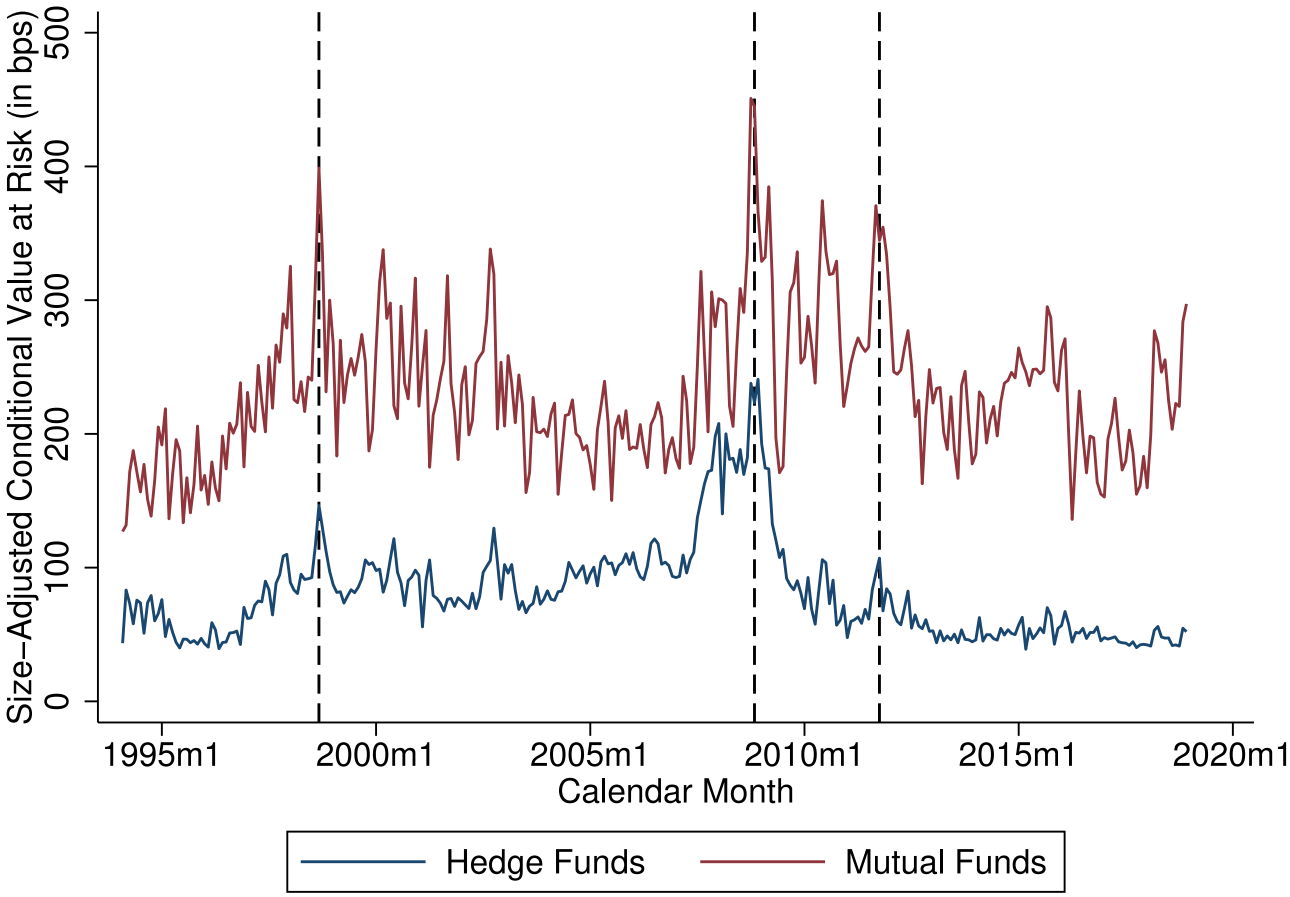

Table 1:
Descriptive Statistics - Fund Level

This table provides summary statistics for the main variables used in the subsequent analysis. For the sample period between January 1994 and December 2018, I report the number of funds and cross-sectional mean, median, standard deviation as well as 25% and 75% percentiles of fund characteristics. Panel A reports summary statistics for hedge funds, Panel B for mutual funds. ΔCoVaR, fund assets under management, fund flows, fund returns, the standard deviation of fund returns, and the measure for fund asset liquidity θ_0 are winsorized at the top and bottom 1% before averaging at the fund level. Following Jylhä et al. (2014), I classify a fund as a liquidty supplier or demander using a 36-month rolling window. The last two rows of each panel show how often a fund is classified as a liquidity supplier or liquidity demander as a fraction of his lifetime. The unit of measurement for the variables is given in brackets.

Panel A: Descriptive Statistics - Hedge Funds

	N	Mean	Median	SD	25%	75%
ΔCoVaR (in bps)	4083	359.44	355.41	484.99	75.29	961.64
MES (in bps)	4083	278.58	210.00	359.81	38.23	749.20
Fund AUM (in mn USD)	4083	113.35	35.43	234.44	10.73	273.27
Fund Flow (in % of AUM)	4083	0.68	0.45	2.86	-0.74	3.75
Fund Age (in months)	4083	111.45	95.80	62.28	63.06	200.15
Fund Asset Liquidity	4070	0.95	0.92	0.24	0.78	1.24
Fund Standard Deviation (in %)	4083	3.65	3.35	2.16	2.10	6.13
Fund Return (in %)	4083	0.40	0.39	0.52	0.14	0.99
Management Fee (in %)	4057	1.45	1.50	0.70	1.00	2.00
Liquidity Supplier (% of fund months)	4083	16.13	7.32	21.94	0.00	45.10
Liquidity Demander (% of fund months)	4083	10.34	3.28	16.45	0.00	29.81

Panel B: Descriptive Statistics - Mutual Funds

	N	Mean	Median	SD	25%	75%
ΔCoVaR (in bps)	7212	316.57	182.28	318.54	68.11	857.27
MES (in bps)	7212	502.19	552.91	351.56	257.70	872.72
Fund AUM (in mn USD)	7212	799.78	195.86	1879.06	55.06	1850.71
Fund Flow (in % of AUM)	7212	0.80	0.52	1.57	-0.23	2.78
Fund Age (in months)	7212	199.60	168.10	136.35	95.05	365.26
Fund Asset Liquidity	7211	1.11	1.09	0.22	0.97	1.36
Fund Standard Deviation (in %)	7212	3.78	3.98	1.91	2.31	6.00
Fund Return (in %)	7212	0.51	0.51	0.34	0.33	0.88
Management Fee (in %)	6546	0.66	0.66	0.37	0.45	1.02
Liquidity Supplier (% of fund months)	7212	6.71	3.47	8.45	0.00	18.67
Liquidity Demander (% of fund months)	7212	14.00	12.00	12.18	2.78	31.00

Table 2:
Panel Regression - Main Result

This table presents results of a fixed-effect panel regression with $\Delta \text{CoVaR}_{1\%}^{Size}$ as the dependent variable. The calculation of the systemic risk measure and the procedure to classify funds as liquidity suppliers and liquidity demanders is outlined in Section 3. All control variables, except for the dummy variables, are de-meaned. Time-varying control variables are lagged by one month. Details on the definition and calculation of the variables are given in Section 4. The sample period is January 1994 to December 2018, at a monthly frequency. The first two columns contain results for the pooled sample of hedge funds and mutual funds. Columns 3 and 4 contain results for the hedge fund subsample, Columns 5 and 6 for the mutual fund subsample. Standard errors are clustered at the fund and time level. *t*-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	Pooled Sample		Hedge Funds		Mutual Funds	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Size)_{t-1}	187.07***	185.60***	361.70***	370.61***	177.51***	176.06***
	(29.55)	(29.93)	(13.29)	(13.96)	(27.34)	(27.62)
Flow_{t-1}	-1.66***	-1.40***	-2.42***	-2.12***	-1.16***	-1.07***
	(-8.87)	(-7.88)	(-5.33)	(-4.66)	(-4.35)	(-4.17)
Log(Age)_{t-1}	28.45**	36.36***	139.91***	178.06***	11.89	16.81
	(2.50)	(3.23)	(2.94)	(4.03)	(1.02)	(1.46)
Theta_{t-1}	0.13*	0.01	-2.32***	-1.31***	0.30***	0.06
	(1.79)	(0.21)	(-4.94)	(-3.06)	(4.54)	(0.99)
Fund SD_{t-1}	35.11***	14.26***	-12.20	8.64	45.52***	14.77***
	(14.09)	(5.16)	(-1.49)	(1.10)	(14.56)	(3.60)
Return_{t-1}	-2.68***	-2.94***	-3.98	-4.48**	-1.91**	-2.29***
	(-2.96)	(-4.37)	(-1.54)	(-2.59)	(-2.32)	(-3.68)
Mgmt Fee	-91.49***	-99.17***	-55.04	-9.95	-199.61***	-220.51***
	(-5.50)	(-5.64)	(-1.64)	(-0.34)	(-8.39)	(-9.03)
Hedge Fund	241.96***					
	(13.46)					
LS_{t-1}	4.76	2.24	-17.96	-19.69	14.25**	15.92**
	(0.74)	(0.35)	(-0.58)	(-0.70)	(1.97)	(2.23)
LD_{t-1}	-14.07**	-13.60***	112.80***	74.53***	-18.63***	-18.81***
	(-2.48)	(-2.61)	(4.13)	(2.88)	(-3.33)	(-3.57)
adj. R^2	0.3141	0.3265	0.2580	0.2891	0.3192	0.3288
Obs	912541	912541	185257	185257	727284	727284
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Strategy FE	No	Yes	No	Yes	No	Yes

Table 3:
Panel Regression - Aggregate Analysis

This table presents results of a panel regression with $\Delta\text{CoVaR}^{Size}_{1\%}$, aggregated at the fund style-level, as the dependent variable. For the aggregation, I average ΔCoVaR for each style in each month, multiply it by total assets under management for the respective style, and divide it by the cross-sectional average of total assets under management across styles. $Size$ is the total assets under management for each style. $Flow$ is the aggregated flows. $Theta$, SD, and $Return$ are asset-weighted averages of the illiquidity measure, standard deviation of fund returns, and fund returns for each style, respectively. LS and LD gives the fraction of funds which supply or demand liquidity for each style. The sample period is January 1994 to December 2018, at a monthly frequency. The first two columns contain results for the hedge fund subsample, columns 3 and 4 for the mutual fund subsample. Standard errors are Newey-West standard errors with three lags. t-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	Hedge Funds		Mutual Funds	
	(1)	(2)	(3)	(4)
$Size_{t-1}$	14.24***	1.55	0.22***	0.00
	(13.43)	(1.52)	(14.77)	(0.27)
$Flow_{t-1}$	2.75***	0.03	6.02	5.24**
	(2.87)	(0.05)	(1.51)	(2.21)
$Theta_{t-1}$	0.04***	0.02***	0.01	0.00
	(6.48)	(4.20)	(1.33)	(1.34)
SD_{t-1}	30.57***	64.66***	103.32***	109.64***
	(2.65)	(5.27)	(12.94)	(13.46)
Return	2.68	-1.42	-0.02	-0.39
	(0.56)	(-0.45)	(-0.01)	(-0.27)
LS_{t-1}	-1.22	-0.40	0.47	-0.32
	(-0.90)	(-0.54)	(0.36)	(-0.35)
LD_{t-1}	6.13***	2.51**	-1.23***	0.71***
	(4.04)	(2.35)	(-2.71)	(2.60)
adj. R^2	0.4082	0.7899	0.6825	0.8839
Obs	2831	2831	1056	1056
Strategy FE	No	Yes	No	Yes

Table 4:
Panel Regression - Interaction Terms

This table presents results of a fixed-effect panel regression with $\Delta\text{CoVaR}_{1\%}^{Size}$ as the dependent variable. The calculation of the systemic risk measure and the procedure to classify funds as liquidity suppliers and liquidity demanders is outlined in Section 3. All control variables, except for the dummy variables, are de-meaned. Time-varying control variables are lagged by one month. Details on the definition and calculation of the controls are given in Section 4. The sample period is January 1994 to December 2018, at a monthly frequency. The first column contain results for the subsample of hedge fund. Columns 2 contains results for the subsample of mutual funds. Standard errors are clustered at the fund and time level. *t*-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	Hedge Funds	Mutual Funds
Log(Size)$_{t-1}$	347.13***	174.40***
	(12.89)	(27.36)
Flow$_{t-1}$	-1.91***	-1.02***
	(-3.91)	(-3.61)
Log(Age)$_{t-1}$	163.86***	18.10
	(3.62)	(1.57)
Theta$_{t-1}$	-1.17**	0.07
	(-2.42)	(1.09)
Fund SD$_{t-1}$	10.19	12.73***
	(1.26)	(3.14)
Return$_{t-1}$	-4.66**	-2.15***
	(-2.48)	(-3.45)
Mgmt Fee	-18.77	-205.58***
	(-0.62)	(-8.21)
LS$_{t-1}$	22.22	-30.56***
	(0.46)	(-3.54)
LS$_{t-1}$ x Log(Size)$_{t-1}$	96.98***	20.67**
	(3.02)	(2.48)
LS$_{t-1}$ x Flow$_{t-1}$	0.79	0.21
	(0.79)	(0.35)
LS$_{t-1}$ x Log(Age)$_{t-1}$	127.99***	33.85**
	(2.79)	(2.52)
LS$_{t-1}$ x Theta$_{t-1}$	-0.65	-0.13
	(-1.20)	(-0.94)
LS$_{t-1}$ x Fund SD$_{t-1}$	-19.46**	8.60**
	(-2.29)	(2.42)
LS$_{t-1}$ x Return$_{t-1}$	1.79	-0.64
	(0.55)	(-0.97)
LS$_{t-1}$ x Mgmt Fee	45.16	-78.95***
	(1.47)	(-3.11)
LD$_{t-1}$	160.71***	-6.40
	(2.92)	(-0.86)
LD$_{t-1}$ x Log(Size)$_{t-1}$	92.00***	-2.56
	(3.04)	(-0.44)
LD$_{t-1}$ x Flow$_{t-1}$	-2.89***	-0.40
	(-2.67)	(-0.84)
LD$_{t-1}$ x Log(Age)$_{t-1}$	-28.10	-25.31***
	(-0.60)	(-2.69)
LD$_{t-1}$ x Theta$_{t-1}$	0.13	-0.01
	(0.19)	(-0.12)
LD$_{t-1}$ x Fund SD$_{t-1}$	4.33	8.68***
	(0.40)	(3.12)
LD$_{t-1}$ x Return $_{t-1}$	0.76	-0.21
	(0.24)	(-0.44)
LD$_{t-1}$ x Mgmt Fee	22.23	-23.13
	(0.57)	(-1.10)
adj. R^2	0.2928	0.3299
Obs	185257	724998
Time FE	Yes	Yes
Strategy FE	Yes	Yes

Table 5:
Panel Regression - CoVaR Decomposition

In this table, the dependent variables are the three components of the $\Delta\text{CoVaR}_{1\%}$ decomposition as described in Brunnermeier et al. (2019). In columns (1), (4), and (7), the dependent variable is the proxy for interconnectedness *gamma*. In columns (2), (5) and (8), the dependent variable is the proxy for tail risk *alpha*. In columsn (3), (6) and (9), the dependent variable is the proxy for exposure to fundamental macroeconomic and finance factors *beta*. All control variables, except for the dummy variables, are de-meaned. Time-varying control variables are lagged by one month. Details on the definition and calculation of the variables are given in Section 4. The sample period is January 1994 to December 2018, at a monthly frequency. The first three columns contain results for the pooled sample of hedge funds and mutual funds. Columns 4 to 6 contain results for the hedge fund subsample, Columns 7 to 9 for the mutual fund subsample. Standard errors are clustered at the fund and time level. *t*-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	Pooled Sample			Hedge Funds			Mutual Funds		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log(Size)_{t-1}	-0.0270***	0.0008***	-0.0004	0.0019	-0.0003	0.0007	-0.0381***	0.0012***	-0.0008**
	(-7.14)	(2.81)	(-1.40)	(0.19)	(-0.42)	(0.86)	(-10.22)	(3.74)	(-2.44)
Flow_{t-1}	-0.0013***	0.0003***	-0.0002***	0.0007	0.0001**	-0.0001***	-0.0023***	0.0004***	-0.0002***
	(-4.19)	(8.67)	(-5.91)	(1.60)	(2.19)	(-3.15)	(-7.14)	(8.21)	(-3.41)
Log(Age)_{t-1}	-0.0475***	-0.0095***	0.0169***	0.0770**	-0.0019	0.0098***	-0.0471***	-0.0109***	0.0185***
	(-4.59)	(-11.22)	(14.78)	(2.44)	(-0.79)	(3.94)	(-4.66)	(-12.65)	(15.52)
Theta_{t-1}	-0.0006***	0.0001***	-0.0000***	-0.0032***	0.0001***	-0.0000	0.0002***	0.0000***	-0.0000***
	(-4.07)	(7.60)	(-2.70)	(-8.22)	(3.54)	(-0.92)	(3.29)	(3.72)	(-2.80)
Fund SD_{t-1}	-0.0544***	0.0057***	0.0131***	-0.1241***	0.0106***	0.0073***	-0.0452***	0.0014***	0.0132***
	(-14.19)	(10.76)	(22.97)	(-13.37)	(9.40)	(6.91)	(-11.56)	(2.64)	(19.94)
Return_{t-1}	0.0012	0.0003	-0.0022***	-0.0002	-0.0001	-0.0008***	0.0003	0.0005**	-0.0026***
	(0.79)	(1.49)	(-6.33)	(-0.11)	(-0.80)	(-3.06)	(0.37)	(2.42)	(-7.51)
Mgmt Fee	-0.0928***	0.0056***	-0.0006	-0.0814***	0.0059**	-0.0063***	-0.1111***	0.0011	0.0060***
	(-4.80)	(3.13)	(-0.38)	(-3.10)	(2.57)	(-2.90)	(-4.89)	(0.58)	(3.11)
Hedge Fund	0.3258***	0.0056**	-0.0058**						
	(11.88)	(2.43)	(-2.58)						
LS_{t-1}	0.0210**	-0.0028***	0.0017**	-0.0420	0.0009	-0.0011	0.0123*	-0.0024***	0.0021**
	(2.48)	(-3.63)	(2.03)	(-1.51)	(0.57)	(-0.58)	(1.86)	(-3.12)	(2.53)
LD_{t-1}	0.0190**	0.0014**	-0.0011	0.1783***	-0.0014	0.0008	-0.0130**	0.0010*	-0.0001
	(2.08)	(2.23)	(-1.65)	(5.89)	(-0.87)	(0.50)	(-2.14)	(1.74)	(-0.08)
adj. R^2	0.0986	0.1389	0.3544	0.2099	0.1907	0.1434	0.0845	0.1626	0.4545
Obs	918176	918176	918176	189202	189202	189202	728974	728974	728974
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strategy FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Table 6:
Panel Regression - Macroeconomic Conditions

This table presents results of a fixed-effect panel regression with $\Delta\text{CoVaR}^{Size}_{1\%}$ as the dependent variable. The calculation of the systemic risk measure and the procedure to classify funds as liquidity suppliers and liquidity demanders is outlined in Section 3. High VIX is a dummy variable equal to one for months in which the VIX exceeds its 75th percentile value (measured up to this month). High TED Spread ($LIBOR_t - TBill_t$)is defined accordingly. Low Repo Volume is a dummy variable equal to one for months in which dealer repo volume is below its 25th percentile value (measured up to this month). Dealer repo volume is the cumulative difference in short-term lending by U.S. primary dealers. All control variables, except for the dummy variables, are de-meaned. Time-varying control variables are lagged by one month. Details on the definition and calculation of the variables are given in Section 4. The sample period is January 1994 to December 2018, at a monthly frequency. The first three columns contain results for the subsample of hedge fund. The last three columns contain results for the subsample of mutual funds. Standard errors are clustered at the fund and time level. t-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	Hedge Funds			Mutual Funds		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Size)_{t-1}	370.72***	370.54***	370.52***	175.76***	175.65***	175.63***
	(13.97)	(13.95)	(13.96)	(27.65)	(27.66)	(27.66)
Flow_{t-1}	-2.47***	-2.43***	-2.56***	-1.12***	-1.14***	-1.15***
	(-5.31)	(-5.25)	(-5.43)	(-4.21)	(-4.30)	(-4.28)
Log(Age)_{t-1}	177.88***	177.78***	177.71***	17.03	17.24	17.23
	(4.04)	(4.03)	(4.03)	(1.48)	(1.50)	(1.50)
Theta_{t-1}	-1.33***	-1.34***	-1.33***	0.08	0.07	0.07
	(-3.19)	(-3.20)	(-3.18)	(1.27)	(1.17)	(1.19)
Fund SD_{t-1}	9.48	9.26	9.24	15.19***	15.19***	15.16***
	(1.22)	(1.18)	(1.18)	(3.78)	(3.77)	(3.76)
Return_{t-1}	-7.40***	-8.05***	-8.49***	-4.49***	-5.54***	-5.66***
	(-4.66)	(-4.73)	(-4.92)	(-5.06)	(-6.02)	(-5.97)
Mgmt Fee	-10.18	-10.16	-10.13	-220.62***	-220.75***	-220.72***
	(-0.35)	(-0.35)	(-0.35)	(-9.04)	(-9.04)	(-9.03)
LS_{t-1}	14.26	-23.43	-18.76	11.73*	13.48*	16.09**
	(0.52)	(-0.85)	(-0.65)	(1.71)	(1.78)	(2.24)
LD_{t-1}	42.96*	49.44**	66.46***	-16.68***	-19.55***	-17.44***
	(1.91)	(2.10)	(2.61)	(-3.01)	(-3.49)	(-3.31)
$\text{High VIX}_{10\%}$	108.54***			49.32***		
	(6.10)			(5.55)		
LS_{t-1} x $\text{High VIX}_{10\%}$	-178.32***			13.30		
	(-4.72)			(1.25)		
LD_{t-1} x $\text{High VIX}_{10\%}$	147.71**			2.66		
	(2.26)			(0.31)		
$\text{High TED Spread}_{10\%}$		120.26***			16.08	
		(4.66)			(1.22)	
LS_{t-1} x $\text{High TED Spread}_{10\%}$		-3.30			11.26	
		(-0.06)			(0.92)	
LD_{t-1} x $\text{High TED Spread}_{10\%}$		215.18**			23.47**	
		(2.23)			(2.30)	
$\text{Low Repo Volume}_{10\%}$			6.07			11.14
			(0.52)			(1.28)
LS_{t-1} x $\text{Low Repo Volume}_{10\%}$			-170.66**			-14.41
			(-2.09)			(-0.81)
LD_{t-1} x $\text{Low Repo Volume}_{10\%}$			-6.37			15.98
			(-0.09)			(1.42)
adj. R^2	0.2879	0.2875	0.2868	0.3246	0.3240	0.3239
Obs	185257	185257	185257	727284	727284	727284
Time FE	No	No	No	No	No	No
Strategy FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7:
Panel Regression - Bubble Periods

This table presents results of a fixed-effect panel regression with $\Delta\text{CoVaR}_{1\%}^{Size}$ as the dependent variable. The calculation of the systemic risk measure and the procedure to classify funds as liquidity suppliers and liquidity demanders is outlined in Section 3. *Boom* and *Bust* indicate bubble phases of the MSCI Global Index using the BSADF approach of Phillips, Shi, and Yu (2015a,b). Details on the procedure are described in Section 6. The regression models include interaction terms between the control variables and the boom/bust indicators. All control variables, except for the dummy variables, are de-meaned. Time-varying control variables are lagged by one month. Details on the definition and calculation of the variables are given in Section 4. The sample period is January 1994 to December 2017, at a monthly frequency. The first column contains results for the subsample of hedge fund. The second column contains results for the subsample of mutual funds. Standard errors are clustered at the fund and time level. *t*-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	Hedge Funds	Mutual Funds
Boom	106.99**	7.42
	(1.99)	(0.47)
Bust	216.06***	-40.61***
	(3.11)	(-3.56)
$\text{Log(Size)}_{\text{t-1}}$	352.53***	172.28***
	(13.32)	(26.60)
$\text{Flow}_{\text{t-1}}$	-2.10***	-1.14***
	(-4.50)	(-4.13)
$\text{Log(Age)}_{\text{t-1}}$	177.91***	13.61
	(4.16)	(1.15)
$\text{Theta}_{\text{t-1}}$	-1.17***	-0.01
	(-2.62)	(-0.09)
$\text{Fund SD}_{\text{t-1}}$	11.66	14.39***
	(1.55)	(3.52)
$\text{Return}_{\text{t-1}}$	-6.38***	-3.10***
	(-4.14)	(-4.53)
Mgmt Fee	-8.57	-220.06***
	(-0.29)	(-9.02)
$\text{LS}_{\text{t-1}}$	-7.42	8.79
	(-0.25)	(1.19)
$\text{LD}_{\text{t-1}}$	51.76**	-17.05***
	(2.18)	(-3.13)
$\text{Log(Size)}_{\text{t-1}}$ x Boom	293.67***	36.56*
	(3.79)	(1.66)
$\text{Log(Size)}_{\text{t-1}}$ x Bust	459.28***	91.03***
	(5.63)	(4.01)
$\text{Flow}_{\text{t-1}}$ x Boom	-6.21	3.75
	(-0.53)	(0.79)
$\text{Flow}_{\text{t-1}}$ x Bust	-0.70	-2.84
	(-0.08)	(-0.59)
$\text{Age}_{\text{t-1}}$ x Boom	-12.62	16.78
	(-0.17)	(1.17)
$\text{Age}_{\text{t-1}}$ x Bust	54.06	16.42
	(0.49)	(0.71)
$\text{Theta}_{\text{t-1}}$ x Boom	-55.77*	12.75**
	(-1.72)	(2.17)
$\text{Theta}_{\text{t-1}}$ x Bust	-9.15	-0.33
	(-0.22)	(-0.06)
$\text{Fund SD}_{\text{t-1}}$ x Boom	-81.39**	6.38
	(-2.11)	(0.91)
$\text{Fund SD}_{\text{t-1}}$ x Bust	-78.03**	-7.59
	(-2.15)	(-1.27)
$\text{Return}_{\text{t-1}}$ x Boom	19.53	-7.10
	(1.05)	(-1.08)
$\text{Return}_{\text{t-1}}$ x Bust	-16.59	-2.62
	(-0.73)	(-0.34)
$\text{LS}_{\text{t-1}}$ x Boom	-45.62	19.94
	(-0.78)	(1.18)
$\text{LS}_{\text{t-1}}$ x Bust	-7.77	45.77**
	(-0.10)	(2.51)
$\text{LD}_{\text{t-1}}$ x Boom	413.62**	-15.37
	(2.47)	(-0.92)
$\text{LD}_{\text{t-1}}$ x Bust	465.60**	-26.46
	(2.57)	(-1.09)
adj. R^2	0.2954	0.3279
Obs	185257	727284
Time FE	No	No
Strategy FE	Yes	Yes

Table 8:
Panel Regression - Alternative ΔCoVaR Calculation

This table presents results of a fixed-effect panel regression with the rolling $\Delta \text{CoVaR}_{1\%}^{Size}$, using historical Value at Risk estimates, as the dependent variable. The calculation of the systemic risk measure is outlined in Section 7. All control variables, except for the dummy variables, are de-meaned. Time-varying control variables are lagged by one month. Details on the definition and calculation of the variables are given in Section 4. The sample period is January 1994 to December 2018, at a monthly frequency. The first two columns contain results for the pooled sample of hedge funds and mutual funds. Columns 3 and 4 contain results for the hedge fund subsample, Columns 5 and 6 for the mutual fund subsample. Standard errors are clustered at the fund and time level. *t*-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	Hedge Funds		Mutual Funds	
	(1)	(2)	(3)	(4)
$\text{Log(Size)}_{t\text{-}1}$	345.08***	353.05***	213.32***	211.60***
	(12.93)	(13.49)	(25.76)	(25.98)
$\text{Flow}_{t\text{-}1}$	-2.61***	-2.32***	-1.44***	-1.32***
	(-5.69)	(-5.12)	(-4.45)	(-4.26)
$\text{Log(Age)}_{t\text{-}1}$	96.49**	137.39***	-5.00	2.75
	(2.17)	(3.30)	(-0.35)	(0.19)
$\text{Theta}_{t\text{-}1}$	-2.72***	-1.79***	0.30***	0.06
	(-5.45)	(-3.92)	(3.81)	(0.75)
$\text{Fund SD}_{t\text{-}1}$	-1.78	19.23**	63.76***	31.93***
	(-0.22)	(2.43)	(16.33)	(6.07)
$\text{Return}_{t\text{-}1}$	-3.20	-3.63**	0.23	-0.09
	(-1.24)	(-1.97)	(0.33)	(-0.19)
Mgmt Fee	-62.92*	-21.20	-267.40***	-285.57***
	(-1.91)	(-0.74)	(-8.79)	(-9.24)
$\text{LS}_{t\text{-}1}$	-66.49**	-67.53***	11.37	13.72
	(-2.46)	(-2.70)	(1.29)	(1.57)
$\text{LD}_{t\text{-}1}$	145.79***	108.24***	-15.41**	-17.08**
	(4.62)	(3.60)	(-2.13)	(-2.45)
adj. R^2	0.2542	0.2849	0.3188	0.3278
Obs	185866	185866	728950	728950
Time FE	Yes	Yes	Yes	Yes
Strategy FE	No	Yes	No	Yes

Table 9:
Panel Regression - Marginal Expected Shortfall

This table presents results of a fixed-effect panel regression with the size-adjusted Marginal Expected Shortfall ($MES_{5\%}^{Size}$) as the dependent variable. The calculation of the systemic risk measure is outlined in Section 7. All control variables, except for the dummy variables, are de-meaned. Time-varying control variables are lagged by one month. Details on the definition and calculation of the variables are given in Section 4. The sample period is January 1994 to December 2018, at a monthly frequency. The first two columns contain results for the pooled sample of hedge funds and mutual funds. Columns 3 and 4 contain results for the hedge fund subsample, Columns 5 and 6 for the mutual fund subsample. Standard errors are clustered at the fund and time level. *t*-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	Hedge Funds		Mutual Funds	
	(1)	(2)	(3)	(4)
$Log(Size)_{t-1}$	105.86***	112.07***	464.35***	459.90***
	(7.51)	(8.06)	(24.62)	(24.75)
$Flow_{t-1}$	-1.86***	-1.68***	-4.08***	-3.98***
	(-5.19)	(-4.79)	(-4.96)	(-5.25)
$Log(Age)_{t-1}$	27.50	50.37***	147.66***	159.01***
	(1.35)	(2.72)	(5.97)	(6.52)
$Theta_{t-1}$	-1.47***	-0.88***	0.89***	0.22
	(-5.00)	(-3.25)	(4.27)	(1.29)
Fund SD_{t-1}	40.74***	50.23***	146.46***	52.65***
	(6.85)	(8.50)	(15.75)	(4.58)
$Return_{t-1}$	-3.67	-3.90	6.42	5.19
	(-1.27)	(-1.46)	(1.52)	(1.45)
Mgmt Fee	-44.87**	-21.25	-399.21***	-482.27***
	(-2.23)	(-1.24)	(-9.58)	(-10.88)
LS_{t-1}	-88.67***	-92.82***	-86.85***	-81.96***
	(-4.42)	(-4.72)	(-4.54)	(-4.57)
LD_{t-1}	33.42**	15.19	-63.10***	-61.51***
	(2.08)	(0.99)	(-3.99)	(-4.08)
adj. R^2	0.1272	0.1598	0.3980	0.4099
Obs	185866	185866	728603	728603
Time FE	Yes	Yes	Yes	Yes
Strategy FE	No	Yes	No	Yes

Table 10:
Panel Regression - Robustness Tests Hedge Fund Sample

This table presents results of a fixed-effect panel regression with $\Delta \text{CoVaR}_{1\%}^{Size}$ as the dependent variable. The sample is limited to hedge funds. The calculation of the systemic risk measure and the procedure to classify funds as liquidity suppliers and liquidity demanders is outlined in Section 3. All control variables, except for the dummy variables, are de-meaned. Time-varying control variables are lagged by one month. Details on the definition and calculation of the variables are given in Section 4. The sample period is January 1994 to December 2018, at a monthly frequency. The first column controls for the backfilling bias by deleting the first 12 months of observations for each fund. In the second column, I control for strategy-time fixed effects. Column 3 includes fund fixed effects. In Column 4, I use β^{LP}, a fund's exposure to the liquidity provision strategy described in Section 3.2, as an additional regressor. The variable is winsorized at the upper and lower 1% level. Standard errors are clustered at the fund and time level. *t*-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	Backfilling	Strategy-Time FE	Fund FE	Liquidity Beta
Log(Size)_{t-1}	377.07***	371.29***	-0.96	371.28***
	(13.45)	(13.87)	(-0.23)	(13.97)
Flow_{t-1}	-2.14***	-2.02***	-0.33***	-2.12***
	(-4.23)	(-4.32)	(-3.13)	(-4.63)
Log(Age)_{t-1}	190.34***	179.04***	8.36	177.23***
	(3.63)	(4.05)	(0.44)	(4.01)
Theta_{t-1}	-1.35***	-1.21***	-0.39***	-1.30***
	(-2.96)	(-2.70)	(-3.84)	(-3.03)
Fund SD_{t-1}	11.11	10.56	91.62***	8.86
	(1.31)	(1.34)	(10.70)	(1.13)
Return_{t-1}	-4.08**	-4.58**	-1.49**	-4.45**
	(-2.35)	(-2.47)	(-2.28)	(-2.56)
Mgmt Fee	-3.52	-8.53	0.00	-10.13
	(-0.11)	(-0.29)	(0.00)	(-0.35)
LS_{t-1}	-2.04	-33.65	-20.45***	
	(-0.06)	(-1.16)	(-2.94)	
LD_{t-1}	70.43***	80.49***	27.69**	
	(2.76)	(3.11)	(2.29)	
$\beta^{LP}{}_{t-1}$				-46.71***
				(-3.13)
adj. R^2	0.2952	0.2892	0.8441	0.2893
Obs	163513	185211	185161	185257
Time FE	Yes	Yes	Yes	Yes
Strategy FE	Yes	Yes	No	Yes
Strategy x Time FE	No	Yes	No	No
Fund FE	No	No	Yes	No

Table 11:
Panel Regression - Robustness Tests Mutual Fund Sample

This table presents results of a fixed-effect panel regression with $\Delta \text{CoVaR}_{1\%}^{Size}$ as the dependent variable. The sample is limited to mutual funds. The calculation of the systemic risk measure and the procedure to classify funds as liquidity suppliers and liquidity demanders is outlined in Section 3. All control variables, except for the dummy variables, are de-meaned. Time-varying control variables are lagged by one month. Details on the definition and calculation of the variables are given in Section 4. The sample period is January 1994 to December 2018, at a monthly frequency. The first column controls for the backfilling bias by deleting the first 12 months of observations for each fund. In the second column, I control for strategy-time fixed effects. Column 3 includes fund fixed effects. In Column 4, I use β^{LP}, a fund's exposure to the liquidity provision strategy described in Section 3.2, as an additional regressor. The variable is winsorized at the upper and lower 1% level. Standard errors are clustered at the fund and time level. t-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	Backfilling	Strategy-Time FE	Fund FE	Liquidity Beta
$\text{Log(Size)}_{t\text{-}1}$	178.75***	176.02***	151.48***	175.97***
	(27.22)	(27.53)	(24.43)	(27.63)
$\text{Flow}_{t\text{-}1}$	-1.08***	-1.11***	-0.29*	-1.05***
	(-3.90)	(-4.35)	(-1.68)	(-4.10)
$\text{Log(Age)}_{t\text{-}1}$	22.88*	16.40	123.99***	16.77
	(1.72)	(1.43)	(6.35)	(1.46)
$\text{Theta}_{t\text{-}1}$	0.07	0.06	-0.05	0.08
	(1.00)	(0.82)	(-1.36)	(1.36)
$\text{Fund SD}_{t\text{-}1}$	16.05***	12.70**	18.69***	14.59***
	(3.59)	(2.53)	(6.55)	(3.55)
$\text{Return}_{t\text{-}1}$	-2.52***	-0.40	-3.01***	-2.27***
	(-3.84)	(-0.65)	(-4.83)	(-3.59)
Mgmt Fee	-230.67***	-219.63***	-161.95***	-219.78***
	(-8.70)	(-8.91)	(-10.19)	(-9.01)
$\text{LS}_{t\text{-}1}$	19.01**	16.67**	12.20***	
	(2.52)	(2.25)	(2.95)	
$\text{LD}_{t\text{-}1}$	-19.81***	-20.29***	-11.19***	
	(-3.60)	(-3.73)	(-3.86)	
${\beta^{LP}}_{t\text{-}1}$				40.67***
				(3.53)
adj. R^2	0.3318	0.3304	0.7910	0.3288
Obs	684159	727284	727278	727284
Time FE	Yes	Yes	Yes	Yes
Strategy FE	Yes	Yes	No	Yes
Strategy x Time FE	No	Yes	No	No
Fund FE	No	No	Yes	No