Hedge funds and prime brokers: The role of funding risk

This Version: May 25, 2009

Abstract

Using a unique data set with information on individual hedge funds and prime brokers this paper analyses three potential determinants of hedge funds' funding risk: financial distress of prime brokers, reliance on multiple prime brokers and large investor redemptions. The paper thereby contributes to our understanding of the embeddedness of hedge funds in the financial system. Our findings show that an increase in prime brokers' distress is associated with a significant decline in fund performance. Hedge funds benefit from relying on multiple prime brokers in having significantly higher returns. Depending on the length of the restriction period, requests for large investor redemptions affect fund returns over consecutive months, indicating the investment into more illiquid assets.

Keywords: Hedge Funds, Prime Brokers, Funding Liquidity Risk, Investor Redemptions, Multiple Prime Brokers

JEL Classification: G00, G11, G12, G23

1 Introduction

The global financial system has undergone a period of massive turbulence. Triggered by escalating losses on subprime mortgages, banks and prime brokers were facing funding pressure when asset prices and market liquidity declined. In particular, prime brokers such as Bear Stearns suffered from a maturity mismatch and were not able to roll over their short-term liabilities, leading to a system-wide distrust in financial institutions. In such a situation of declining confidence in the interbank market, the banks' willingness and ability to continue extending credit has been reduced, causing a tightening of monetary and financial conditions (International Monetary Fund, 2008). In addition, the worldwide decline in asset prices forced investors to settle their positions and to put their money into cash.

Against this background, the aim of this paper is to empirically analyse to what extent a funding risk has affected the performance of hedge funds. To this end, we investigate three factors which potentially impact hedge funds' funding risk: (i) financial distress of prime brokers, (ii) reliance on multiple prime brokers and (iii) large investor redemptions. In addition, we analyse whether the funding risk driven by these three factors has been magnified after the start of the financial turmoil in 2007. To our knowledge this is the first paper that empirically analyses the relationship between the number of a hedge fund's funding sources and its performance.

First, we estimate the extent to which the financial distress of a prime broker or bank has translated into a funding pressure for the corresponding hedge fund. As the funding by prime brokers is subject to bilateral negotiations and remains opaque to outsiders, the effects of a credit tightening can only be indirectly evaluated. Throughout our analysis we assume that the greater the financial distress of prime brokers, the greater the likelihood that they reduce the availability of credit to hedge funds. We measure the financial distress of each prime broker or bank by its distance-to-default, credit default swap (CDS) spread and option-implied volatility.

Second, hedge funds are increasingly relying on multiple prime brokers (Greenwich Associates, 2007; FitchRatings, 2007). While various studies investigate the relationship between the number of banks and the credit available to firms (see e.g. Houston and James, 1996; Petersen and Rajan, 1994), no paper focuses on hedge funds. We therefore analyse whether hedge funds relying on multiple prime brokers or banks had a better performance during the sample period than those funds that declare to have only one prime broker. This aspect is motivated by the reasoning that if one prime broker reduces the credit line or increases margins, there is still the chance for a hedge fund to get funding from another prime broker it is associated with.

Third, we investigate the extent to which fund performance is affected by large investor redemptions. Although this issue has been addressed in the mutual fund literature (see e.g. Chordia, 1996; Nanda et al., 2000), there are only very few studies that focus on hedge funds (European Central Bank, 2007, pp. 56-59). In contrast to mutual funds, hedge funds are protected to some extent from the risk of a run by investors due to their redemption restrictions. When analysing the impact of redemptions on fund performance we explicitly take the fund's redemption restriction into account.

Finally, we use a 24-months rolling estimation to analyse whether the funding risk of hedge funds has been amplified after the financial crisis started in 2007. According to the International Monetary Fund (2008), financial institutions tried to reduce their risks during the financial turmoil leading to a reduction in their willingness and ability to continue extending credit. Therefore, it is likely that the funding pressure of prime brokers has translated into tighter credit conditions for hedge funds.

Our paper contributes to the growing literature that investigates contagion-related issues surrounding hedge funds. For example, Boyson et al. (2007) analyse contagion effects between hedge funds and asset markets. Their study documents contagion across fund styles, but no systematic evidence of contagion from asset markets to hedge funds. Boyson et al. (2008), using data on hedge fund style indices, examine clustering of worst fund returns and find that adverse shocks to asset and funding liquidity increase the probability of simultaneous worst returns across hedge fund styles. Adrian and Brunnermeier (2009) also use data on hedge fund style indices for measuring tail risk dependency based on quantile regression. They document that low returns of hedge funds predict a higher Value-at-Risk for investment banks in the following months. Brunnermeier and Pedersen (2009) emphasize the role of funding liquidity and market liquidity as amplifying contagion mechanisms by providing a theoretical model in which funding liquidity and market liquidity interact. Plantin and Shin (2006) develop a model where the unwinding of carry trades is associated with de-leveraging of hedge funds because of a reduction in funding liquidity.

Our approach is different in the sense that we explicitly focus on funding risk in hedge funds' balance sheets. Instead of using hedge fund index data, we use data on about 2,200 individual hedge funds and their prime brokers and/or banks over the period January 2004 to June 2008. This unique data set allows us to evaluate the extent to which funding liquidity risk, stemming from the deteriorating financial conditions of prime brokers or from large investor redemptions, has affected hedge fund returns. Our paper also provides insights into the role of multiple prime brokers in the performance of hedge funds, an aspect that has not yet been analysed. By applying a 24-months rolling estimation we are able to gauge how the impact of funding risk on fund performance has varied over time.

We find that deteriorations in the financial condition of a hedge fund's prime broker, captured by a change in its 5-year CDS spread and in the negative of its distance-to-default, are associated with significantly lower fund returns. Furthermore, diversifying funding sources seems to be beneficial as hedge funds having more than one prime broker or bank have a significantly better performance than those funds relying on just one prime broker. Regarding funding risk stemming from investor redemptions, we find a strong relation between investors' requests for large capital withdrawals and fund performance. In addition, greater managerial flexibility due to longer lockup, redemption notice and payout periods is associated with higher returns. Regarding the time-varying nature of the impact of funding risk on hedge fund returns, we find that the impact of prime brokers' distress and of relying on more than one prime broker became more pronounced after the start of the financial turmoil in 2007.

The remainder of the paper is organised as follows. Section 2 presents the sources of funding liquidity risk in hedge funds' balance sheets and proposes testable hypotheses. Section 3 describes the data and the construction of variables, in particular the indicators of prime brokers' financial fragility and the indicator capturing large investor withdrawals. Section 4 presents our estimation methodology and the corresponding empirical results and section 5 concludes.

2 Funding risk in hedge funds' balance sheets

This section deals with funding liquidity that refers to the ease with which one can borrow money, either uncollateralized or with assets as collateral (Brunnermeier, 2009). The analysis focuses more precisely on funding liquidity risk in hedge funds' balance sheets, which encompasses margin funding risk, redemption risk and rollover risk. Margin funding risk arises as most hedge funds rely on short-term financing from prime brokers to pursue leveraged investment strategies. This is done by posting part of their assets as collateral and by financing the difference between the amount of the loan and the collateral value, the margin, by their own capital. As a consequence, if margins increase, which is also referred to as 'margin-calls', hedge funds have to use more of their own capital and might therefore be forced to de-leverage their positions. These margin-calls may arise for several reasons, for example as a consequence of a market disruption involving a non-temporary decline in the value of the hedge fund's collateral. In this paper, we focus on prime brokers' own funding liquidity pressures, which they are likely to transfer to hedge funds via tighter credit conditions. As a matter of fact, liquidity issues in the banking sector throughout the crisis have gradually led to tighter credit conditions for hedge funds. According to the Global Financial Stability Report of the International Monetary Fund, haircuts on collateral used to obtain funding from prime brokers have at least doubled for fixed-income securities and increased by a factor of five for asset-backed securities since the start of the turmoil (International Monetary Fund, 2008).

Redemption risk is another important source of funding liquidity risk in funds' balance sheets and materialises when investors withdraw their money out of the hedge fund industry. Therefore, we also focus on investor redemptions as a potential driver of funding liquidity risk and its impact on hedge fund returns during the sample period. The Bank of England states in its Financial Stability Report that hedge funds have recently experienced additional funding pressures due to redemption requests of investors, especially from funds of hedge funds as a response to their own redemption requests (Bank of England, 2008*a*).

These causes of funding liquidity risk may be amplified by certain conditions such as leverage and concentrated market positions (also referred to as crowded trades). In fact, hedge funds that operate near their maximum leverage limits are more dependent on the stability of their funding. Any margin calls by their prime broker or bank, market shocks to the fund's assets or investor redemptions, even of small magnitude, may prompt significant fire sales in unfavourable market conditions and thereby trigger a so-called "margin spiral" (Brunnermeier and Pedersen, 2009; Adrian and Shin, 2007). Forced selling has contributed to erode market liquidity as well as adversely affect prices, reducing thereby the value of collateral posted by hedge funds to their prime brokers. A liquidity spiral has emerged when the erosion of the collateral value has triggered further margin calls (Brunnermeier and Pedersen, 2009). One indication of the amplifying effect of leverage is that fixed income and convertible arbitrage funds, which are among the most leveraged funds, posted the worst performance in March 2008, one of the main peaks of the crisis (Bank of England, 2008*b*).

2.1 Funding liquidity risk from prime brokers

Funding liquidity pressure faced by the major prime brokers and banks arose from August 2007 onwards when it had become apparent that off-balance-sheet conduits and structured investment vehicles would draw on credit lines by their sponsor credit banks.[1] The resulting uncertainty about future liquidity needs by each individual bank triggered a generalised distrust in the interbank lending market, leading to precautionary hoarding and to a sharp pick-up in the LIBOR rate.

Prime brokers that have been heavily hit by the financial turmoil have likely transferred part of their own funding pressure to hedge funds, via reduced credit lines, increased margin requirements and limited credit availability such as loans (European Central Bank, 2008). Hedge funds relying on the service of the most affected brokers such as Bear Stearns or Lehman Brothers were as a result more likely to face a heightened funding liquidity risk and therefore to obtain lower returns.

One limitation in the context of investigating this propagation channel rests on the fact that prime brokers do not disclose the margins they require to individual hedge funds. Therefore, the tightening of credit availability to hedge funds may only be indirectly gauged. Ideally, market-based indicators measuring the intensity of liquidity pressure faced by individual prime brokers would indicate the risk of hedge funds being affected by stricter credit conditions. However, such indicators do not exist for individual institutions. Hence, subsequently, we introduce a set of credit risk indicators which aim at capturing financial fragility of individual prime brokers. As these institutions have to constantly roll over their debt, any deterioration in their credit risk should translate into a funding liquidity pressure, especially during periods of financial turmoil.

To quantify the credit risk of individual prime brokers and banks, their credit default swap (CDS) spread, distance-to-default and option-implied volatility are considered. These indicators summarise information over and above those contained in traditional balance sheet data used to evaluate the fragility of financial institutions and are furthermore available at a higher frequency. The higher the CDS spread or implied volatility and the lower the distance-to-default of prime brokers, the more likely these institutions face a funding liquidity pressure. The higher the intensity of their liquidity pressure, resulting potentially from their exposure to mortgage backed securities or subprime credit, the higher the probability that credit conditions to hedge funds will be tightened. This leads to our first hypothesis:

Hypothesis 1 *All else equal, deteriorations in prime brokers' financial conditions, measured by their (i) 5-year CDS spread, (ii) distance-to-default or (iii) option-implied volatility, should translate into a tightening of credit conditions and therefore into a funding liquidity risk for the corresponding hedge fund associated with a decline in return.*

[1] Off-balance-sheet vehicles are contingent contracts of banks which are, as the name suggests, not recorded on banks' balance sheets. They usually invest in long-term, possibly illiquid, assets and borrow money using short-term papers, which exposes them to a funding liquidity risk (Gorton and Pennacchi, 1989; Brunnermeier, 2009).

If deteriorating financial conditions of prime brokers or banks translate into a funding liquidity risk for hedge funds, it might be beneficial for a fund to have more than one prime broker or bank (see European Central Bank, 2007, p. 55). In case that one prime broker reduces the credit line or increases margins, there is still the chance for a hedge fund to get funding from another prime broker it is associated with. To our knowledge, no other paper has investigated the relationship between the hedge funds' number of funding sources and their performance. One reason for this might be a lack of information, since hedge funds are not obliged to disclose the number of their prime brokers and also have no incentive to do so as this might limit their credit availability. In the case of banks the empirical evidence is mixed. While Houston and James (1996) and Harhoff and Körting (1998) find that borrowing from several banks increases credit availability, Petersen and Rajan (1994; 1995) and Cole (1998) report that it reduces credit availability. However, the situation for prime brokers is different from that for banks since it is more difficult for a prime broker to evaluate the financial health of a hedge fund than it is for a bank to analyse the creditworthiness of a firm, before extending its credit line.[2] Against this background, we propose our second hypothesis:

Hypothesis 2 *All else equal, relying on more than one prime broker should reduce a possible funding liquidity risk through diversification of liquidity sources and should therefore be associated with higher hedge fund returns.*

2.2 Funding liquidity risk from investor redemptions

In addition to margin-calls by hedge funds' prime brokers, funding liquidity risk may also materialise through investor redemptions. On the one hand, the individual cancellation policy of each hedge fund, captured by the lockup, redemption notice and payout period as well as by the redemption frequency, provides a redemption restriction and thereby protects the fund to some extent from the risk of run by investors. At the same time it gives the fund manager more flexibility to pursue investment strategies involving assets with a higher degree of illiquidity without worrying too much about investor withdrawals. Therefore, it is reasonable to argue that longer lockup, redemption notice and payout periods as well as a lower redemption frequency should be associated with higher fund returns. This aspect has been studied quite extensively in the literature (see for example, Liang (1999) and Agarwal et al. (2009)).

[2] This is due to several reasons such as limited regulatory and auditing standards that apply to hedge funds, the lack of an accepted market standard to appropriately quantify a fund's leverage or the difficulty to value illiquid positions (see Garbaravicius and Dierick, 2005, p. 51).

On the other hand, these redemption restrictions can only delay investor withdrawals, but not prevent them.[3] Thus, if investors request to withdraw large amounts of their capital from a hedge fund, the manager has to sell part of the fund's assets to meet these redemption requests, which creates costs such as liquidity-based trading, commissions and price impact, especially in an unfavourable market environment. In addition, the fund's performance is affected, since the fund manager has to maintain a large cash position to mitigate the impact of withdrawals (Chordia, 1996; Nanda et al., 2000; Edelen, 1999). As a consequence, these redemptions impose a negative externality on the remaining investors in the fund, whose expectation that other investors will withdraw their money as well might lead to a 'self-fulfilling run' (Chen et al., 2007). Therefore, we propose our third hypothesis as follows:

Hypothesis 3 *All else equal, investors' requests for large withdrawals from hedge funds' capital force fund managers to sell part of the fund's assets, possibly at an unfavourable time, which creates costs and should therefore be associated with declining returns.*

In its Global Financial Stability Report, the International Monetary Fund states that due to the financial turmoil "the effects of easing monetary conditions on firms' financing costs [. . .] have been more than offset by equity price declines and wider credit spreads" (International Monetary Fund, 2008, p. 4). Since financial institutions try to reduce their risks, their willingness and ability to continue extending credit has been reduced. Against this background, it is reasonable to argue that the funding liquidity pressure on prime brokers and banks has increased during the turmoil, compared to a tranquil period, which is likely to have translated into tighter credit conditions for hedge funds. In addition, it also likely that the number of investors' requests for withdrawals has been higher during this period of uncertainty and in the presence of a worldwide decline in asset prices. This leads us to our fourth hypothesis:

Hypothesis 4 *All else equal, a financial turmoil should amplify the funding liquidity risk of hedge funds arising from (i) deteriorating financial conditions of prime brokers and (ii) investors' requests for large redemptions, compared to a tranquil period. Relying on multiple prime brokers should reduce a funding risk. The impact*

[3]There are two exceptions, specified in the legal documents. So-called "gate provisions" limit the amount of withdrawals and intend to prevent a run on the fund, while "redemption suspensions" are an even more restrictive form which completely prohibit withdrawals. However, the TASS database does not provide any information on both characteristics. There is an ongoing debate about the role of these restrictions in the recent crisis. According to Herbst-Bayliss (2009) "by imposing so-called gate provisions [...] hedge funds may have simply fanned the panic among investors afraid of losing all their money."

of these three factors on hedge funds' return should therefore be more pronounced during a period of financial turmoil than during a tranquil period.

3 Data and descriptive statistics

3.1 Hedge funds

In this paper, we use data on hedge funds obtained from Lipper TASS, one of the main databases used in academic and commercial hedge fund studies. TASS provides monthly information on individual hedge fund performance returns net of all fees and transactions costs, on assets under management as well as on other fund characteristics. These include, among other aspects, information on the fund's cancellation policy, such as redemption frequency, lockup and redemption notice periods, on high-watermark provisions, incentive and management fees. In addition, TASS classifies funds according to their investment strategy into eleven categories: Convertible Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro, Long/Short Equity Hedge, Managed Futures, Multi-Strategy and Funds of Hedge Funds. One important feature of the database is that it distinguishes between so-called 'Live' and 'Graveyard' funds. The 'Graveyard' funds include seven sub-categories of funds: (i) liquidated, (ii) closed to new investment, (iii) unable to contact, (iv) dormant, (v) no longer reporting to TASS, (vi) merged into another entity and (vii) unknown. In order to mitigate a potential survivorship bias, we use both 'Live' and 'Graveyard' funds in our analysis.[4] Although hedge fund data on both 'Live' and 'Graveyard' funds is available since 1994, our sample period only starts in January 2004, owing to data availability issues for some financial variables, and ends in June 2008.

Since hedge funds voluntarily report to a database such as TASS for advertising reasons, they may stop to do so, for example, because of bad performance in recent months and continue to report when this bad performance turned out to be only temporarily. In our analysis, one aim is to evaluate if the impact of funding risk on fund performance was more pronounced after the start of the crisis in 2007. As this period reflects the most current information in the version of the database we use, the return data might be biased, compared to the period before, as it is likely that some funds stopped reporting to TASS during this period of turmoil, since their performance was much worse compared to the 'non-crisis' period (see Table 1).

Due to numerous blanks in the TASS database, we apply a filtering procedure

[4] For a discussion on the survivorship bias in hedge fund databases see e.g. Fung and Hsieh (1997*b*) and Liang (2000).

to the data. This process consists of dropping funds which report only quarterly data, which have more than three consecutive missing values in their assets under management and those that do not report information on their prime broker or bank.[5] The initial sample – before data filtering – covers 6,916 'Live' and 3,292 'Graveyard' funds. After filtering, the sample size turns to be 2,248 with 1,267 'Live' and 981 'Graveyard' funds, which corresponds to 67% of funds being dropped from the initial sample. Table 1 reports the summary statistics of various hedge fund characteristics and the indicators of prime brokers' financial fragility over the sample period from January 2004 to June 2008. On average over time and across all funds in the sample, the monthly hedge fund return is 0.75%, the mean age of a fund is 5.07 years and the mean size of a fund amounts to 168 million USD.

To deal with autocorrelation and volatility clustering of hedge fund returns, we fit AR-GARCH models to the return data and use the residuals as our dependent variable. First, we estimate our models using raw return data and in a second step we use the filtered hedge fund returns to check the robustness of the results. The procedure is described in detail in section 4.1.

One aim of this paper is to analyse whether large investor redemptions affect hedge fund returns. To this end, we follow Sirri and Tufano (1998) and others and compute flows into hedge fund i during month t as

$$Flows_{i,t} = \frac{AUM_{i,t} - AUM_{i,t-1}(1 + Return_{i,t})}{AUM_{i,t}},$$

where $AUM_{i,t}$ and $Return_{i,t}$ are, respectively, the assets under management and the return of fund i in month t.

Using the actual capital outflows to evaluate the impact of investor redemptions on fund returns is, however, not appropriate due to the redemption restrictions of a hedge fund. To illustrate this point, the sequence of events in the context of investor redemptions is shown in Figure 1. If an investor gives notice to the fund about his intention to withdraw capital, he has to wait until the restriction period has passed before he can actually withdraw the money.[6] During this period, depending on the size of the upcoming redemptions, the fund manager has to sell part of the fund's assets to meet the redemption request of the investor. As explained in section 2.2, this forced selling creates costs, which therefore affect fund returns during this period before the actual capital outflows occur.

To account for this issue, we proceed as follows. First of all, to capture only large investor withdrawals, we construct a redemption indicator $I(outflows)_{i,t}$ which

[5] Up to three consecutive missing values in assets under management are filled using the available monthly return.

[6] The restriction period refers to the sum of redemption notice and payout period.

equals 1 if the flows of hedge fund i during month t are smaller or equal than -0.20 (which means that the outflows are larger or equal than 20% of the fund's assets) and 0 otherwise.[7] In a second step, we construct an indicator for the redemption request corresponding to the actual capital outflow captured in step 1

$$I(redreq)_{i,t} = \begin{cases} 1 & \text{if } I(outflows)_{i,t+1} = 1 \text{ and } restrp_i = 1 \\ 1 & \text{if } I(outflows)_{i,t+2} = 1 \text{ and } restrp_i = 2 \\ 1 & \text{if } I(outflows)_{i,t+3} = 1 \text{ and } restrp_i = 3 \\ 1 & \text{if } I(outflows)_{i,t+4} = 1 \text{ and } restrp_i = 4 \\ 1 & \text{if } I(outflows)_{i,t+5} = 1 \text{ and } restrp_i = 5 \\ 0 & \text{otherwise} \end{cases}$$

where $restrp_i$ denotes the restriction period of hedge fund i.[8] We truncate decimal places to get an integer value for the restriction period $restrp_i$ such that, for example, 1.6 becomes 1. This procedure seems reasonable as a hedge fund with a restriction period of 1.6 months facing large withdrawals, for example, at the end of July would have received the corresponding redemption request by mid-June. Even if the fund manager would have immediately started selling part of the fund's assets, the first impact on fund returns would only be captured by end of June return data.

3.2 Prime brokers

One interesting characteristic of the TASS database is that it provides information on the name and location of the prime broker and/or bank the hedge fund is associated with. In the initial version version of the database, before filtering, 48% of all hedge funds report to have a prime broker or bank. The prime brokerage business appears to be highly concentrated with ten brokers accounting for nearly 80% of the

[7]As there is strong empirical evidence that money flows chase returns (see e.g. Sirri and Tufano, 1998; Getmansky, 2005; Agarwal et al., 2005), we regress contemporaneous flows on returns of the past 12 months and use the residuals to construct our dummy variable. According to Edelen (1999), the necessity of a liquidity-based trading, which is performed after the 'flow shock' to get back to an efficient portfolio, depends on the magnitude of the withdrawals. Therefore, we focus only on large investor redemptions.

[8]Since we cannot differentiate whether a hedge fund classified in the database as having a restriction period of zero (i) does not report its restriction period or (ii) declares to have a restriction period of zero, we drop these funds from our sample. In addition, we discard funds that declare to have a restriction period larger than the 99th percentile to control for outliers.

services provided to hedge funds.[9] The vast majority of hedge funds that report to have a prime broker or bank declare to rely on a single prime broker: only 10% of funds report to have multiple brokers.[10] This paper intends to examine the impact of deteriorating financial conditions of prime brokers on hedge funds' performance returns. To evaluate the financial fragility of a prime broker or bank, we use three indicators described below, namely its CDS spread, option-implied volatility and distance-to-default.

Credit default swaps are contingent claims whose payoffs are related to the creditworthiness of a given firm or sovereign entity. They allow market participants to explicitly trade the credit risk of the reference entity. According to Longstaff et al. (2005), CDS spreads consist of a large default component and a smaller non-default component capturing liquidity and, to a lesser extent, tax aspects. Since the liquidity of the CDS market is relatively high, especially for investment grade reference entities and for 5-year maturities, CDS spreads are expected to serve as an appropriate indicator of market participants' perceived credit risk of the corresponding firm. We therefore use the 5-year senior mid-market CDS spread for each prime broker or bank in our analysis, which we obtain from Bloomberg.

Option-implied volatilities are inferred from exchange-traded option prices by solving the pricing model for the volatility that sets the model and market prices equal. In contrast to estimating realized volatility from historical price data, the implied volatility is based on current market prices and is therefore often regarded as the market's volatility forecast. It captures the market participants' expectations about the uncertainty of the corresponding stock return and it reveals information about risk aversion (see e.g. Bliss and Panigirtzoglou, 2004; Bollerslev et al., 2004). Implied-volatilities are obtained from Bloomberg and are calculated as the mean of the implied volatility of at-the-money call and put options, while at-the-money volatilities themselves are computed as the average of the three volatilities that are closest to the at-the-money strike price.

The **distance-to-default** is a widely used market-based measure of corporate default risk, which has also been applied to financial institutions (see e.g. Gropp et al., 2002; Chan-Lau and Sy, 2006). This measure of credit risk is based on Merton (1974), who models the equity of a firm as a call option on the value of its assets: shareholders are only residual claimants on the firm's assets after the bondholders'

[9]In June 2008, the ten major prime brokers, ranked according to their coverage of hedge funds in the database, were, respectively, Morgan Stanley (22.1%), Goldman Sachs (17.8%), Bear Stearns (9.2%), UBS (9%), Citigroup (3.9%), Credit Suisse (3.9%), Merrill Lynch (3.9%), Deutsche Bank (3.8%), Bank of America (3.2%), and Lehman Brothers (2.7%). In total, these ten brokers account for 79.5% of the funds that declare to have a prime broker and/or bank.

[10]According to Greenwich Associates (2007), the average number of prime brokers per hedge fund is 2.1.

obligations have been met. The exercise price of the option is equal to the book value of the liabilities since the firm defaults when its asset value falls below the face value of its debt. The distance-to-default is therefore associated with the probability that the market value of a firm's assets falls below the value of its debt.[11] This measure of failure risk aims at supplementing more traditional analyses based on financial and income account statements with the added value of using more forward-looking information incorporated into security prices. Compared to balance sheet data that are available with lags and reported only on a quarterly basis, market-based risk measures using information from liquid equity and bond markets have been found to be more reliable (Hillegeist et al., 2004).

To compute the distance-to-default, for each prime broker or bank in the database we collect data on its (i) market value of equity outstanding, (ii) short-term liabilities, (iii) long-term liabilities, (iv) total liabilities and (v) on the 1-year US Treasury Bill rate.[12] We follow the procedure in Gropp et al. (2002) by solving the following two equations for the asset value and the asset volatility iteratively until the values from two consecutive iterations converge

$$
\begin{aligned}
V_E &= V_A N(d_1) - De^{-rT} N(d_2), \\
\sigma_E &= (V_A/V_E) N(d_1) \sigma_A,
\end{aligned}
$$

where

$$
d_1 = \frac{\ln(V_A/D) + (r + \sigma_A^2/2)T}{\sigma_A\sqrt{T}}, \quad d_2 = d_1 - \sigma_A\sqrt{T},
$$

and $V_E, V_A, D, r, \sigma_E, \sigma_A$ are respectively the institution's market value of equity outstanding, asset value, face value of debt, 1-year US Treasury Bill rate, volatility of equity and volatility of assets. The maturity T is assumed to be one year and $N(\cdot)$ is the cumulative density function of the standard normal distribution. The estimation of the equity volatility is based on daily stock returns of the last 30 trading days. To reduce noise, we take the 6-month moving average. As starting values for the asset value and the asset volatility, we follow Hillegeist et al. (2004) and use $V_A = D + V_E$ and $\sigma_A = \sigma_E V_E/(D + V_E)$, respectively. To proxy for the face value of debt, we use, if available, short-term liabilities plus one half long-term liabilities (see Vassalou and Xing, 2004), otherwise we use total liabilities.[13] Once monthly values

[11] More precisely, the distance-to-default measures the number of standard deviations by which the log of the value of bank assets to debt ratio needs to deviate from its mean in order for default to occur.

[12] Following Gropp et al. (2002), we use interpolation to obtain monthly data for all liabilities used in the analysis.

[13] Using total liabilities rather than short-term liabilities plus one half long-term liabilities does not change the results.

of asset value and asset volatility are obtained for each institution, we compute the distance-to-default DD as follows

$$DD = \frac{\ln(V_A/D) + (r - \sigma_A^2/2)T}{\sigma_A \sqrt{T}}.$$

In our analysis, we follow Gropp et al. (2002) and use the negative of the distance-to-default ($-DD$) as an indicator of financial fragility in addition to CDS spread and option-implied volatility.

Figure 2 shows the evolution over time of our three indicators of financial fragility for all 45 prime brokers and banks with available data. To capture the distribution of each indicator across the financial institutions at each point in time, we plot the 25th, 50th and 75th percentile. It becomes clear from all three measures, that the financial conditions of the prime brokers and banks in our sample were rather robust from January 2004 until July 2007. However, from August 2007 onwards prime brokers' financial fragility increased significantly. This is not only evident by the increase in the medians of negative of distance-to-default, CDS spread and option-implied volatility, but also in the decreasing interquartile ranges of the negative of the distance-to-default. It suggests that the deterioration in prime brokers and banks financial conditions became more and more widespread, especially at the beginning of 2008.

3.3 Control variables

To isolate the impact of funding liquidity risk on hedge funds' performance returns, we introduce control variables, which encompass two types of information. First, hedge fund specific characteristics include information about age, live/graveyard status, fund size, management and incentive fees and high watermark.[14] Second, financial variables are used to capture the evolution of common factors which potentially drive hedge fund returns. These variables, obtained from Datastream and Bloomberg, include the eight standard asset classes of Fung and Hsieh (1997*a*), the mid-market spreads of the 5-year CDX North America and iTraxx Europe investment grade CDS indices, the change in the VIX index and the bid-ask spread of the S&P 500 stock index.

[14] With a high watermark, a hedge fund manager will only receive performance fees if he did not loose money over a period. If the investment value drops below its previous greatest one, then the manager must bring it back above the high watermark before receiving a performance bonus again.

4 Empirical results

This section aims at assessing the extent to which the funding risk of hedge funds, potentially affected by the financial distress of prime brokers, the reliance on multiple prime brokers or large investor redemptions, has affected their performance over the period January 2004 to June 2008. In a first step, we perform panel estimations covering about 2,200 hedge funds to examine how the three factors were related to fund performance during the entire sample period. In a second step, we use a 24-months rolling estimation to address the question whether the impact of funding risk on performance was more pronounced after the financial crisis started in 2007.

4.1 Baseline model

There is a large literature dealing with hedge fund performance returns. The primary focus of this literature has been to explain the time series variation in fund returns and to assess different types of biases in hedge fund databases. One of the main biases affecting performance returns of hedge funds is the so-called survivorship bias, which arises from the high number of funds being liquidated compared to the existing funds in the estimation sample (high attrition rates). One way to deal with this bias is usually to incorporate fund returns until the time of their liquidation (Brown et al., 1999; Liang, 2000; Baquero et al., 2005). Beyond the survivorship bias, the literature also investigates termination and self-selection bias (Ackermann et al., 1999), backfilling bias and illiquidity bias (Asness et al., 2001; Getmansky et al., 2004) and look ahead bias (Baquero et al., 2005). Another important issue is related to the persistence of hedge fund returns. To eliminate the spurious positive persistence in raw return, deriving in part from the presence of cross-sectional variation in expected fund returns, we first incorporate dummies capturing the heterogeneity in funds' investment strategies, as recommended by Brown and Goetzmann (2003).

Pooled regressions are first performed on raw return data and then on filtered returns to check the robustness of the results.[15] The filtering procedure consists of fitting AR-GARCH models to the hedge fund return series to remove autocorrelation

[15]We use pooled ordinary least squares (OLS) as well as random and fixed effects methods to estimate the coefficients of our models. The results for the time-varying regressors are very similar for all three estimation methods. Since we are particularly interested in the effect of having more than one prime broker on fund returns, which is captured by an indicator variable, the fixed effects approach is not appropriate here. In the paper we only report the results of pooled OLS, the other results are available upon request.

and heteroscedasticity as in Boyson et al. (2008).[16] The residuals are then used as the dependent variable $r_{i,t}$ in our baseline model, which is specified as follows:

$$r_{i,t} = \mathbf{x}_{i,t}\boldsymbol{\beta} + \nu_{i,t}. \tag{1}$$

Here $r_{i,t}$ is the net-of-fee return of fund i in month t, $\mathbf{x}_{i,t}$ is a vector of hedge fund characteristics including age, assets under management, live/graveyard status, high watermark, management and incentive fees, and $\nu_{i,t} = c_i + \varepsilon_{i,t}$ represents the composite errors, i.e. the sum of the unobserved time-invariant fund specific effect c_i and an idiosyncratic error. To capture the heterogeneity across different investment strategies, $\mathbf{x}_{i,t}$ includes also indicator variables for 10 out of 11 hedge fund categories. The strategy "Long/Short Equity Hedge" is chosen as the reference category. In addition, we control for common factors driving hedge fund returns by including the eight standard asset classes of Fung and Hsieh (1997*a*): MSCI North America Equity returns, MSCI Non-US Equity returns, IFC Emerging Market returns, JPMorgan US Government Bond returns, JPMorgan Non-US Government Bond returns, 1-month euro/dollar deposit rate of the previous month, Gold returns and returns of the trade weighted index of US dollar against major currencies. We also include the change in the mid-market spreads of the 5-year CDX North America and iTraxx Europe investment grade CDS indices, the change in the VIX index and the bid-ask spread of the S&P 500 stock index.

Since hedge funds' exposure to the different asset classes can be highly nonlinear, various papers suggest to use the Fung and Hsieh (2001) seven-factor model which represents the payoffs of several trend-following strategies. When using these seven factors as our financial control variables our overall results remain unchanged.[17] However, as the eight standard asset classes of Fung and Hsieh (1997*a*) are able to explain a larger part of the variation in hedge fund returns, we only report the results using those variables as our financial controls. To estimate this model, a sample of N hedge funds $i = \{1, 2, ..., N\}$, observed over T periods $t = \{1, 2, ..., T\}$ is used.

The results shown in the lower part of Table 3 indicate that younger and larger hedge funds have a better performance, suggesting that the management of younger funds is working harder to build up reputation and that larger funds benefit from economies of scale. This is consistent with the findings of Liang (1999) and Getman-

[16] The Bayesian information criterion is used to determine the number of lags in the AR component, while the model order of the GARCH component is specified based on the significance of the coefficients. This procedure is performed for each hedge fund separately. Ljung-Box tests on the residuals indicate that for most of the hedge funds in our sample, an AR(1)-GARCH(1,1) specification was sufficient to remove the autocorrelation and heteroscedasticity.

[17] The results are available upon request.

sky (2005), while Agarwal et al. (2009) find that larger funds are associated with worse performance. Furthermore, a higher management fee is related to a higher return of the corresponding hedge fund. The management fee, which represents an annual percentage of assets under management, may act as an incentive for fund managers to increase the size of their fund via better performance. The style dummies are included in the estimation, but the coefficients are not reported for brevity. However, the summary statistics on monthly hedge fund returns presented in Table 2 indicate the strong heterogeneity across hedge fund strategies, with funds focussing on "Managed Futures" having the highest and those operating in "Dedicated Short Bias" having the lowest return during sample period. The coefficients on the financial control variables give some insights into the average exposure of hedge funds to common factors (asset classes) from January 2004 to June 2008.[18] On average, hedge funds seem to have been a buyer of credit protection in North America, they have taken a long position in stocks and a short position in bonds. There has also been a positive exposure of hedge fund returns to the 1-month euro/dollar deposit rate and to gold returns during the period under consideration. Regarding the importance of the different asset classes, according to these results, hedge fund returns have been mostly driven by (i) Non-US stock returns, (ii) US government bond returns and (iii) Emerging Market stock returns.

4.2 Prime brokers financial conditions

The main objective of this paper is to evaluate to which extent the deterioration of financial conditions of prime brokers and banks has translated into tighter credit availability to hedge funds and as a consequence into heightened funding liquidity risk, weighing on their performance returns. To this end, we estimate in a first step this so-called prime broker channel

$$\begin{aligned} r_{i,t} = \mathbf{x}_{i,t}\boldsymbol{\beta} + \sum_{j=0}^{1} \left[\phi_{1,j}\Delta CDS_{i,t-j} + \phi_{2,j}\Delta(-DD)_{i,t-j} + \phi_{3,j}\Delta IV_{i,t-j}\right] \\ + \phi_4 I(PB_i) + \nu_{i,t}, \end{aligned} \tag{2}$$

where $\Delta CDS_{i,t}$ denotes the change from $t-1$ to t in the 5-year CDS spread of the prime broker or bank associated with hedge fund i. Following this logic, $\Delta(-DD)_{i,t}$ is the change in the negative of the distance-to-default and $\Delta IV_{i,t}$ represents the

[18] This factor exposure is of course different for every hedge fund in the database due to different investment strategies and different use of leverage and it may also change frequently over time (see Fung and Hsieh, 1997a). Nevertheless, the coefficients may provide an indication of the average exposure of hedge funds to different asset classes.

change in the prime broker's option-implied volatility.[19] In addition, $I(PB_i)$ is an indicator variable which equals 1 if the number of prime brokers or banks of hedge fund i is larger than one and 0 otherwise. For all three indicators of prime brokers' financial fragility, we include contemporaneous as well as lagged values in the regression. We choose a maximum lag length of one month as it seems reasonable to argue that prime brokers or banks getting into financial stress have to react within a relatively short period of time, for example by tightening the credit conditions to their clients, to mitigate their funding problems.[20] As we use changes in the fragility indicators in our analysis, they should reflect the change in the actual or perceived credit risk of the corresponding institution during month t or $t-1$, which seems appropriate for our investigation.

Before presenting the results, it should be mentioned that our three indicators of prime brokers' financial fragility are expected to contain, at least to some extent, similar information. According to Cao et al. (2007), there is a strong relation between option-implied volatility and CDS spreads. They argue that the volatility risk premium embedded in option prices plays a crucial role in explaining CDS spreads. In addition, as the (historical) equity volatility is used for computing the distance-to-default, we also expect the distance-to-default to be correlated with the implied volatility, albeit only to a small extent. To check whether a significant relation between prime brokers' distress and fund returns is simply due to the presence or lack of one or several of the three indicators, we apply a stepwise procedure by regressing hedge fund returns consecutively on the three indicators until all of them are included simultaneously. We find no evidence of a spurious relation or dominance of one of the three indicators potentially affecting the results.[21]

The results of this prime broker channel presented in column 2 of Table 3 show that the coefficients on changes in the CDS spread ($\phi_{1,1} = -0.011$) and in the negative of the distance-to-default ($\phi_{2,0} = -0.070$ and $\phi_{2,1} = -0.237$) of a prime broker are negative and significant, implying that a deterioration in the financial condition of a hedge fund's prime broker(s) is associated with lower fund returns. These effects are also economically significant. If ΔCDS_{t-1} increases from zero to 10 basis points, this is associated with a decrease in the monthly return of the corresponding hedge

[19]Since, in our sample, the number of prime brokers or banks associated with a hedge fund ranges between 1 and 4, we take the average of their change in CDS spread, negative of distance-to-default and implied volatility, respectively. All three measures of prime broker fragility as well as the CDX North America and the iTraxx Europe index are integrated of order one. Therefore, in our analysis, we use changes in the corresponding measures rather than levels.

[20]In particular prime brokers used to rely heavily on short-term debt and were therefore forced to constantly roll over their liabilities, which exposed them to a funding liquidity risk (International Monetary Fund, 2008).

[21]The results are available upon request.

fund in t of 0.11%. The lower (upper) bound of the corresponding 95% confidence interval equals -0.13% (-0.08%). If $\Delta(-DD)_{t-1}$ increases from zero to 1 standard deviation, this is related to a reduction in fund return in t of 0.24%, with a lower (upper) bound of a 95% confidence interval of -0.32% (-0.15%).

In addition, we find the coefficient on the dummy variable of having more than one prime broker to be positive ($\phi_4 = 0.192$) and significant. This implies that hedge funds having more than one prime broker or bank have a significantly better performance than those funds relying on just one prime broker. In terms of its economic significance this means that the return of a hedge fund having more than one prime broker is 0.19 percentage points higher than the return of a fund relying on just one prime broker, all else being equal. The lower (upper) bound of the corresponding 95% confidence interval equals 0.10% (0.28%). It is consistent with the argument that a hedge fund's funding liquidity risk is smaller if the number of its potential funding sources is larger than one (see also European Central Bank, 2007). Overall, these findings provide strong support to our hypotheses 1 and 2.

4.3 Investor redemptions

Since a funding liquidity risk may also materialise via investor redemptions, we estimate in a second step the following model

$$\begin{aligned} r_{i,t} = \mathbf{x}_{i,t}\boldsymbol{\beta} + \gamma_1 lock_i + \gamma_2 redf_i + \gamma_3 rednp_i + \gamma_4 pay_i \\ + \sum_{j=0}^{2} \gamma_{5,j}\, I(redreq_{i,t-j}) + \nu_{i,t}, \end{aligned} \tag{3}$$

where $lock_i$, $redf_i$, $rednp_i$ and pay_i are, respectively, the lockup period, the redemption frequency, the redemption notice period and the payout period of fund i, and $I(redreq_{i,t-j})$ is an indicator variable which equals 1 if hedge fund i received a redemption request in period $t-j$ as defined in section 3.1 and 0 otherwise.

The results are presented in column 3 of Table 3. We find that the coefficients on the lockup period ($\gamma_1 = 0.007$), on the redemption notice period ($\gamma_3 = 0.002$) and on the payout period ($\gamma_4 = 0.005$) are significantly positive. This implies that greater managerial flexibility due to longer lockup, redemption notice and payout periods is associated with better fund performance, which is in line with the findings of Liang (1999) and Agarwal et al. (2009). The coefficient on the funds' redemption frequency is negative but only slightly significant and turns out to be insignificant in the combined model. In addition, we find that the coefficients on the dummy variables indicating an investor's request for withdrawals of at least 20% of the fund's assets in t and $t-1$ ($\gamma_{5,0} = -0.373$) and ($\gamma_{5,1} = -0.247$) are negative and significant.

This implies that if a fund manager received a request for large withdrawals either in the previous or in the current month, the fund return in the current month is negatively affected.[22]

Another interesting aspect is to examine whether the impact of a redemption request on fund returns depends on the lengths of the restriction period. To this end, we re-estimate the model in equation (3) for funds with different restriction periods. In addition, we report the estimation results in each column for a different size of the redemption request. The results are presented in Table 4. First of all, we find that relatively small capital withdrawals (10% of AUM) have a significantly negative impact on fund returns only in the same month. This implies that the fund manager immediately starts selling part of the fund's assets, thereby negatively affecting the return of the fund. For larger capital withdrawals (20% and 30% of AUM) and in particular for funds with a restriction period of two months, in addition to redemption requests in t affecting returns in t, we find that a redemption request occurring in $t-1$ also negatively affects fund returns in t. This finding suggests that indeed a fund with a longer restriction period invests into less liquid assets, which takes the fund manager more time to sell these assets in the case of a redemption request and thereby adversely affecting fund returns over consecutive months. Regarding funds with a restriction period of three months, we find that a redemption request occurring in $t-2$ also negatively affects fund returns in t. However, the effect is not significant which might be due to the fact that only 25% of funds in our data set report to have a restriction period longer than 2 months. Overall, these findings provide strong support to our hypothesis 3.

4.4 Combining prime brokers and investor redemptions

Furthermore, in order to assess the robustness of the prime broker and the redemption channel, both specifications are estimated simultaneously

$$r_{i,t} = \mathbf{x}_{i,t}\boldsymbol{\beta} + \sum_{j=0}^{1} \left[\phi_{1,j}\Delta CDS_{i,t-j} + \phi_{2,j}\Delta(-DD)_{i,t-j} + \phi_{3,j}\Delta IV_{i,t-j}\right] + \phi_4 I(PB_i)$$

$$+ \gamma_1 lock_i + \gamma_2 redf_i + \gamma_3 rednp_i + \gamma_4 pay_i + \sum_{j=0}^{2} \gamma_{5,j}\, I(redreq_{i,t-j}) + \nu_{i,t}. \tag{4}$$

[22]This impact is also economically significant. If a fund manager receives a request for capital withdrawals of 20% of the fund's assets or more during month t, the fund's return in the same month is 0.37 percentage points lower compared to a fund having no redemption request. The lower (upper) limit of the corresponding 95% confidence interval equals -0.56% (-0.19%).

The results shown in column 4 of Table 3 are very similar to those presented in columns 2 and 3. Based on this, we find again support to our hypotheses 1, 2 and 3. This is consistent with a funding liquidity risk in hedge funds' balance sheets being affected by (i) deteriorating financial conditions of prime brokers, (ii) reliance on multiple prime brokers and (iii) investors' requests for large capital withdrawals.

4.5 The effect of the crisis on funding liquidity risk

In addition to examine whether and to which extent hedge funds' performance was affected by these three determinants of funding risk, the question arises whether the impact of funding risk on the performance of hedge funds was more pronounced after the financial crisis started in 2007. Therefore, we re-estimate equation 4 using a 24-month rolling estimation window. This procedure is performed for those four regressors capturing funding risk which show the most pronounced impact on fund returns, namely for ΔCDS_{t-1}, $\Delta(-DD)_{t-1}$, $I(PB)$ and $I(redreq_t)$. The evolution of the corresponding regression coefficients over time is presented in Figure 3. As already mentioned in section 3.1, the return data towards the end of our sample period might be biased as it is likely that some funds stopped reporting to TASS during this period of turmoil, since their performance was much worse compared to the period before 2007. This aspect might affect our results.

From the first panel in Figure 3 it becomes obvious that until mid-2007 the impact of a change in a prime broker's CDS spread on the return of the corresponding hedge fund is not significantly different from zero. Only from mid-2007 onwards, when the financial turmoil started, the impact becomes significantly negative, with a decreasing standard error.

Panel two shows a similar pattern. While there is no significant impact of a change in a prime brokers negative of the distance-to-default on the return of the corresponding hedge fund until mid-2006, the effect becomes significantly negative thereafter. In addition, the graph reveals that this effect becomes more pronounced after the start of the financial turmoil in 2007.

The time-varying impact of having more than one prime broker on fund returns is shown in panel three. The impact is significantly positive almost over the entire sample period and it is obvious that the impact becomes more pronounced over time, especially at the beginning of 2008, when the financial turmoil was already more severe.

Panel four depicts the impact on fund returns of an investor's request for a redemption of 20% of the fund's assets. The impact is significantly negative over almost the entire sample period, only from spring 2008 onwards the impact turns out to be not significantly different from zero. The graph reveals that the impact decreases over time as the financial turmoil becomes more pronounced, while at the same time the standard error is increasing. This result is a bit puzzling, but it could be related to the data issues mentioned above. Since the large investor redemptions in the hedge fund industry occurred towards the end of 2008, it would be interesting to repeat the analysis with an extended sample period.

Overall, although our data set does not cover the later parts of the financial turmoil, these findings provide support to our hypothesis 4 at least in terms of funding risk stemming from prime brokers. Regarding funding risk from investor redemptions we find no support to hypothesis 4, but this is very likely due to the fact that our sample period ends in June 2008.

5 Conclusion

Hedge funds are exposed to funding liquidity risk. During the ongoing financial turmoil, banks and prime brokers were facing severe funding pressures, in particular prime brokers suffered from a maturity mismatch as they were not able to roll over their short-term liabilities. Since most hedge funds rely on short-term financing from prime brokers (Greenwich Associates, 2007) to pursue leveraged investment strategies, a funding liquidity risk arises as it is likely that prime brokers and banks transfer their own funding pressure to hedge funds via tighter credit conditions. In addition, a funding liquidity risk may also materialise through investor redemptions. Investors' requests for large capital withdrawals create costs and impose a negative externality on the remaining investors in the fund which might lead to a self-fulfilling run.

Using a unique data set that incorporates data on individual hedge funds from TASS and on their associated prime brokers and/or banks, we analyse how funding risk, stemming from a deterioration in prime brokers' financial conditions and investors' requests for large redemptions, has affected hedge fund returns over the period January 2004 to June 2008. In addition, we investigate whether funds relying on multiple prime brokers had a better performance during the sample period than those funds with only one prime broker. To our knowledge, this aspect has not yet been analysed in the literature on hedge funds. Since there is no direct measure of a prime brokers' liquidity pressure, we use three credit risk indicators: CDS spread, distance-to-default and option-implied volatility to capture the financial fragility of each prime broker or bank. As these institutions have to constantly roll over their debt, any deterioration in their credit risk should translate into a funding pressure. In order to analyse the impact of redemptions on fund performance, we construct an indicator capturing large capital withdrawals while explicitly taking the fund's restriction period into account.

We find that an increase in the financial fragility of a hedge fund's prime broker or bank, captured by a change in its CDS spread and in the negative of its distance-to-default in month $t-1$, is related to a significantly lower performance of the corresponding hedge fund in month t. This effect is also economically significant as a 10 basis points increase in the change of a prime brokers 5-year CDS spread in month $t-1$ reduces a fund's return in month t by 0.11%. In addition, a hedge fund relying on more than one prime broker or bank has a significantly better performance than a fund having only one prime broker. With an increase in fund return of 0.19% the effect is also economically significant. This finding seems to indicate that a potential funding liquidity risk stemming from prime brokers or banks can be reduced through a diversification of funding sources.

With regard to funding liquidity risk arising from investor redemptions, we find a strong relation between a request for large capital withdrawals and fund performance. We perform the same regression separately for funds with different restriction periods. Our findings, that a request for large capital withdrawals adversely affects fund returns over consecutive months, indicate that hedge funds with a longer restriction period indeed invest into more illiquid assets (as suggested in the literature) which would in general take the fund manager more time to sell when trying to mitigate negative effects on returns. In addition, redemption restrictions such as longer lockup, redemption notice and payout periods are associated with higher returns. When analysing the time-varying effect of funding risk on hedge fund performance, we find that the impact of prime brokers' distress and of relying on more than one prime broker became more pronounced after the start of the financial turmoil in 2007.

From a policy perspective these findings support the view that hedge funds should provide information to the regulatory authorities on their prime brokers and on the amount and characteristics of funding they obtain from these institutions. Basically, this is equivalent to obtaining information on hedge fund leverage, an aspect that has been suggested repeatedly in the recent debate on hedge fund regulation.

References

Ackermann, Carl, Richard McEnally and David Ravenscraft (1999), 'The performance of hedge funds: Risk, return, and incentives', *Journal of Finance* **54**(3), 833–874.

Adrian, Tobias and Hyun S. Shin (2007), Liquidity and leverage, Working paper.

Adrian, Tobias and Marcus K. Brunnermeier (2009), CoVar, Working paper.

Agarwal, Vikas, Naveen D. Daniel and Narayan Y. Naik (2005), Role of managerial incentives, flexibility, and ability: Evidence from performance and money flows in hedge funds, Working paper.

Agarwal, Vikas, Naveen D. Daniel and Narayan Y. Naik (2009), 'Role of managerial incentives and discretion in hedge fund performance', *Journal of Finance, forthcoming*.

Asness, Clifford, Robert Krail and John Liew (2001), 'Do hedge funds hedge?', *Journal of Portfolio Management* **28**(1), 6–19.

Bank of England (2008*a*), Financial Stability Report, October 2008, Issue No. 24.

Bank of England (2008*b*), Financial Stability Report, April 2008, Issue No. 23.

Baquero, Guillermo, Jenke ter Horst and Marno Verbeek (2005), 'Survival, look-ahead bias, and persistence in hedge fund performance', *Journal of Financial and Quantitative Analysis* **40**(3), 493–517.

Bliss, Robert R. and Nikolaos Panigirtzoglou (2004), 'Option-implied risk aversion estimates', *Journal of Finance* **59**(1), 407–446.

Bollerslev, Tim, Michael Gibson and Hao Zhou (2004), Dynamic estimation of volatility risk premia and investor risk aversion from option-implied and realized volatilities, Federal reserve board working paper.

Boyson, Nicole M., Christof W. Stahel and René M. Stulz (2007), Is there hedge fund contagion?, Working paper.

Boyson, Nicole M., Christof W. Stahel and René M. Stulz (2008), Why do hedge funds' worst returns cluster? common liquidity shocks vs. contagion, Working paper.

Brown, Stephen and William Goetzmann (2003), 'Hedge funds with style', *Journal of Portfolio Management* **29**(2), 101–112.

Brown, Stephen, William Goetzmann and Roger G. Ibbotson (1999), 'Offshore hedge funds: Survival and performance, 1989-95', *Journal of Business* **72**(1), 91–117.

Brunnermeier, Marcus K. (2009), 'Deciphering the liquidity and credit crunch 2007-08', *Journal of Economic Perspectives* **22**(1), 77–100.

Brunnermeier, Marcus K. and Lasse H. Pedersen (2009), 'Market liquidity and funding liquidity', *Review of Financial Studies, forthcoming.*

Cao, Charles, Fan Yu and Zhaodong Zhong (2007), The information content of option-implied volatility for credit default swap valuation, FDIC Center for Financial Research, Working paper No. 2007-08.

Chan-Lau, Jorge A. and Amadou N. Sy (2006), Distance-to-default in banking: A bridge too far?, IMF Working paper No. wp/06/215.

Chen, Qi, Itay Goldstein and Wei Jiang (2007), Payoff complementarities and financial fragility: Evidence from mutual fund outflows, Working paper.

Chordia, Tarun (1996), 'The structure of mutual fund charges', *Journal of Financial Economics* **41**(1), 3–39.

Cole, Rebel A. (1998), 'The importance of relationships to the availability of credit', *Journal of Banking and Finance* **22**(6-8), 959–977.

Edelen, Roger M. (1999), 'Investor flows and the assessed performance of open-end mutual funds', *Journal of Financial Economics* **53**(3), 439–466.

European Central Bank (2007), Financial Stability Review, December 2007.

European Central Bank (2008), Financial Stability Review, December 2008.

FitchRatings (2007), Hedge funds: The credit market's new paradigm, Special Report, June 2007.

Fung, William and David A. Hsieh (1997*a*), 'Empirical characteristics of dynamic trading strategies: The case of hedge funds', *Review of Financial Studies* **10**(2), 275–302.

Fung, William and David A. Hsieh (1997*b*), 'Survivorship bias and investment style in the returns of ctas', *Journal of Portfolio Management* **24**(1), 30–41.

Fung, William and David A. Hsieh (2001), 'The risk in hedge fund strategies: Theory and evidence from trend followers', *Review of Financial Studies* **14**(2), 313–341.

Garbaravicius, Tomas and Frank Dierick (2005), Hedge funds and their implications for financial stability, ECB Occasional Paper Series, No. 34, August 2005.

Getmansky, Mila (2005), The life cycle of hedge funds: Fund flows, size and performance, Working paper.

Getmansky, Mila, Andrew W. Lo and Igor Makarov (2004), 'An econometric model of serial correlation and illiquidity in hedge fund returns', *Journal of Financial Economics* **74**(3), 529–609.

Gorton, Gary and George Pennacchi (1989), 'Are loan sales really off-balance sheet?', *Journal of Accounting, Auditing and Finance* **4**(2), 125–145.

Greenwich Associates (2007), Global hedge fund and prime brokerage trends, May 2007.

Gropp, Reint, Jukka Vesala and Giuseppe Vulpes (2002), Equity and bond market signals as leading indicators of bank fragility, ECB Working paper No. 150.

Harhoff, Dietmar and Timm Körting (1998), 'Lending relationships in germany - empirical evidence from survey data', *Journal of Banking and Finance* **22**(10-11), 1317–1353.

Herbst-Bayliss, Svea (2009), 'Gate' provisions may have hurt more than helped hedge funds, Reuters, March 27, 2009, http://www.reuters.com/article/hedgefundsnews/iduslne52q02f20090327.

Hillegeist, Stephen A., Elizabeth K. Keating, Donald P. Cram and Kyle G. Lundstedt (2004), 'Assessing the probability of bankruptcy', *Review of Accounting Studies* **9**(1), 5–34.

Houston, Joel and Christopher James (1996), 'Bank information monopolies and the mix of private and public debt claims', *Journal of Finance* **51**(5), 1863–1889.

International Monetary Fund (2008), Global Financial Stability Report, October 2008.

Liang, Bing (1999), 'On the performance of hedge funds', *Financial Analysts Journal* **55**(4), 72–85.

Liang, Bing (2000), 'Hedge funds: The living and the dead', *Journal of Financial and Quantitative Analysis* **35**(3), 309–326.

Longstaff, Francis A., Sanjay Mithal and Eric Neis (2005), 'Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market', *Journal of Finance* **60**(5), 2213–2253.

Merton, Robert C. (1974), 'On the pricing of corporate debt: The risk structure of interest rates', *Journal of Finance* **29**(2), 449–470.

Nanda, Vikram, M. P. Narayanan and Vincent A. Warther (2000), 'Liquidity, investment ability, and mutual fund structure', *Journal of Financial Economics* **57**(3), 417–443.

Petersen, Mitchell A. and Raghuram G. Rajan (1994), 'The benefits of lending relationships: Evidence from small business data', *Journal of Finance* **49**(1), 3–37.

Petersen, Mitchell A. and Raghuram G. Rajan (1995), 'The effect of credit market competition on lending relationships', *Quarterly Journal of Economics* **110**(2), 407–443.

Plantin, Guillaume and Hyun S. Shin (2006), Carry trades and speculative dynamics, Working paper.

Sirri, Erik R. and Peter Tufano (1998), ‘Costly search and mutual fund flows’, *Journal of Finance* **53**(5), 1589–1622.

Vassalou, Maria and Yuhang Xing (2004), ‘Default risk in equity returns’, *Journal of Finance* **59**(2), 831–868.

Table 1: Summary statistics of hedge fund and prime broker variables

This table shows the summary statistics of various hedge fund characteristics and prime broker variables over the sample period from January 2004 until June 2008.

Variables	**Mean**	**SD**	**25th pc**	**50th pc**	**75th pc**
Hedge fund variables					
Return per month in %	0.75	3.50	-0.56	0.72	2.06
Age in years	5.07	4.04	2.00	3.92	7.17
AUM in mn USD	167.90	328.22	15.89	53.50	164.70
Graveyard (% of funds)	32.75				
Management fee in %	1.43	0.44	1.00	1.50	1.50
Incentive fee in %	18.66	4.67	20.00	20.00	20.00
High watermark (% of funds)	85.08				
Lockup period in months	4.71	6.63	0.00	0.00	12.00
Redemption frequency in months	2.64	2.97	1.00	3.00	3.00
Redemption notice period in months	1.45	0.71	1.00	1.00	2.00
Payout period in months	0.68	0.55	0.23	0.70	1.00
Large investor redemptions (% of obs.)	2.57				
Prime broker variables					
5-year CDS spread	37.77	40.71	16.59	25.45	33.71
Negative of distance-to-default	-5.31	1.93	-6.13	-5.34	-4.22
Option-implied volatility	25.47	11.03	19.08	22.24	27.20
Change in 5-year CDS spread	1.85	17.14	-1.79	-0.21	2.00
Change in negative of distance-to-default	0.07	0.37	-0.15	0.03	0.29
Change in option-implied volatility	0.50	6.10	-1.80	0.28	2.42
Number of prime brokers $>$ 1 (% of funds)	10.12				

Table 2: Summary statistics of monthly hedge fund returns

This table shows the summary statistics of monthly hedge fund returns across the 11 investment styles used in the analysis over the sample period from January 2004 until June 2008. The columns report, respectively, the number of observations (N), the mean of the monthly return, the standard deviation (SD) and the 25th, 50th and 75th percentile of monthly fund returns in the corresponding investment style. The summary statistics are reported separately for 'alive' funds (Panel A) and for 'graveyard' funds (Panel B).

Hedge fund style	**N**	**Mean**	**SD**	**25th pc**	**50th pc**	**75th pc**
Panel A: Alive funds						
Multi-Strategy	2368	0.83	2.90	-0.27	0.79	1.87
Long / Short Equity Hedge	19610	0.91	4.14	-0.87	0.91	2.78
Global Macro	1482	0.99	3.63	-0.68	0.66	2.50
Event Driven	4764	0.74	2.19	-0.18	0.77	1.69
Fund of Funds	4750	0.67	2.49	-0.26	0.83	1.87
Convertible Arbitrage	2042	0.32	2.43	-0.32	0.61	1.31
Managed Futures	904	1.34	4.50	-0.82	1.16	3.53
Fixed Income Arbitrage	2719	0.42	2.74	-0.21	0.62	1.38
Equity Market Neutral	2980	0.68	2.43	-0.25	0.62	1.64
Dedicated Short Bias	153	0.20	3.53	-2.37	-0.21	2.37
Emerging Markets	3342	1.31	4.43	-0.32	1.06	2.97
Total	45299	0.82	3.55	-0.53	0.79	2.17
Panel B: Graveyard funds						
Multi-Strategy	961	0.53	2.50	-0.17	0.56	1.41
Long / Short Equity Hedge	10329	0.67	3.91	-1.00	0.68	2.30
Global Macro	1012	0.27	2.74	-1.02	0.24	1.42
Event Driven	2532	0.67	2.45	-0.25	0.65	1.54
Fund of Funds	1596	0.54	3.04	-0.53	0.65	1.77
Convertible Arbitrage	1117	0.13	1.60	-0.57	0.31	0.91
Managed Futures	443	0.49	5.02	-1.75	0.18	2.15
Fixed Income Arbitrage	1554	0.36	2.30	0.14	0.57	1.05
Equity Market Neutral	1469	0.39	1.64	-0.48	0.43	1.24
Dedicated Short Bias	93	0.51	4.25	-1.60	-0.20	1.90
Emerging Markets	860	1.45	5.28	-0.66	1.06	3.71
Total	21967	0.59	3.41	-0.66	0.58	1.79

Table 3: Regression results: Funding risk

This table reports the coefficient estimates of the models in equation (2) to (4) using monthly hedge fund returns in period t as the dependent variable. The baseline regressor variables are as follows: *age* denotes the age of the hedge fund, *laumusd* is the natural logarithm of the assets under management, *graveyard* is a dummy variable being one if the fund is 'graveyard' and zero if it is 'alive', *manf* is the management fee, *incf* is the incentive fee, *hwm* is a dummy variable being one if the fund has a high watermark and zero otherwise, *cdxmid_d* is the change in the CDX North America, *itrxeumid_d* is the change in the iTraxx Europe, *msci_na* is the return of MSCI North America stock index, *msci_exus* is the return of the MSCI Ex-US stock index, *ifc_eme* is the return of the IFC Emerging Markets stock index, *us_govb* is the return of the JPMorgan US Government Bonds index, *nonus_govb* is the return of the JPMorgan non-US Government Bonds index, *eurusd_1m* is the 1-month Eurodollar deposit rate of the previous month, *gold* is the return of investing in Gold, *usd_neer* is the return of the NEER of the US dollar, *chg_vix* is the change in the VIX index and *sp500ba* is the bid-ask spread of the S&P500 stock index. The style dummies capturing hedge funds' investment strategies are included in the estimation, as specified in the baseline model of equation (1). The sample period exceeds from January 2004 until June 2008. Standard errors are reported in parentheses. Coefficients marked with ***, **, * are significant at the 1%, 5% and 10% level, respectively.

Regressors	(2)		(3)		(4)	
Prime broker variables						
ΔCDS_t	0.000	(0.002)			0.000	(0.002)
ΔCDS_{t-1}	-0.011***	(0.001)			-0.011***	(0.001)
$\Delta(-DD)_t$	-0.070*	(0.042)			-0.071*	(0.042)
$\Delta(-DD)_{t-1}$	-0.237***	(0.042)			-0.241***	(0.042)
ΔIV_t	-0.003	(0.004)			-0.003	(0.004)
ΔIV_{t-1}	-0.005	(0.003)			-0.005	(0.003)
$I(PB)$	0.192***	(0.045)			0.197***	(0.045)
Redemption variables						
$lock$			0.007***	(0.002)	0.007***	(0.002)
$redf$			-0.000*	(0.000)	-0.000	(0.000)
$rednp$			0.002**	(0.001)	0.002**	(0.001)
pay			0.005***	(0.001)	0.005***	(0.001)
$I(redreq_t)$			-0.373***	(0.094)	-0.371***	(0.094)
$I(redreq_{t-1})$			-0.247**	(0.101)	-0.231**	(0.101)
$I(redreq_{t-2})$			0.240**	(0.103)	0.242**	(0.103)

Table 3: (continued)

Regressors	(2)		(3)		(4)	
Baseline variables						
age	−0.016***	(0.004)	−0.012***	(0.004)	−0.013***	(0.004)
laumusd	0.041***	(0.008)	0.042***	(0.008)	0.039***	(0.008)
graveyard	−0.421***	(0.028)	−0.411***	(0.029)	−0.422***	(0.028)
manf	0.177***	(0.035)	0.178***	(0.035)	0.179***	(0.035)
incf	0.008***	(0.003)	0.008***	(0.003)	0.008***	(0.003)
hwm	−0.021	(0.035)	−0.069*	(0.035)	−0.076**	(0.035)
cdxmid_d	0.019***	(0.005)	0.029***	(0.004)	0.019***	(0.005)
itrxeumid_d	−0.002	(0.005)	−0.009**	(0.004)	−0.002	(0.005)
msci_na	0.047***	(0.011)	0.079***	(0.011)	0.048***	(0.011)
msci_exus	0.241***	(0.013)	0.275***	(0.012)	0.241***	(0.013)
ifc_eme	0.083***	(0.007)	0.063***	(0.006)	0.083***	(0.007)
us_govb	−0.118***	(0.019)	−0.094***	(0.019)	−0.118***	(0.019)
nonus_govb	−0.078***	(0.019)	−0.154***	(0.018)	−0.077***	(0.019)
eurusd_1m	0.063***	(0.011)	0.009	(0.010)	0.061***	(0.011)
gold	0.038***	(0.004)	0.049***	(0.004)	0.038***	(0.004)
usd_neer	−0.015	(0.022)	−0.054***	(0.020)	−0.013	(0.022)
chg_vix	0.006	(0.009)	0.031***	(0.008)	0.007	(0.009)
sp500ba	−0.081***	(0.031)	−0.099***	(0.030)	−0.081***	(0.031)
Style dummies	Yes		Yes		Yes	
adj. R^2	0.168		0.166		0.169	
N	67080		67080		67080	

Table 4: Regression results: Investor redemptions - by restriction period

This table reports the coefficient estimates of the model in equation (3) for different subsamples of hedge funds with different restriction periods using monthly hedge fund returns in period t as the dependent variable. The columns report the regression results for a redemption request of 10%, 20% and 30% of the funds' assets under management, respectively. The regressors of the baseline model as specified in equation (1) are included in the estimations. The sample period exceeds from January 2004 until June 2008. Standard errors are reported in parentheses. Coefficients marked with ***, **, * are significant at the 1%, 5% and 10% level, respectively.

Regressors	(3)		(3)		(3)	
Size of redemp. request	10% of AUM		20% of AUM		30% of AUM	
Panel A: Funds with a restriction period of 1 month						
$I(redreq_t)$	-0.256^{***}	(0.095)	-0.320^{**}	(0.127)	-0.375^{**}	(0.160)
$I(redreq_{t-1})$	0.096	(0.099)	-0.026	(0.144)	-0.447^{**}	(0.175)
$I(redreq_{t-2})$	0.179^{*}	(0.099)	0.419^{***}	(0.150)	0.497^{**}	(0.201)
Baseline regressors incl.	Yes		Yes		Yes	
adj. R^2	0.179		0.179		0.179	
N	26559		26559		26559	
Panel B: Funds with a restriction period of 2 months						
$I(redreq_t)$	-0.092	(0.108)	-0.434^{***}	(0.138)	-0.423^{**}	(0.171)
$I(redreq_{t-1})$	-0.046	(0.102)	-0.210	(0.148)	-0.477^{**}	(0.215)
$I(redreq_{t-2})$	-0.016	(0.121)	0.120	(0.180)	0.059	(0.271)
Baseline regressors incl.	Yes		Yes		Yes	
adj. R^2	0.166		0.167		0.167	
N	24496		24496		24496	
Panel C: Funds with a restriction period of 3 months						
$I(redreq_t)$	0.174	(0.235)	-0.577	(0.400)	-0.330	(0.525)
$I(redreq_{t-1})$	-0.281	(0.222)	-0.875^{**}	(0.401)	-1.067	(0.659)
$I(redreq_{t-2})$	0.240	(0.210)	-0.100	(0.245)	-0.039	(0.303)
Baseline regressors incl.	Yes		Yes		Yes	
adj. R^2	0.136		0.137		0.136	
N	10907		10907		10907	

Figure 1: Sequence of events in the context of investor redemptions

In this figure, which only aims at illustrating the sequence of events in the context of an investor's redemption request by using a specific example, the corresponding hedge fund has a restriction period of 1.6 months. The actual capital withdrawals occur at the end of July. Therefore, the fund manager received the investor's request for withdrawals around mid-June. Depending on the size of the redemption request, the fund manager has immediately started selling part of the fund's assets to meet the upcoming redemption request. Thus, the fund returns were affected in June and July, before the actual withdrawals took place.

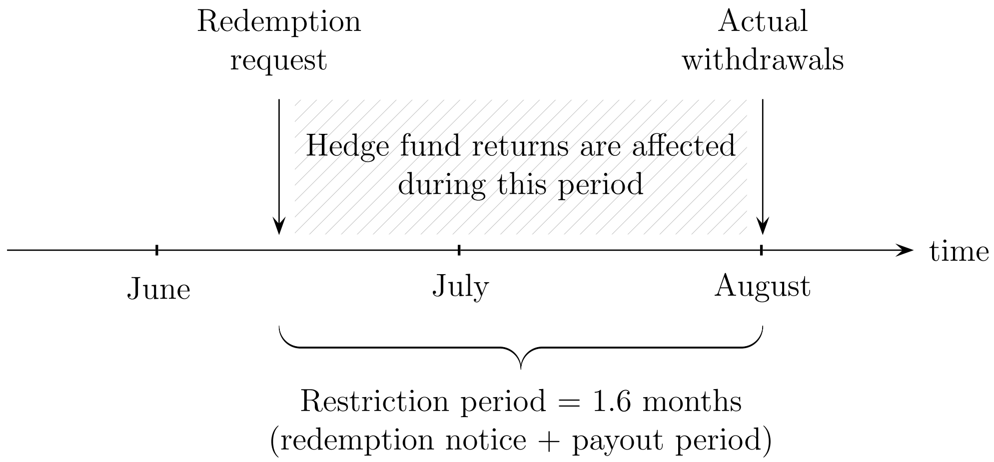

Figure 2: Evolution of the three indicators of financial fragility

This figure shows the evolution of the three indicators of financial fragility of prime brokers and banks over time. The solid line represents the median of the corresponding indicator for all prime brokers and banks with available data, while the dotted lines depict the 25th and the 75th percentile, respectively.

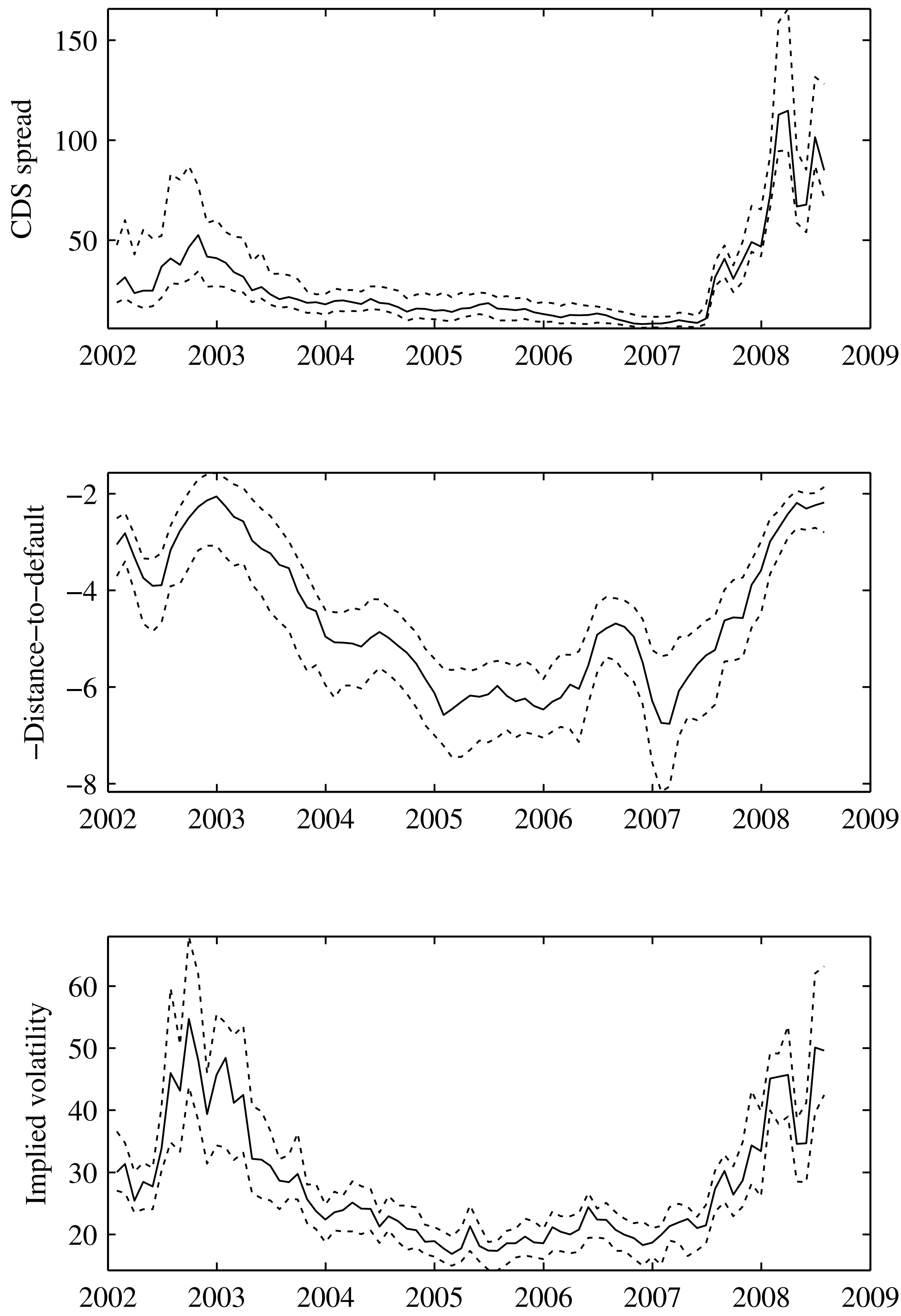

Figure 3: Time-varying coefficients of selected regressors

This figure shows the time-varying coefficients of selected regressors using a 24-month rolling estimation window. $\phi_{1,1}$ is the coefficient on the change in the CDS spread in $t-1$, $\phi_{2,1}$ is the coefficient on the change in the negative of the distance-to-default in $t-1$, ϕ_4 is the coefficient on the indicator of having more than one prime broker and $\gamma_{5,0}$ is the coefficient on the indicator of a request for large withdrawals in t. All estimations are based on equation (4). The solid line represents the point estimator, while the dotted lines depict the 95% confidence interval.