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THE ROLE OF REDEMPTIONS AND FUND FAILURES

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In 2009 all ECB publications feature a motif taken from the €200 banknote.

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Abstract

This paper aims at analysing the mortality patterns of hedge funds over the period January 1994 to May 2008. In particular, we investigate the extent to which a spillover of risk among hedge funds through redemptions and failures of other funds has affected the probability of fund failure. We find that risk spillover is significantly related to the failure probability of hedge funds, with the relation being more pronounced for redemptions than for failures of other funds. Hedge funds within the same investment style are adversely affected through both channels of risk spillover. In addition, we find that funds being diversified in assets and geographically have a significantly lower failure probability and are not affected by risk spillover via redemptions.

Keywords: Hedge Funds; Survival Analysis; Risk Spillover; Diversification

JEL Classification: G11; G20; G23; G33

Non-Technical Summary

Against the background of the financial turmoil, investigating the extent to which hedge funds may pose a risk for financial stability is of interest for policymakers. The Financial Stability Forum (2007) identified three main sources of concerns from the hedge fund industry: a systemic risk arising from their excessive leverage, the potentially disorderly impact of their failures on banks and markets, and a market dynamics issue related to their concentrated market positions. Although a spillover of risk among hedge funds was not considered as a main issue, identifying the propagation channels of tension from one fund to another may nevertheless prove to be particularly important from a financial stability perspective. So far, policy debates about hedge funds have come up against a lack of empirical research on risk spillover among hedge funds (Financial Stability Forum, 2007; Banque de France, 2007). There are only few papers that empirically investigate contagion-related issues surrounding 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.

This paper aims to contribute to this literature by analysing the mortality patterns of hedge funds and investigating two potential channels of risk spillover. The first spillover channel involves redemptions by investors, which impose a negative externality on the remaining investors, whose expectation that other investors will withdraw their money as well might lead to a "self-fulfilling run" (Chen et al., 2007; Liu and Mello, 2009). The second rests on failures of other funds, which prime brokers may rationally take into account, in the presence of incomplete information, when forming their priors about the financial health of hedge funds. This could lead to a re-appraisal of risk and prompt prime brokers to tighten financial conditions to existing hedge funds, thereby propagating initial stress within the industry (Chowdry and Nanda, 1998). In both cases, we differentiate between a risk spillover within funds displaying similar investment strategies and across hedge funds pursuing different types of investment.

In addition, the paper analyses whether the degree of diversification of individual investment portfolios might amplify a spillover of risk. Finally, this paper also seeks to provide policy recommendations about financial information that could be disclosed by hedge funds, based on an assessment of the importance of the variables driving hedge fund failures.

We analyse a panel of monthly data from TASS covering about 5,500 hedge funds from January 1994 to May 2008. To assess risk spillover, we use a logistic framework assuming an underlying binomial distribution as in Eichengreen et al. (1996) and Bae et al. (2003). The spillover of risk in this paper is thus measured by the increase in the failure probability of hedge funds, which stems from redemptions or failures experienced by other hedge funds in previous months. Our measure of portfolio diversification incorporates both a geographical and an asset type dimensions.

We find that, in addition to hedge fund characteristics, a spillover of risk from one fund to another, via redemptions and/or failures of other funds, is statistically and economically significantly related to hedge funds' failure probability. Comparing the two channels of risk spillover, investor redemptions are more strongly related to funds' failure probability than failures of other hedge funds. Our results also show that funds within the same investment style are adversely affected through both channels of risk spillover. With regard to the impact of portfolio diversification, we find that hedge funds being diversified either in terms of assets or geographically have a significantly lower failure probability than funds being invested in just one asset class or one geographical region. In addition, hedge funds seem to benefit from diversification in the sense that diversified funds are not affected by risk spillover via investor redemptions. Finally, based on our analysis, assets under management, capital flows, restriction periods, investments into derivatives and compensation-related characteristics have a large impact on hedge funds' failure probability and should therefore be disclosed on a confidential basis to regulators in order to enable them to get a more precise view on hedge funds' impact on systemic risk.

1. Introduction

Against the background of the financial turmoil, investigating the extent to which hedge funds may pose a risk for financial stability is of interest for policymakers. The Financial Stability Forum (2007) identified three main sources of concerns from the hedge fund industry: a systemic risk arising from their excessive leverage, the potentially disorderly impact of their failures on banks and markets, and a market dynamics issue related to their concentrated market positions. Although a spillover of risk among hedge funds was not considered as a main issue, identifying the propagation channels of tension from one fund to another may nevertheless prove to be particularly important from a financial stability perspective.

The financial stress experienced by the major prime brokers affected the hedge fund industry via increases in margin requirements or tightening of credit availability (International Monetary Fund, 2008). Therefore hedge funds had to withstand significant financial shocks on the funding side, as well as on the asset side during the market downturn. In such a situation, a spillover of risk among hedge funds might materialise and thereby affect the entire industry. In this context, it may be essential for bank regulatory authorities to consider a clustering of hedge fund failures, larger than envisioned in the traditional default risk models of banks. As hedge funds and banks are interconnected, hedge fund failures may cause losses and thereby reduce banks' capital. This could be even worse if a risk spillover is present among hedge funds. It is precisely the discontinuous nature of spillover processes, when compared to cyclical patterns of corporate default correlations, which may call for an explicit accounting of hedge fund risk spillover phenomena in the design of bank capital provisions (Giesecke, 2004). In addition, a risk spillover among hedge funds is likely to prompt funds to reduce their exposure and withdraw liquidity which in turn may disrupt the function of the corresponding markets. Brunnermeier and Pedersen (2009) explicitly emphasize the role of market and funding liquidity as amplifying mechanisms in a financial turmoil. So far, policy debates about hedge funds have come up against a lack of empirical research on risk spillover among hedge funds (Financial Stability Forum, 2007; Banque de France, 2007). There are only two papers that empirically investigate contagion-related issues surrounding 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.

This paper aims to contribute to this literature by analysing the mortality patterns of hedge funds, quantifying phenomena of risk spillover among individual funds and identifying potential channels for a spillover of risk over the period January 1994 to May 2008. In particular, one dimension that will be investigated focuses on whether the degree of diversification of individual investment portfolios might amplify a spillover of risk. In the analysis of risk spillover the paper differentiates between a spillover *within* funds displaying similar investment strategies and *across* hedge funds pursuing different types of investment: spillover effects are expected to be of larger magnitude when occurring *within* funds with similar market and risk exposures. Finally, this paper also seeks to provide policy recommendations about financial information that could be disclosed by hedge funds, based on an assessment of the importance of the variables driving hedge fund failures.

The literature on financial contagion attempts to identify whether financial shocks are transmitted between different countries, markets or institutions due to contagion or interdependence (see, e.g., Allen and Gale, 2000; Forbes and Rigobon, 2002; Pesaran and Pick, 2007). However, there exists no theoretical or empirical identification procedure on which the authors agree. In this paper, we aim at unravelling at least some of the channels through which negative shocks propagate from one hedge fund to another. Therefore, in our specific analysis, it is not essential to distinguish between contagion and interdependence. Instead, we focus on two channels of risk spillover in analysing the extent to which the failure probability of hedge funds is affected by investor redemptions and failures among other funds. It is the shift from a good to a bad equilibrium, which triggers a risk spillover via self-fulfilling expectations propagating redemptions and/or failures among hedge funds. From this specification, it results that our investigation of risk spillover has to be performed at the level of individual hedge funds and excludes *a priori* any aggregating levels such as those chosen by Boyson et al. (2008). This furthermore allows us to investigate how fund characteristics such as the degree of portfolio diversification may aggravate or moderate spillover effects. Two channels of risk spillover are investigated. The first spillover channel considered in this paper involves redemptions by investors, which impose a negative externality on the remaining investors, whose expectation that other investors will withdraw their money as well might lead to a “self-fulfilling run” (Chen et al., 2007). The second rests on failures of other funds, which prime brokers may rationally take into account, in the presence of incomplete information, when forming their priors about the financial health of hedge funds. This could lead to a re-appraisal of risk and prompt prime brokers to tighten financial conditions to existing hedge funds, thereby propagating initial stress within the industry (Chowdry and Nanda, 1998). Along these two channels, distressed hedge funds may be forced to simultaneously liquidate their assets in potentially illiquid markets, which would tend to reduce their performance and increase their probability of failure.

To investigate the relevance of these two propagation mechanisms and to provide thereby some kind of micro-foundations of risk spillover among hedge funds,[1] we analyse a panel of monthly data covering about 5,500 hedge funds from January 1994 through May 2008. The TASS database is used as it provides information on the failed funds, the geographical focus and the type of markets hedge funds have invested in. To assess risk spillover, we use a logistic framework assuming an underlying binomial distribution as in Eichengreen et al. (1996) and Bae et al. (2003). The spillover of risk in this paper is thus measured by the increase in the failure probability of hedge funds, which stems from redemptions or failures experienced by other hedge funds in previous months. However, the estimated model of risk spillover is not a structural model, so that rejecting the null hypothesis cannot be considered as a formal proof of risk spillover, but rather has to be regarded as being consistent with an effect capturing spillover of risk *within* or *across* hedge fund styles (Eichengreen et al., 1996). To control for the effect of common shocks or common risk exposures driving the probability of fund failure we include indicator variables capturing economy-wide effects (Baquero et al., 2005; Chan et al., 2005). Finally, our measure of portfolio diversification incorporates both a geographical and an asset type dimen-

[1] Such aim excludes methods relying on copula functions used in extreme value theory (Longin and Solnik, 2001).

sions: to be classified as geographically diversified, a hedge fund has to invest both in developed and in emerging market economies (EMEs); its portfolio has also to be composed of at least two different types of assets.

We find that, in addition to hedge fund characteristics, a spillover of risk from one fund to another, via redemptions and/or failures of other funds, has a significant impact on hedge funds' failure probability. Comparing the two channels of risk spillover, we find that investor redemptions have a larger impact on funds' failure probability than failures of other hedge funds. Our results also show that funds *within* the same investment style are adversely affected through both channels of risk spillover: a rise in both the redemption and the failure rate significantly increases the probability of fund failure. The result suggests that changes in both variables are recognized by market participants such as investors and prime brokers and are considered in their decision-making process, for example when forming their priors on the riskiness of hedge funds.

On the other hand, hedge funds *across* different style categories are only affected through the redemption spillover channel: an increase in the redemption rate reduces the failure probability of funds operating in the style category not affected by the redemptions, i.e. it is actually beneficial for the corresponding funds. This finding indicates that investors reallocate their capital to funds which are perceived as superior since they did not suffer from outflows in previous months.

When investigating the impact of portfolio diversification, we find that hedge funds being diversified either in terms of assets or geographically have a significantly lower failure probability than funds being invested in just one asset class or one geographical region. In addition, hedge funds seem to benefit from diversification in the sense that diversified funds are not affected by risk spillover via investor redemptions.

The rest of the paper is organised as follows: section 2 presents the hedge fund data as well as some descriptive statistics. Section 3 presents the factors driving hedge fund liquidation, in particular the two channels of risk spillover and formulates testable hypotheses. Section 4 discusses the role of diversification in fund failure and risk spillover and presents our measures of portfolio diversification and our hypotheses. Section 5 describes the empirical modelling of hedge fund failure and presents our estimation results. Section 6 presents some robustness tests. Section 7 provides policy recommendations about financial information which could be disclosed by hedge funds and section 8 concludes.

2. Data and descriptive statistics

The Lipper TASS database provides information on monthly returns, on assets under management of individual hedge funds and on their governance structure, such as cancellation policy, incentive and management fees and use of leverage.[2] It also distinguishes between 'Alive' 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 in another entity and (vii.) unknown.[3] Hedge funds report information to commercial data providers on a voluntary basis and may stop doing for two main reasons. First, bad performance could potentially trigger redemptions and therefore a hedge fund might prefer to temporary suspend its recording, waiting for better performance. Second, to the extent that free reporting to a data provider may provide some forms of advertising, the incentive to continue reporting diminishes significantly when the customer base reaches an adequate size. In the TASS database, the hedge funds that do not report any information for several months are transferred from a status of 'Alive' to 'Graveyard' after a period of 8 to 10 months. This introduces a bias, as using the August 2008 version of the database leads to a possible misclassification of funds from October 2007. However, the number of existing hedge funds in the August version of the database only plunges sharply from June 2008, so that our sample ends in May 2008. Furthermore, although TASS started to collect data since 1974, it only reports information on dissolved funds since 1994. The period under consideration therefore extends from January 1994 to May 2008.

The TASS database classifies hedge funds according to their investment strategy: Convertible Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neu-

[2] See Chan et al., (2005) and Baba and Goko (2006) for a more detailed description of the TASS database.
[3] Chan et al., (2005) use 'Graveyard' funds rather than 'Liquidated' funds in their survival analysis, which introduces a bias as not all the 'Graveyard' funds are liquidated (Fung and Hsieh, 1997). The survivorship bias is therefore likely to be underestimated (Liang, 2000; Baquero et al., 2005).

tral, Event Driven, Fixed Income Arbitrage, Global Macro, Long / Short Equity, Managed Futures, Multi-Strategy and Funds of Hedge Funds. These style categories are used to measure risk spillover *within* and *across* hedge fund styles.

Due to missing values in the TASS database, we apply a filtering procedure to the data. The process consists in dropping funds that report only quarterly observations, those which do not have at least one full year of track record, and those which do not provide information on their geographical focus or on the type of assets they have invested in. Furthermore, funds with more than three consecutive missing values in their assets under management have also been discarded. For those funds with up to three consecutive missing values in assets under management we use the most recent observation of the fund's size and the corresponding fund return to approximate the evolution of the fund's assets under management.[4] The initial sample – before data filtering – covers 6,905 'Alive' funds and 4,842 'Graveyard' funds, of which 1,851 were liquidated. After filtering, the sample size turns then to be 5,501 with 2,653 'Alive' and 2,653 'Graveyard' funds, of which 1,144 funds were liquidated, which corresponds to about 53% of funds being dropped from the initial sample. Table 1 reports descriptive statistics on the population dynamics of hedge funds (i.e. number of existing hedge funds, new entries, exits and failures as well as attrition and failure rates) for each year of the sample period using the 'after-filtering' data. Table 1 also reports summary statistics on monthly returns and assets under management of 'Alive' and 'Liquidated' funds. The 'Liquidated' funds have significantly lower, but not necessarily more volatile, returns than the 'Alive' funds.

Control variables: In order to isolate the impact of risk spillover on hedge fund mortality patterns, control variables are introduced, which encompass two types of information: investment style and time fixed effects as well as fund-specific characteristics that have been shown to be significant in explaining hedge fund failure.[5] Hedge fund

[4] For example, Chan et al. (2005) and Baba and Goko (2006) impose two years of track record for a hedge fund to be kept in the sample and also require that funds report all the necessary data without a break over their life time. In our paper, the selection criteria on these two aspects have been less demanding. This is because funds to be kept in our sample were required to provide additional information on their investment, i.e. geographical focus and type of assets they have invested in. This leads *de facto* to an additional drop of about 27% funds from the initial sample. Missing values for assets under management have been filled using the available monthly performance return.
[5] Brown, Goetzmann and Park (2001) find that survival depends on performance returns, excess volatility and on fund age. Chan et al. (2005) show that age, capital, cumulative returns and fund flows decrease the default prob-

characteristics include returns, assets under management, capital flows and age. They also include incentive and management fees, high watermark provision[6] and variables capturing cancellation policies such as redemption frequency, lockup, redemption notice and payout periods as well as minimum investment.[7] A December dummy, information about the use of leverage and about the investment in derivatives such as options and swaps are also included in the analysis. Finally, yearly dummies intend to capture the impact of common shocks such as broad market performance on the failure probability of hedge funds and style dummies intend to account for the differences in the investment styles.

3. Determinants of hedge fund liquidation

3.1. Fund specific factors

Several authors have analysed the determinants of hedge fund liquidation. According to Getmansky (2005), fund liquidation can occur due to failure or due to closure of the fund. As the main factors that seem to have an impact on hedge fund failure, fund performance, capital withdrawals, assets under management, risk, redemption restrictions, age and investment style have been identified (Baquero et al., 2005; Gregoriou, 2002; Chan et al., 2005, Brown et al., 2001). On the other hand, empirical evidence suggests that the closure of hedge funds is a decision that is taken strategically by investment companies if, for example, a fund underperforms relative to the average of a fund family (Kolokolova, 2009).

ability of hedge funds. Baquero et al. (2005) show that the higher the size and past returns the lower the default probability; they do not find any significant relationship between incentive fees and survival rates. Baba and Goko (2006) show that funds with higher returns, assets under management, fund flows and a longer redemption notice period together with a lower redemption frequency have a higher survival probability, while funds with elevated incentive fees display lower survival probabilities. Gregoriou (2002) finds that leverage, returns and capital matter for hedge funds' probability of default.

[6] 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.

[7] The lock-up period refers to the time during which the invested money in a hedge fund cannot be withdrawn. The payout period is the period before which the investor will not get any return from his investment in the hedge fund's capital.

3.2. *Risk spillover among hedge funds*

Hedge fund failure may not only be related to fund specific factors, it may also arise from a spillover of risk from one fund to another, in particular during periods of financial turmoil. This paper intends to investigate two different channels through which a spillover of risk might materialise: investor redemptions and fund failures. In particular, the main objectives of this paper are to analyse (i.) whether risk spillover through redemptions and/or failures of other funds has a significant impact on hedge funds' failure probability and (ii.) whether portfolio diversification of hedge funds amplifies or dampens a spillover of risk.

The literature on financial contagion attempts to identify whether financial shocks are transmitted between different countries, markets or institutions due to contagion or interdependence. However, there exists no theoretical or empirical identification procedure on which the authors agree. In recent papers, contagion is defined as a significant increase in asset price correlation during a 'crisis' compared to a 'tranquil period' as opposed to interdependence where crises propagate due to 'fundamental' real and financial links (Dungey et al., 2005; Pericoli and Sbracia, 2003; Pesaran and Pick, 2007). In this paper, we aim at unravelling at least some of the channels through which negative shocks propagate from one hedge fund to another, after conditioning on common factors. Therefore, in our specific analysis, it is not essential to distinguish between contagion and interdependence. Instead, we focus on two channels of risk spillover in analysing the extent to which the failure probability of hedge funds is affected by investor redemptions and failures among other funds.

Redemption channel: Large investor redemptions affect the performance of a hedge fund as 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, whose expectation that other investors will withdraw their money as well might lead to a "self-fulfilling run" (Chen et al., 2007). Therefore, we argue that significant capital withdrawals taking place among funds of one investment style (redemptions *within*) are observed by the remaining investors in this style category who could then also decide to withdraw their capital (Liu and Mello, 2009). These withdrawals should in turn increase the failure probability of the corresponding hedge funds, for example, as their portfolios might include illiquid assets, which could be difficult to sell in periods of stress.

Hypothesis 1: All else equal, capital outflows within funds of one style category serve as a signal to the remaining investors in this investment style to also withdraw their capital which increases the funding risk of the corresponding hedge funds and should therefore be associated with an increase in their failure probability.

On the other hand, if significant capital withdrawals take place in 9 out of 10 investment styles (redemptions *across*), those hedge funds belonging to the investment style not affected by the capital outflows might benefit from it. For example, large institutional investors[8] are often required to invest a certain proportion of their portfolio in "alternative investments" and may thus seek other hedge funds (likely to operate in different styles than those experiencing large redemptions) to invest in.

Hypothesis 2: All else equal, capital outflows across funds of different investment styles highlight those funds which belong to the style category not affected by the investor redemptions as more favourable. This induces investors to reallocate their capital to those funds and should therefore be associated with a decline in their failure probability.

We measure relative capital withdrawals by a "redemption rate", which provides information on capital outflows as a ratio to total money flows in a given month. To this end, we first compute the capital flows in US Dollar into hedge fund i at time t as

$$FlowsUSD_{i,t} = AUM_{i,t} - AUM_{i,t-1}(1 + r_{i,t}),$$

where $AUM_{i,t}$ and $r_{i,t}$ are, respectively, the assets under management and the return of fund i at time t. Using these individual fund flows, we then compute the redemption rate *within* investment style k and *across* all fund styles $K \neq k$ at time t as

[8] Hedge funds rely on large investors' money such as pension funds or high net-worth individuals to finance their activity. The share of large institutional investors in the hedge fund capital has been rising over the last years and reached more than 30% at the end of 2005 and is expected to increase further with the ageing of the population (Casey et al., 2006).

$$RedemptionWithin_{k,t} = \frac{NegFlowsUSD_{k,t}}{TotalFlowsUSD_{k,t}}$$

$$RedemptionAcross_{K \neq k,t} = \frac{NegFlowsUSD_{K \neq k,t}}{TotalFlowsUSD_{K \neq k,t}}$$

where $NegFlowsUSD_{k,t}$ is the absolute value of the sum of negative flows at time t considering all funds which belong to the style category k, while $TotalFlowsUSD_{k,t}$ denotes the sum of positive and the absolute value of negative flows of funds within investment style k.

Failure channel: A cluster of hedge fund failures is also likely to have an impact on the failure probability of existing funds. As hedge funds mostly rely on short-term financing from prime brokers to pursue leveraged investment strategies (Greenwich Associates, 2007), prime brokers are likely to tighten their credit conditions if the failure rates of hedge funds suddenly increase. Since prime brokers have only incomplete information about the financial health of hedge funds, they may rationally take into account an increase in the failure rate of hedge funds when forming their priors about the risk of fund failure. As a consequence, prime brokers could then decide to increase hedge funds' margin requirements, reduce their maximum leverage limit or credit lines, thereby propagating initial stress within the industry (Chowdry and Nanda, 1998). As a result, hedge funds operating near their maximum leverage limit could then be forced to simultaneously sell their assets in potentially unfavourable market conditions (Ewerhart and Valla, 2007). According to Brunnermeier and Pedersen (2009), a "margin spiral" arises if higher margins increase the funding problems of a hedge fund and therefore cause even higher margins. In addition, a "loss spiral" arises as losses on a fund's initial position force the fund to sell more of its assets which causes a further decline in prices. Both spirals reinforce each other leading to a combined effect which is larger than the sum of their individual effects. Declining fund returns and a rising failure probability could then follow. The effect should be more pronounced if failures occur *within* funds having similar risk and market exposures than *across* funds from different investment styles (Cifuentes et al. 2005).

Hypothesis 3: All else equal, in the presence of incomplete information, an increase in the failure rate of hedge funds serves as a signal for the deterioration of the financial health of hedge funds. As a consequence, prime brokers should tighten the credit conditions for existing hedge funds which is related to an increase in their failure probability due to a heightened funding risk.

We measure the failure rate of hedge funds *within* investment style k and *across* all fund styles $K \neq k$ at time t as

$$FailureRateWithin_{k,t} = \frac{FailedFunds_{k,t}}{ExistingFunds_{k,t}}$$

$$FailureRateAcross_{K \neq k,t} = \frac{FailedFunds_{K \neq k,t}}{ExistingFunds_{K \neq k,t}}$$

where $FailedFunds_{k,t}$ and $ExistingFunds_{k,t}$ are, respectively, the number of fund failures during month t and the number of existing funds at the end of month t in style category k.

4. The role of portfolio diversification in risk spillover

A policy issue of interest is to investigate whether hedge funds with well diversified investment portfolios tend to have lower failure probabilities than less diversified funds in both 'tranquil' and 'crisis' periods. In tranquil periods, we could expect that diversification increases the survival probability, as empirical evidence tends to document positive international diversification benefits, when emerging markets (EM) are involved.[9] Therefore, the variance of hedge fund portfolios could be reduced for a given level of expected returns when extending the geographical focus to EM, even after accounting for their short-sale constraints and high transaction costs (Li et al.,

[9] The early studies that ignored short-sale constraints and market frictions have documented low correlation across international markets and some diversification benefits (Harvey, 1995; Bekaert and Urias, 1996; De Santis and Gerard, 1997). For those studies that account for the short-sale constraints, empirical evidence has been rather mixed. On the one hand, De Roon et al. (2001) showed that after major liberalisation in emerging markets, diversification benefits vanish once such market frictions are taken into account. On the other hand, Li et al. (2003) show that international diversification benefits remain substantial for US equity investors even when they are prohibited from short-selling in emerging markets, while Driessen and Laeven (2007) also find that global diversification benefits remain large after controlling for short-sales constraints in developing stock markets.

2003). Although hedge funds used to prefer rather liquid markets as they may exit them rapidly without incurring prohibitive costs of liquidation, a significant proportion of funds invest in emerging markets (59%).[10] We could thus expect that there are positive benefits from international diversification in 'tranquil' periods. On the other hand, during financial turmoil, diversified portfolios could also amplify the effects of risk spillover, potentially offsetting the positive benefits of diversification (Butler and Joaquin, 2002). The final impact is therefore undetermined.

To assess the effect of diversification in hedge fund failure patterns, it is crucial to measure diversification correctly in the first place. The use of the TASS database for this purpose raises several concerns that should be considered when interpreting our results. Each fund reports in which geographical areas it invests, for example in India and in the US. However, no quantitative data are available to gauge the proportion of investment in each region.[11] The same caveat applies for the type of assets: hedge funds only report whether they invest in equities, fixed-income, currencies, commodities or property (or a combination of these assets). However, as hedge funds provide information on their investment focus to TASS to attract new investors, it seems reasonable to argue that the information declared by the manager of the fund are accurate. Based on the available information, the evaluation of the degree of diversification of hedge fund portfolios can only be qualitative. Several sets of dummy variables are introduced to classify hedge funds as either 'diversified from a geographical perspective' or 'diversified in terms of asset types' or 'diversified according to the two dimensions' or 'not diversified at all'.[12]

[10] Based on the information given in the TASS database, 10% of hedge funds invest only in EMEs, 10% disclose to invest both in EMEs and in mature markets, while 39% declare to invest globally, which has been treated as involving an investment in EMEs.

[11] In the TASS database, there are seven emerging market areas (Africa, Asia-Pacific excluding Japan, Asia-Pacific, Eastern Europe, India, Latin America and Russia), while there are seven mature geographical focuses (United States, Japan, North America, United Kingdom, Western Europe, Western Europe excluding UK, North America excluding the US).

[12] As we use dummy variables to define diversification of a hedge fund, the effect on fund failure might be overstated. This aspect should therefore be taken into account when interpreting our results. An alternative would be to determine the exposure of each fund to different regions and assets classes (and thereby the degree of diversification) using the beta coefficients of style-type regressions. However, this approach may also have some drawbacks, in particular as hedge funds often have nonlinear exposures to one or several asset classes which could make it difficult to identify their degree of diversification (see, e.g., Agarwal and Naik, 2004).

Geographical diversification dimension: Our definition of geographical diversification rests on the distinction between mature and emerging markets. One could expect a low correlation between asset returns from EMEs and mature economies and therefore positive diversification benefits reducing the failure probability of hedge funds. The dummy variable equals 1 if a hedge fund invests simultaneously in mature and emerging markets and 0 otherwise.[13] About 49% of hedge funds in the filtered database report that they invest in these two geographical areas, while about 41% only invest in mature economies and 10% only in emerging market economies.

Assets diversification dimension: A portfolio is assumed to be diversified if it encompasses at least two different types of assets, such as equities and bonds. In a first step, the asset diversification dummy is equal to 1 in this case and 0 otherwise. Furthermore, we want to measure the potential different benefits of diversification from an initial situation where portfolios are either composed of equities only or of bonds only. Therefore we define an additional variable that has three outcomes: (i.) invested only in equities, (ii.) invested only in bonds, (iii.) diversified in equities and bonds.[14] In the filtered database, about 86% of hedge funds report that they invest in equities, while 45% invest in both equities and bonds.

Both geographical and asset diversification: Another set of dummy variables is introduced, which combines the two previous diversification dimensions. Hedge funds are then classified as (i.) diversified in the two dimensions (36%), (ii.) not diversified at all (27%), (iii.) diversified in assets (24%) or (iv.) geographically diversified (13%).

Hypothesis 4: All else equal, on the one hand, hedge funds should be able to lower their portfolio risk through diversification across different geographical regions and/or asset classes. This should be related to a lower failure probability compared to funds not being diversified. On the other hand, risk spillovers are likely to be amplified through diversification which should be associated with a higher failure prob-

[13] Hedge funds which report to follow a global investment strategy are classified as diversified in our definition, while those funds that do not provide any information on this issue or that report to invest in "other" areas have been discarded from the analysis.
[14] We ignore two other possible categories: (i.) not diversified in the other asset classes like commodities or currencies and (ii.) diversified in other categories than equities and bonds. Since the non-diversified portfolios in these asset classes account for a very small proportion of hedge funds, we don't report the estimation results for these categories. Empirical results are available upon request.

ability. Therefore, due to these two competing effects, the overall effect of diversification on hedge funds' failure probability is a priori unknown.

5. Empirical results

This section aims at assessing whether the spillover of risk from one hedge fund to another had a significant impact on funds' failure probability over the period January 1994 to May 2008.[15] It also intends to gauge the impact of portfolio diversification on the spillover of risk: is risk spillover more likely in the presence of diversified investment portfolios as opposed to concentrated market positions? The modelling of the failure process of hedge funds and estimation of the baseline model are described first. Then, the empirical results of the two channels of risk spillover are presented. Finally, the effect of portfolio diversification on funds' mortality patterns is investigated.

5.1. Baseline model

Our specification of the hedge fund failure process uses a binary logit model, which explains the outcome of a continuous latent variable $y^*_{i,t}$, representing the unobserved failure probability of fund i at time t, by a matrix of explanatory variables $\mathbf{x}_i$:[16]

$$y^*_{i,t} = \mathbf{x}_i \boldsymbol{\beta} + \varepsilon_{i,t}\,. \qquad (1)$$

To estimate this model we use a sample of N hedge funds $i = \{1, 2, \ldots, N\}$, observed over T periods $t = \{1, 2, \ldots, T\}$. Each hedge fund i in every month t is classified as either failed or alive.[17] This information is specified by the indicator variable $y_{i,t}$, which is linked to the latent failure probability $y^*_{i,t}$ in the following way:

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[15] TASS classifies funds that stopped reporting as 'Graveyard' after a period of 8 to 10 months. To reduce the risk of misclassification, the sample discards June to July 2008 data. Reducing the sample further does not significantly change the results.

[16] As some explanatory variables enter equation (1) with lags and to simplify notation, the time index t is omitted. When we examine the robustness in section 6, we also report the results from a Cox proportional hazards model which are similar to those of the logit model.

[17] We follow Gregoriou (2002) and treat 'Graveyard' funds not classified as 'Liquidated' as censored at the date of last report, rather than as failed at that date. To examine the robustness of our results with regard to this specification, we repeat our analysis with a sample that (i.) discards all 'Graveyard' funds not classified as 'Liquidated' and

$$y_{i,t} = \begin{cases} 1 & \text{if fund } i \text{ is liquidated in month } t \quad (\text{if } y_{i,t}^* > 0) \\ 0 & \text{otherwise} \quad (\text{if } y_{i,t}^* \leq 0) \end{cases} . \tag{2}$$

The probability that hedge fund i fails at time t, conditional on the values of the explanatory variables, is then given by:

$$\begin{aligned} \Pr(y_{i,t} = 1 \mid \mathbf{x}_i) &= \Pr(y_{i,t}^* > 0 \mid \mathbf{x}_i) \\ &= \frac{1}{1 + \exp(-\mathbf{x}_i \boldsymbol{\beta})} \end{aligned} . \tag{3}$$

The baseline model is specified as follows:

$$y_{i,t}^* = \alpha + \mathbf{x}_i \boldsymbol{\beta} + \sum_{h=1}^{14} \phi_h I(year_{h,i,t}) + \sum_{h=1}^{10} \xi_h I(style_{h,i,t}) + \varepsilon_{i,t} , \tag{4}$$

where the vector of hedge fund characteristics $\mathbf{x}_i$ includes age, returns, size and capital flows as well as information on the use of leverage, the fees' structure, cancellation policy, minimum investment and investment in derivatives. In order to account for economy-wide effects, indicator variables for 14 out of 15 calendar years denoted by $I(year_{h,i,t})$ and for 10 out of 11 investment styles denoted by $I(style_{h,i,t})$ are included.[18] We also include a December dummy to capture the fact that fund management companies tend to close their funds towards the end of the year. We expect a negative sign for the coefficients of age, returns, size and capital flows since older, more successful, bigger funds and those with larger inflows are less likely to fail (Chan et al., 2005 and Baquero et al., 2005). Moreover, we expect a high watermark, low redemption frequency, high redemption notice, payout and lockup periods to reduce the probability of fund failure (Goetzmann et al., 2003; Brown et al., 2001; Pangeas and Westerfield, 2008).

(ii.) classifies funds as 'Liquidated' if their aggregated capital flows over the last twelve months preceding disappearance are negative. The results presented in section 6 are similar to those in this section.

[18] We also included financial control variables such as the 3-month US Treasury bill rate, broad stock and bond indices, but they turned out to be not significant. Therefore, they have been dropped from the list of regressors.

The logit models are estimated by maximum likelihood through pooled regressions to address the right censoring issue.[19] In order to ease the convergence during the estimation and simplify the comparison of coefficients, all non-indicator variables have been standardised to have a zero mean and a standard deviation of one. The results of the baseline model are reported in the first column of Table 3. As expected, larger fund returns, size and capital flows reduce the probability of fund failure.[20] This is in line with the findings of Chan et al. (2005) and mostly consistent with Baba and Goko (2006) and Baquero et al. (2005). Regarding the fee structure, management fees prove to be insignificant, while higher incentive fees increase the failure probability of hedge funds. Furthermore, we find that a high watermark lowers the failure probability, which could reflect the incentive for fund managers to implement less risky investment strategies. Focusing on cancellation policy, our empirical results reveal that the longer the lockup, redemption notice and payout periods, the lower the failure probability. Furthermore, the industry practice to close a hedge fund at the end of the year seems to be reflected in the large positive coefficient of the Month 12 dummy. Finally, investment in options and swaps tends to be related to a higher failure probability.

5.2. Risk spillover within and across hedge fund styles

This section presents the procedure for testing the presence of risk spillover *within* and *across* hedge fund categories as well as the empirical results regarding the significance of the redemption and failure channel. These two channels are tested separately in equation (5a) and then simultaneously in (5b):

[19] A right censoring issue generally arises in survival analysis as most of the individuals observed over a given period did not experience the "event", which requires maximum likelihood estimation.
[20] Following Chan et al. (2005) and Baba and Goko (2006) we include only assets under management in *t-1* in the estimation to avoid multicollinearity problems. Using assets under management in *t* instead yields almost identical results.

$$y_{i,t}^{*} = \alpha + \mathbf{x}_i \boldsymbol{\beta} + \sum_{h=1}^{14} \phi_h \; year_{h,i,t} + \sum_{h=1}^{10} \xi_h \; I(style_{h,i,t}) \quad \text{for } k = 1,2$$
$$+ \sum_{j=1}^{2} \left(\gamma_j^{k,w} c_{i,t-j}^{k,w} + \gamma_j^{k,a} c_{i,t-j}^{k,a} \right) + \varepsilon_{i,t} \tag{5a}$$

$$y_{i,t}^{*} = \alpha + \mathbf{x}_i \boldsymbol{\beta} + \sum_{h=1}^{14} \phi_h \; year_{h,i,t} + \sum_{h=1}^{10} \xi_h \; I(style_{h,i,t})$$
$$+ \sum_{k=1}^{2} \sum_{j=2}^{2} \left(\gamma_j^{k,w} c_{i,t-j}^{k,w} + \gamma_j^{k,a} c_{i,t-j}^{k,a} \right) + \varepsilon_{i,t} \tag{5b}$$

where $c_{i,t-j}^{k,s}$ defines the variable capturing channels of risk spillover, with *k=1* (*k=2*) referring to the redemption (failure) variable, and with *s=w* (*s=a*) denoting risk spillover *within* (*across*) hedge fund styles corresponding to fund *i* at time *t-j*. The coefficient $\gamma_j^{k,w}$ ($\gamma_j^{k,a}$) measures the spillover effect *within* (*across*) hedge fund styles in month *t-j*. As investor redemptions can only be observed by market participants once they are reported in TASS (or in the press for well-known funds) it seems reasonable to argue that the failure probability of hedge funds is affected only one or two months after the initial redemptions *within* or *across* fund styles occurred. In the case of failures of other funds, it is also likely that it takes some time until prime brokers tighten their credit conditions and the failure probability of existing funds is affected. Therefore, we only include lagged values of our spillover variables in the models.

The estimation results on risk spillover are presented in columns 2 to 4 of Table 3. Column 2 shows that the higher the redemption rate *within* hedge funds of one investment style in *t-2*, the higher the likelihood that a fund belonging to the same style category fails in *t*. This result is economically significant. If the redemption rate *within* a certain hedge fund style increases from its sample mean by one standard deviation, the monthly failure probability of a hedge fund increases by about 11% relative to its “baseline” failure probability. On the other hand, a higher redemption rate *across* hedge funds from different styles in *t-1* or *t-2* is related to a lower failure probability in *t* of a fund not belonging to the style category where the initial redemptions occurred. If the redemption rate *across* hedge fund styles in *t-1* (*t-2*) increases by one standard deviation, the monthly failure probability of a hedge fund decreases by about 13% (9%) relative to its “baseline” failure probability.

Regarding the second channel of risk spillover, column 3 (Table 3) shows that a rise in the failure rate of hedge funds *within* one investment style in *t-1* or *t-2* is associated with an increase in the failure probability of an existing fund belonging to the same style category in *t*. These results are economically significant. If the failure rate of hedge funds *within* a particular style category in *t-1* or *t-2* increases by one standard deviation, the failure probability of an existing fund in the same style increases by about 5% relative to its "baseline" failure probability. There is no significant relation between the failure rate *across* funds from different investment styles and the failure probability of existing funds not belonging to one of these style categories. Compared with the redemption channel, the effect of an increase in the failure rate on the failure probability of existing funds is smaller. This seems plausible as the transmission mechanism (fund failures being recognized by prime brokers which tighten hedge funds credit conditions and therefore increase their funding risk) is supposed to be weaker in the case of fund failures compared to that of investor redemptions.

When testing simultaneously the relevance of the two spillover channels, the coefficients are almost unchanged. Finally, we also test and reject the null hypothesis $H_0 : \gamma_j^{k,s} = 0, \forall\ s = \{w, a\}, \forall\ j = \{1,2\}, \forall\ k = \{1,2\}$ that the coefficients on redemption ratios and failure rates *within* and *across* hedge fund styles are simultaneously non-significant.[21] Spillover effects from the two identified channels have therefore significantly increased the failure probability of hedge funds over the period under consideration. Although rejecting the null hypothesis is not a formal proof of risk spillover, it is at least consistent with the presence of spillover effects *within* and *across* hedge fund categories. Overall, these findings provide strong support to our hypotheses 1, 2 and 3.

5.3. Effect of diversification

This section aims at evaluating whether spillover effects are magnified or reduced if investment portfolios of hedge funds are diversified. We might expect that well diversified portfolios reduce the failure probability of hedge funds in quiet periods,

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[21] The value of the corresponding likelihood ratio (LR) test is given in the lower part of Table 4.

whereas it could increase failure potential during periods of financial stress. We first analyse the impact of diversification on failure probability, before introducing risk spillover channels in the estimation.

5.3.1. Effect of diversification on failure probability

The impact of diversification on failure probability of hedge funds is investigated in three stages. First, we evaluate the effect of the two diversification dimensions (geography and assets) separately. That is,

$$y^*_{i,t} = \alpha + \mathbf{x}_i\boldsymbol{\beta} + \sum_{h=1}^{14}\phi_h \; year_{h,i,t} + \sum_{h=1}^{10}\xi_h \; I(style_{h,i,t}) + \delta^d div^d_i + \varepsilon_{i,t} \qquad \text{for } d = 1,2 \tag{6a}$$

where the dummy variable div^d_i equals 1 if hedge fund i is diversified and 0 otherwise. The superscript d refers to the diversification dimension, with d=1 for geography and $d=2$ for the type of assets. As expected, a diversified portfolio tends to reduce the failure probability of hedge funds, suggesting the presence of some diversification benefits (Table 4). Such findings hold for a portfolio diversified from a geographical or from an assets perspective, with the geographical diversification between mature and emerging markets having the smallest impact in lowering the failure probability (columns 1 to 2). These results are economically significant. If a hedge fund is diversified from a geographical perspective (in terms of assets), its failure probability is about 17% (19%) lower relative to its "baseline" failure probability than for a fund which is not diversified at all.

Second, we investigate in more detail the diversification dimension related to the asset types. We distinguish three possible states for a portfolio: (i.) invested in equities only ($adiv^1_i$), (ii.) invested in bonds only ($adiv^2_i$), (iii.) diversified in equities and bonds ($adiv^3_i$). Since the asset diversification dimension has three outcomes, each of these dummies is used once as a reference category in the estimation, displayed in columns 3 to 5 in Table 4. As an example, the following equation uses $adiv^1_i$ as the reference category:

$$y_{i,t}^{*} = \alpha + \mathbf{x}_i\boldsymbol{\beta} + \sum_{h=1}^{14}\phi_h \; year_{h,i,t} + \sum_{h=1}^{10}\xi_h \; I(style_{h,i,t}) \\ + \eta^2 adiv_i^2 + \eta^3 adiv_i^3 + \varepsilon_{i,t} , \tag{6b}$$

where the coefficient η^3 measures the effect on the failure probability of a shift from a portfolio composed of only equities to a diversified portfolio in assets. According to the estimation results, a fund with a non-diversified portfolio would significantly reduce its failure probability by increasing the number of assets in its portfolio. Such positive effect appears to be slightly larger when the fund has initially invested in bonds (-0.326, column 4 compared to -0.254, column 3). These results are also economically significant. If a hedge fund is initially invested only in equities (bonds) and decides to invest both in bonds and equities, this is related to a decrease in the failure probability of the fund by about 22% (28%) relative to its "baseline" failure probability.

Third, the combination of the two diversification dimensions – assets and geography – is analysed. A new variable is introduced, which has four outcomes: (i.) diversified in assets and geographically ($cdiv_i^1$), (ii.) not diversified at all ($cdiv_i^2$), (iii.) diversified in assets only ($cdiv_i^3$), (iv.) diversified geographically only ($cdiv_i^4$). As an example, when $cdiv_i^2$ is taken as the reference category, the specification turns to:

$$y_{i,t}^{*} = \alpha + \mathbf{x}_i\boldsymbol{\beta} + \sum_{h=1}^{14}\phi_h \; year_{h,i,t} + \sum_{h=1}^{10}\xi_h \; I(style_{h,i,t}) \\ + \kappa^1 cdiv_i^1 + \kappa^3 cdiv_i^3 + \kappa^4 cdiv_i^4 + \varepsilon_{i,t} , \tag{6c}$$

where κ^p measures the effect of increasing the degree of diversification from a situation where the portfolio is initially not diversified at all. The effect of diversification on failure probability when both the geographical and the asset dimensions are combined is presented in columns 6 to 9 in Table 4. The largest diversification benefits arise when a fund is not diversified at all and decides to diversify its portfolio both geographically and in terms of assets (-0.345, column 7). Interestingly, as mentioned before, the benefits stemming from geographical diversification (-0.125, column 7) appear lower than those from diversification in assets (-0.169, column 7). These results are economically significant. If a hedge fund is not diversified at all and decides to diversify its portfolio both geographically and in terms of assets (only geographically; only in terms of assets), this is related to a decrease in the failure probability of the fund by about 29% (12%; 16%) relative to its "baseline" failure probability. Testing the null hypothesis $H_0 : \kappa^p = 0, \forall\ p = \{1,3,4\}$ reveals that the diversification of portfolios reduces the failure probability of hedge funds significantly.[22] Overall, these results provide strong support to the first part of hypothesis 4 which states that diversification across regions and or asset classes helps to reduce hedge funds' failure probability.

5.3.2. Effect of diversification on risk spillover

In a next step, interaction variables are introduced combining risk spillover with diversification to test whether spillover effects are amplified through diversification. That is,

$$
\begin{aligned}
y^*_{i,t} &= \alpha + \mathbf{x}_i \boldsymbol{\beta} + \sum_{h=1}^{14} \phi_h\ year_{h,i,t} + \sum_{h=1}^{10} \xi_h\ I(style_{h,i,t}) \\
&+ \psi\ div_i + \sum_{k=1}^{2}\sum_{j=1}^{2}\left[\gamma_j^{k,w} c_{i,t-j}^{k,w} + \gamma_j^{k,a} c_{i,t-j}^{k,a}\right] \\
&+ \sum_{k=1}^{2}\sum_{j=1}^{2}\left[\left(\varphi_j^{k,w} c_{i,t-j}^{k,w} + \varphi_j^{k,a} c_{i,t-j}^{k,a}\right) div_i\right] + \varepsilon_{i,t}
\end{aligned}
\tag{7}
$$

where, to simplify matters, we don't differentiate between the types of diversification but instead use the dummy variable div_i which equals 1 if hedge fund *i* is diversified both geographically and in terms of assets and 0 otherwise. A positive $\varphi_j^{k,w}$ or $\varphi_j^{k,a}$ refers to spillover effects being amplified by the presence of a diversified portfolio. The overall effect of diversification on failure probability is *a priori* undetermined. On the one hand, we expect diversification itself to reduce the failure probability, i.e. $\psi < 0$. On the other hand, being diversified could increase risk exposures and therefore the probability of being affected by risk spillover.

[22] The corresponding value of the LR-test is given in the lower part of Table 4.

The results of the model with interaction variables are reported in Table 5. They reveal that, all else being equal, a hedge fund which is diversified both in terms of assets and geographically has a significantly lower failure probability than a fund not diversified in both types (-0.215). This provides again support to the first part of hypothesis 4. As we have included interaction terms, the results of the variables capturing spillover effects refer to hedge funds that are not diversified in both types. They are very similar to the results reported in column 4 of Table 3.

Regarding the results of the interaction variables, two coefficients, which are related to investor redemptions, are significantly different from zero indicating that the degree of diversification only affects the impact of risk spillover on hedge funds' failure probability via redemptions.

First, the coefficient of interacting redemption *within* in *t-2* with the diversification dummy is negative (-0.153) and slightly significant. This implies that a hedge fund which is diversified both in assets and geographically suffers to a smaller extent from risk spillover (via redemptions *within* fund styles) than a fund that is not diversified in both types, which provides support to the first part of hypothesis 4. Overall, the impact of redemptions occurring *within* one investment style in *t-2* on the failure probability of a (diversified) fund in the same style category in *t* is close to zero (0.152-0.153). A possible explanation for this finding might be that diversified funds are perceived as being different from the other funds of one specific investment style and thus do not suffer so much from redemptions occurring *within* funds of one style category.

Second, the coefficient of interacting redemption *across* in *t-1* with the diversification dummy is positive (0.245) and significant. This implies that if a hedge fund is diversified in both types its failure probability is almost not affected (-0.218+0.245) through redemptions occurring *across* funds from different investment styles. In section 4 we argued that in the presence of redemptions *across* funds from different styles those funds belonging to the style category not affected by the capital outflows might benefit from investors' capital reallocations. This result, however, indicates that diversified funds might be perceived as being more similar to funds from the other investment styles which prevent investors from shifting their capital to them.

Overall, these results imply that a hedge fund which is diversified in assets and geographically is not significantly affected by risk spillover through redemptions occurring *within* and *across* fund styles. This means that, in contrast to the second part of hypothesis 4, hedge funds seem to benefit from diversification (in addition to the effect captured by the diversification dummy) in the sense that diversified funds are not affected by risk spillover via investor redemptions.

Finally, we test the null hypothesis that the impact of risk spillover on failure probability does not depend on the level of diversification. That is, we test whether the interaction terms provide no significant additional explanatory power, compared to the model including the baseline scenario and the variables capturing spillover effects and diversification. The corresponding likelihood-ratio test displayed in the lower part of Table 5, leads to a rejection of the null hypothesis at the 5% level.

6. Robustness

This section intends to examine the robustness of our results with regard to three aspects. The first aspect relates to the specification of hedge fund failure used in our analysis. Following Gregoriou (2002), we treat 'Graveyard' funds that stopped reporting to TASS but are not classified as 'Liquidated' as censored at the date of last report, rather than as failed at that date. However, a subset of those funds might still have stopped reporting to TASS due to failure even if TASS did not classify them as 'Liquidated' due to a lack of information. To differentiate between funds that stopped reporting because of failure or due to self-selection, we follow the approach of Baquero et al. (2005) and classify funds as 'Liquidated' if the aggregated capital flows over the 12 months preceding the disappearance are negative. Based on that, about 56% of the 'Graveyard' funds not classified as 'Liquidated' have negative aggregated capital flows and are therefore classified as 'Liquidated' while the remaining funds are treated as censored. The corresponding estimation results are reported in row 1 of Table 6 and are qualitatively similar to those in Table 3. The fact that, compared to the results of Table 3, some of the coefficients are significant at lag two instead of lag one or vice versa does not change our key result that investor redemptions and a large number of failures *within* funds of one investment style increase the likelihood of failure of an 'Alive' fund belonging to the same style category.

As an alternative to the approach of Baquero et al. (2005), we discard those 'Graveyard' funds not classified as 'Liquidated' and repeat the estimation with a sample which therefore only consists of 'Alive' and 'Liquidated' funds. The results shown in Table 6, row 2 are very similar to those reported in Table 3. Both findings show that our key results are robust with respect to the specification of 'Alive' and 'Liquidated' funds.

The second aspect in the context of checking the robustness of our results relates to the model that we use for analysing hedge fund failure. While the binary logit model is widely used in the context of survival analysis (see, e.g., Campbell et al., 2009; Chan et al., 2005; Getmansky, 2005), several authors argue that the semiparametric Cox proportional hazards model has some advantages such as not imposing a particular functional form for the dependence of a fund's hazard rate on its age (see, e.g., Lunde et al., 1999; Brown et al., 2001). To account for this aspect, we repeat the analysis using a semiparametric Cox hazards rate model. The estimation results are reported in row 3 and 4 of Table 6.[23] Using the Cox model yields very similar results as the logit model. It confirms that our results are robust to the way we have modelled hedge fund failure.

Finally, we check whether our results are robust to using risk-adjusted rather than raw returns as a control variable capturing hedge fund performance. We use Sharpe ratios computed with a 6-month rolling window as our measure of risk-adjusted returns. The estimation results are reported in row 5 of Table 6 and are very similar to those reported in Table 3. This confirms that our results are robust to different specifications of hedge fund performance used as a control variable.

7. Policy implications

This section aims at providing a list of variables that have a significant impact on hedge fund failure and for which disclosure might be valuable from a transparency and financial stability perspective.

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[23] The results of the other models are available upon request.

To isolate the impact of individual explanatory variables on the failure probability of hedge funds, we compute the marginal effect of a one standard deviation shock to each regressor, all other variables being unchanged. An initial failure probability is calculated first, where all explanatory variables are set to their sample mean and the dummy variables to zero. As our models include yearly fixed effects, we have to specify a year for which the failure probabilities are computed. We thus assume that the 'exemplary' hedge fund operates in 2007. This yields a monthly 'baseline' failure probability of 0.20% (column 1, Table 7). The failure probability resulting from each explanatory variable being shocked by one standard deviation is reported in column 2. The marginal effect of each regressor is calculated as the difference between the two failure probabilities (column 3).[24] In addition, we provide the 95% confidence interval of the marginal effect in columns 4 and 5. As a result, hedge fund size, capital flows, high watermark provision and the fund's redemption notice period have the largest individual effect in reducing the failure probability. Other hedge fund characteristics also dampen the risk of hedge fund failure, albeit with a lower impact: contemporaneous and past returns, payout and lockup periods as well as redemptions *across* hedge fund styles. On the other hand, the variables contributing to a significant increase in failure probability are investment in derivatives, redemptions *within* funds from one style category, incentive fees and failures among funds *within* one investment style.

In the recent debate on hedge fund regulation several authors have argued that at least systemically important hedge funds should provide more transparency to regulators on a confidential basis (see, e.g., Lo, 2008). Based on our results, it seems to be important that hedge funds provide information on size, capital flows, restriction periods, incentive fees and on their investment into derivatives to regulatory authorities. In particular, information on capital flows and on a fund's restriction periods is important for enabling a regulator to evaluate the funding risk of a hedge fund and thereby its failure probability.

[24] For dummy variables the marginal effects are calculated by setting their values to one in the 'stress' case.

8. Conclusion

This paper analyses the determinants of hedge fund failures over the period January 1994 to May 2008. In addition to fund specific factors, we investigate whether a spillover of risk from one fund to another affects the failure probability of hedge funds. In particular, we test two different channels through which a risk spillover might materialise: investor redemptions and failures of other funds. Furthermore, we differentiate between a spillover of risk taking place *within* funds from one specific investment style and *across* funds from different style categories.

We find that, in addition to hedge fund characteristics, a spillover of risk from one fund to another has a significant impact on the failure probability of hedge funds. Comparing the two channels of risk spillover, we find that investor redemptions have a larger impact on funds' failure probability than failures of other hedge funds.

Our results also show that funds *within* the same investment style are adversely affected through both channels of risk spillover: a rise in both the redemption and the failure rate significantly increases the probability of fund failure. The result suggests that changes in both variables are recognized by market participants such as investors and prime brokers and are considered in their decision-making process, for example when forming their priors on the riskiness of hedge funds.

On the other hand, hedge funds *across* different style categories are only affected through the redemption spillover channel: an increase in the redemption rate reduces the failure probability of funds operating in the style category not affected by the redemptions, i.e. it is actually beneficial for the corresponding funds. This finding indicates that investors reallocate their capital to funds which are perceived as superior since they did not suffer from outflows in previous months.

This paper also analyses whether and to which extent portfolio diversification affects the failure probability of hedge funds. As the TASS database provides only qualitative information on diversification of hedge funds' investment portfolios, we use different definitions of diversification. Overall, we find that hedge funds being diversified either in terms of assets or geographically have a significantly lower failure probability than funds being invested in just one asset class or one geographical region. In addition, we investigate whether diversification amplifies the impact of risk spillover among hedge funds. We find that the degree of diversification only affects the impact of risk spillover on hedge funds' failure probability via investor redemptions. In particular, hedge funds seem to benefit from diversification (in addition to the effect captured by the diversification dummy) in the sense that diversified funds are not affected by risk spillover via investor redemptions.

Finally, the variables that have the largest impact on hedge funds' failure probability and which should therefore be disclosed on a confidential basis to regulators encompass information on funds' size, capital flows, restriction periods, incentive fees and on their investment into derivatives.

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Appendix

Table 1: Number of Hedge Funds, Entries, Exits and Failures

For each year of the sample period, this table shows the number of existing funds, new entries into the TASS database, exits out of the database, fund failures, the attrition and failure rates in percent, the mean and the standard deviation of monthly hedge fund returns in percent and the mean of assets under management in million USD, separately for funds classified as ‘Alive’ and ‘Liquidated’. The number of existing funds refers to the number of funds classified as ‘Alive’ at the end of each year. The attrition (failure) rate is the ratio of exits (failures) to the number of existing funds. The asterisk indicates that for 2008 data have been included only until end of May.

							‘Alive’ Funds			‘Liquidated’ Funds		
Year	Existing Funds	New Entries	Exits	Fail-ures	Attrition Rate in %	Failure Rate in %	Mean Monthly Return	Std. Dev. Monthly Return	Mean AUM in mn USD	Mean Monthly Return	Std. Dev. Monthly Return	Mean AUM in mn USD
1994	524	170	6	3	1.15	0.57	0.11	4.95	74.85	-0.05	4.62	61.63
1995	660	162	26	18	3.94	2.73	1.60	4.60	61.69	0.90	5.08	46.61
1996	790	216	86	37	10.89	4.68	1.82	4.68	72.81	0.99	5.39	43.02
1997	1007	271	54	35	5.36	3.48	1.59	4.92	88.78	1.05	5.60	53.72
1998	1148	245	104	73	9.06	6.36	0.36	6.54	89.48	0.23	6.86	67.15
1999	1350	320	118	70	8.74	5.19	2.11	5.85	84.44	1.27	6.01	48.17
2000	1532	328	146	64	9.53	4.18	1.19	5.94	96.53	0.41	6.69	42.88
2001	1733	359	158	69	9.12	3.98	0.83	4.50	100.49	0.08	4.86	48.48
2002	1983	418	168	92	8.47	4.64	0.45	4.11	102.69	-0.07	3.91	46.68
2003	2268	447	162	107	7.14	4.72	1.51	3.62	118.62	0.88	3.33	50.43
2004	2589	550	229	133	8.85	5.14	0.83	3.08	154.16	0.27	2.85	64.61
2005	2736	472	325	163	11.88	5.96	0.91	3.21	167.13	0.38	3.04	72.22
2006	2930	570	376	144	12.83	4.91	1.05	3.21	183.72	0.32	2.98	82.37
2007	3140	663	452	92	14.39	2.93	0.91	3.50	208.14	0.02	3.16	88.81
*2008	2750	8	243	44	8.84	1.60	-0.04	4.53	222.09	-1.41	3.83	58.12

Table 2: Summary statistics of hedge fund variables

This table shows the summary statistics of various hedge fund characteristics that are used as explanatory variables in our estimations. The summary statistics are computed using the data after filtering over the sample period from January 1994 to May 2008.

Variable	Mean	SD	25th Percentile	Median	75th Percentile
Return per month in %	0.79	4.49	-0.69	0.70	2.16
Age in years	4.51	3.77	1.75	3.42	6.17
AUM in mn USD	111.39	222.13	9.20	32.10	105.54
Monthly capital flows in % of AUM	1.88	11.68	-0.86	0.07	2.69
Leverage (% of funds)	66.95				
Management fee in %	1.47	0.69	1.00	1.50	2.00
Incentive fee in %	16.59	7.19	15.00	20.00	20.00
High watermark (% of funds)	61.67				
Lockup period in months	3.06	5.83	0.00	0.00	3.00
Redemption frequency in months	2.31	2.63	1.00	1.00	3.00
Redemption notice period in months	1.14	0.90	0.47	1.00	1.50
Payout period in months	0.49	0.62	0.00	0.33	1.00
Minimum investment in mn USD	0.77	2.10	0.10	0.32	1.00
Month 12 (% of obs.)	8.37				
Invested in derivatives (% of funds)	61.36				
Redemption within	0.38	0.18	0.24	0.36	0.48
Redemption across	0.37	0.13	0.28	0.37	0.45
Failure rate within	0.19	0.40	0.00	0.00	0.23
Failure rate across	0.39	0.25	0.23	0.34	0.52

Table 3: Estimation Results – Risk Spillover

This table reports the coefficient estimates of a logit model for hedge fund failure of equation (4), referred to as the 'Baseline Model', of equation (5a), which models both channels of risk spillover (investor redemptions and failures of other funds) separately, and of equation (5b), which models both channels of risk spillover simultaneously. The dependent variable takes on the value 1 in the month where the hedge fund fails, and is 0 in all prior months. To facilitate comparisons of the coefficients, all non-indicator explanatory variables have been standardized to have a zero mean and a standard deviation of one. To account for fixed effects associated with the calendar year and the investment style, indicator variables are included in each of the models. The results are not reported here, but are available upon request. The sample period extends from January 1994 to May 2008. The estimation results are obtained by maximum likelihood. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

		Risk Spillover Models		
	(1)	(2)	(3)	(4)
Regressor	Baseline Model	Redemption Ratio	Failure Rate	Combined
Age	-0.073*	-0.072*	-0.073*	-0.072*
Return	-0.279***	-0.274***	-0.273***	-0.267***
Return (t-1)	-0.151***	-0.145***	-0.153***	-0.146***
Return (t-2)	-0.131***	-0.134***	-0.129***	-0.134***
log(AUM (t-1))	-0.688***	-0.688***	-0.688***	-0.688***
Flows	-0.315***	-0.312***	-0.312***	-0.310***
Flows (t-1)	-0.330***	-0.330***	-0.328***	-0.329***
Flows (t-2)	-0.397***	-0.393***	-0.397***	-0.393***
Leverage	0.006	0.004	0.007	0.005
Management fee	0.026	0.026	0.025	0.025
Incentive fee	0.091**	0.091**	0.091**	0.091**
High watermark	-0.371***	-0.375***	-0.372***	-0.375***
Lockup period	-0.093**	-0.096**	-0.094**	-0.096**
Redemption frequency	0.051	0.052	0.052	0.053
Redemption notice period	-0.301***	-0.302***	-0.303***	-0.304***
Payout period	-0.121***	-0.122***	-0.122***	-0.123***
Minimum investment	0.144	0.153	0.146	0.154
Month 12	0.885***	0.928***	0.878***	0.913***
Invested in derivatives	0.269***	0.271***	0.271***	0.272***
Spillover variables				
Redemption within (t-1)		0.001		-0.020
Redemption within (t-2)		0.104***		0.108***
Redemption across (t-1)		-0.131***		-0.140***
Redemption across (t-2)		-0.107**		-0.092*
Failure within (t-1)			0.053**	0.051*
Failure within (t-2)			0.054**	0.050*
Failure across (t-1)			0.036	0.048
Failure across (t-2)			-0.030	-0.002
Constant	-8.438***	-8.383***	-8.394***	-8.279***
Number of Obs.	270747	270747	270747	270747
LR chi2 (df)	1358.23 (43)	1380.98 (47)	1368.53 (47)	1390.92 (51)
Prob > Chi2	0.0000	0.0000	0.0000	0.0000
Pseudo R-Squared	0.1028	0.1045	0.1036	0.1053
Log-Likelihood	-5925.82	-5914.44	-5920.67	-5909.47
LR-test value (df)	-	-	-	32.69 (8)

Table 4: Estimation Results – Diversification

This table reports the coefficient estimates of a logit model for hedge fund failure of equation (6a), which analyses the effect of diversification in terms of geography and asset type, of equation (6b), which investigates the impact of being invested in equities and/or bonds, and of equation (6c), which analyses the impact of different degrees of diversification ranging from 'Not diversified at all' to 'Diversified in assets & geographically'. The dependent variable takes on the value 1 in the month where the hedge fund fails, and is 0 in all prior months. The regressors of the 'Baseline Model' are included in the estimation of all models, but are not reported for brevity. To account for fixed effects associated with the calendar year and the investment style, indicator variables are included in each of the models. The results are not reported here, but are available upon request. Also not reported are the coefficient estimates of diversification accounting for the commodities, FX and real estate markets as they only account for a very small proportion of funds. The sample period extends from January 1994 to May 2008. The estimation results are obtained by maximum likelihood. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

			Reference category			Reference category			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Regressor	Geographical diversification	Assets diversification	Investments in Equity only	Investments in Bonds only	Investments in Bonds & Equities	Diversified in assets & geographically	Not diversified at all	Diversified in assets only	Diversified only geographically
Diversification variables									
Geographical diversification	-0.185**								
Assets type diversification		-0.212***							
Asset diversification variables									
Invest. in equities only			-	-0.073	0.254***				
Invest. in bonds only			0.073	-	0.326*				
Invest. in bonds & equities			-0.254***	-0.326*	-				
Combined diversification variables									
Diversified in assets & geographically						-	-0.345***	-0.176*	-0.220*
Not diversified at all						0.345***	-	0.169*	0.125
Diversified in assets only						0.176*	-0.169*	-	-0.044
Diversified geographically only						0.220*	-0.125	0.044	-
Number of Obs.	270747	270747	270747	270747	270747	270747	270747	270747	270747
LR chi2 (df)	1364.27 (44)	1366.52 (44)	1368.75 (47)	1368.75 (47)	1368.75 (47)	1370.81 (46)	1370.81 (46)	1370.81 (46)	1370.81 (46)
Prob > Chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo R-Squared	0.1033	0.1034	0.1036	0.1036	0.1036	0.1038	0.1038	0.1038	0.1038
Log-Likelihood	-5922.80	-5921.67	-5920.56	-5920.56	-5920.56	-5919.5294	-5919.5294	-5919.5294	-5919.5294
LR-test value (df)	-	-	-	-	-	-	12.580 (3)	-	-

Table 5: Estimation Results – Interaction of Risk Spillover and Diversification

This table reports the coefficient estimates of a logit model for hedge fund failure of equation (7), which analyses the interaction of risk spillover and diversification. The dependent variable takes on the value 1 in the month where the hedge fund fails, and is 0 in all prior months. The regressors of the 'Baseline Model' are included in the estimation, but are not reported for brevity. To account for fixed effects associated with the calendar year and the investment style, indicator variables are included. The results are not reported here, but are available upon request. The sample period extends from January 1994 to May 2008. The estimation results are obtained by maximum likelihood. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Regressor	Coefficient
Diversification variable	
Diversified in assets & geographically	-0.215**
Spillover variables	
Redemption within (t-1)	-0.049
Redemption within (t-2)	0.152***
Redemption across (t-1)	-0.218***
Redemption across (t-2)	-0.055
Failure within (t-1)	0.073**
Failure within (t-2)	0.082**
Failure across (t-1)	0.039
Failure across (t-2)	0.019
Interaction variables	
Diversified x redemption within (t-1)	0.085
Diversified x redemption within (t-2)	-0.153*
Diversified x redemption across (t-1)	0.245**
Diversified x redemption across (t-2)	-0.115
Diversified x failure within (t-1)	-0.059
Diversified x failure within (t-2)	-0.091
Diversified x failure across (t-1)	0.034
Diversified x failure across (t-2)	-0.061
Number of Obs.	270747
LR chi2 (df)	1416.76 (60)
Prob > Chi2	0.0000
Pseudo R-Squared	0.1072
Log-Likelihood	-5896.5541
LR-test value (df)	16.841 (8)

Table 6: Estimation Results – Robustness

This table reports the coefficient estimates of different models for hedge fund failure to analyse the robustness of our results. For convenience, we only report the coefficients of the variables capturing risk spillover and suppress the reporting of the coefficients of other variables. In each of the rows 1 to 4 the estimations are based on equation (5b), using a different model (logit vs. Cox proportional hazards rate) and/or a different specification of fund failure. Row 5 is based on a modified version of equation (5b) using risk-adjusted instead of raw returns as a control variable capturing hedge fund performance. To facilitate comparisons, we also report the estimation results from Table 3, which are based on a logit model where 'Graveyard' funds not classified as 'Liquidated' are treated as censored at the date of last report. The dependent variable takes on the value 1 in the month where the hedge fund fails, and is 0 in all prior months. The regressors of the 'Baseline Model' are included in the estimation of all models, but are not reported for brevity. To account for fixed effects associated with the calendar year and the investment style, indicator variables are included in each of the models. The results are not reported here, but are available upon request. The sample period extends from January 1994 to May 2008. The estimation results are obtained by maximum likelihood. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Row	Type of robustness	Redemption within (t-1)	Redemption within (t-2)	Redemption across (t-1)	Redemption across (t-2)	Failure within (t-1)	Failure within (t-2)	Failure across (t-1)	Failure across (t-2)
	Result from Table 3	-0.02	0.108***	-0.140***	-0.092*	0.051*	0.050*	0.048	-0.002
	Logit model								
1	Baquero et al. (2005) 'flow-procedure'	-0.010	0.080***	-0.146***	0.000	0.043**	0.012	0.013	-0.074**
2	Only 'Alive' and 'Liquidated' funds	-0.016	0.110***	-0.143***	-0.076	0.047*	0.047*	0.056	0.000
	Cox proportional hazards rate model								
3	Baquero et al. (2005) 'flow-procedure'	-0.011	0.077**	-0.139***	-0.001	0.036*	0.011	0.02	-0.074**
4	Only 'Alive' and 'Liquidated' funds	-0.018	0.105***	-0.138***	-0.094*	0.042	0.047*	0.052	-0.002
	Logit model – using risk-adjusted returns								
5	6-month rolling Sharpe ratio	-0.046	0.083**	-0.177***	-0.114**	0.056**	0.058**	0.054	0.002

Table 7: Marginal Effects

This table reports the monthly failure probability of an 'exemplary' hedge fund based on equation (5b), which is referred to as the 'Baseline Failure Probability', where all explanatory variables have been set to the sample mean, the failure probability which results from a one standard deviation increase in the corresponding regressor all other variables left unchanged, the marginal effect which is computed as the difference of the two failure probabilities and the 95% confidence interval of the marginal effect. Dummy variables, labelled with an asterisk, are set to 0 in the 'Baseline' case and 1 in the 'Stress' case. As our models include yearly fixed effects, we have to specify a year for which the failure probabilities in this table are computed. Therefore, we assume that the 'exemplary' hedge fund operates in 2007. Only variables which are significant at the 10% level are reported.

Regressor	Baseline Failure Probability	Failure Probability (1 Std. Dev. Increase in Regressor)	Marginal Effect	95% Conf. Interval of Marginal Effect	
Variables increasing the failure probability					
Invested in derivatives*	0.2005%	0.2629%	0.0624%	0.0118%	0.2466%
Redemption within (t-2)	0.2005%	0.2229%	0.0225%	0.0024%	0.0991%
Incentive fee	0.2005%	0.2193%	0.0188%	0.0008%	0.0910%
Failure within (t-1)	0.2005%	0.2108%	0.0104%	-0.0001%	0.0527%
Failure within (t-2)	0.2005%	0.2106%	0.0102%	-0.0002%	0.0521%
Variables reducing the failure probability					
log(AUM(t-1))	0.2005%	0.1020%	-0.0984%	-0.0427%	-0.2243%
Flows (t-2)	0.2005%	0.1360%	-0.0645%	-0.0304%	-0.1307%
High watermark*	0.2005%	0.1379%	-0.0625%	-0.0338%	-0.0944%
Flows (t-1)	0.2005%	0.1468%	-0.0536%	-0.0262%	-0.1029%
Redemption notice period	0.2005%	0.1481%	-0.0523%	-0.0267%	-0.0926%
Flows	0.2005%	0.1506%	-0.0498%	-0.0246%	-0.0939%
Return	0.2005%	0.1539%	-0.0466%	-0.0221%	-0.0944%
Return (t-1)	0.2005%	0.1736%	-0.0269%	-0.0146%	-0.0426%
Redemption across (t-1)	0.2005%	0.1745%	-0.0260%	-0.0173%	-0.0188%
Return (t-2)	0.2005%	0.1756%	-0.0249%	-0.0139%	-0.0367%
Payout period	0.2005%	0.1774%	-0.0231%	-0.0155%	-0.0162%
Lockup period	0.2005%	0.1820%	-0.0184%	-0.0135%	-0.0058%
Redemption across (t-2)	0.2005%	0.1831%	-0.0173%	-0.0140%	0.0039%
Age	0.2005%	0.1868%	-0.0137%	-0.0111%	0.0023%

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