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COMMONALITY IN HEDGE FUND RETURNS DRIVING FACTORS AND IMPLICATIONS

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Abstract

We measure the commonality in hedge fund returns, identify its main driving factor and analyze its implications for financial stability. We find that hedge funds' commonality increased significantly from 2003 until 2006. We attribute this rise mainly to the increase in hedge funds' exposure to emerging market equities, which we identify as a common factor in hedge fund returns over this period. Our results show that funds with a high commonality were affected disproportionately by illiquidity and exhibited negative returns during the subsequent financial crisis, thereby providing little diversification benefits to the financial system and to investors.

Keywords: Hedge funds, Commonality, Risk factors, Liquidity, Financial crisis

JEL Classification: G01, G10, G11, G23

Non-Technical Summary

In recent years, hedge funds have become very important actors in global financial markets: their total assets under management are estimated at 1.8 trillion USD (International Monetary Fund (2011)), they account for about 80% of credit derivative trading (U.S. Government Accountability Office (2008)) and have close relationships with other financial institutions such as prime brokers (Klaus and Rzepkowski (2009), Aragon and Strahan (2012)). Given their major importance, instability in the hedge fund sector could pose a threat to the stability of the entire financial system. In this paper, we document a build-up of risks and “connectedness” in the hedge fund sector prior to the recent financial crisis. We analyze investment strategies of hedge funds, focusing on the issue of commonality, i.e., the extent to which hedge fund returns are driven by common factors.

Due to the fact that hedge funds are largely unregulated, there is little direct information about hedge funds’ investment strategies and risk exposures. Fortunately, available data on hedge funds’ returns represent a valuable source of information allowing inference on hedge funds’ commonality. We conduct an empirical analysis of hedge fund returns between January 1994 and June 2009 with a database of about 6,400 hedge funds, aiming to (i) measure the degree of hedge funds’ commonality, (ii) identify its potential driving factors, and (iii) characterize the risk exposure of funds with different degrees of commonality. Identifying the major driving factor of commonality allows us to assess whether hedge funds provided diversification benefits to the financial system, an aspect that has not received much attention in the literature to date.

We find that the commonality in hedge fund returns doubled between 2003 and end-2006. When estimating the exposures of hedge funds to twelve broad risk factors (asset classes), we find that hedge funds with a high commonality were particularly exposed to emerging market equities (the asset class providing the highest returns). Moreover, their exposure increased significantly prior to the 2007-2009 financial crisis. During the financial crisis, in particular after the failure of Lehman Brothers, funds with a high commonality exhibited the worst performance and the most substantial increase in the illiquidity-level of their portfolio, thereby providing little diversification benefits to the financial system and to investors.

In sum, we provide evidence that through their investment behavior prior to 2007, hedge funds established pre-conditions for posing risks to the financial system, via their exposure to common risk factors and their specific risk exposures. When such risks

materialize, funds with a high risk exposure following similar strategies could trigger feedback loops involving asset prices and funding liquidity, as emphasized by Brunnermeier et al. (2009), and adverse shocks in the hedge fund sector can be further transmitted to other financial institutions, an aspect analyzed by Billio et al. (2012). While information about hedge funds' investment strategies and risk exposures is currently rather limited and based on voluntarily reported data, our analysis points at benefits of more transparency, enabling more accurate monitoring and assessment of the build-up of potential risks in the hedge funds sector.

1 Introduction

In recent years, hedge funds have become very important actors in global financial markets: their total assets under management are estimated at 1.8 trillion USD (International Monetary Fund (2011)), they account for about 80% of credit derivative trading (U.S. Government Accountability Office (2008)) and have close relationships with other financial institutions such as prime brokers (Klaus and Rzepkowski (2009), Aragon and Strahan (2012)). Given their major importance, instability in the hedge fund sector could pose a threat to the stability of the entire financial system. In this paper, we document a build-up of risks and “connectedness” in the hedge fund sector prior to the recent financial crisis. We analyze investment strategies of hedge funds, focusing on the issue of commonality, i.e., the extent to which hedge fund returns are driven by common factors. We show that commonality in hedge fund returns increased prior to the recent financial crisis and that hedge funds exposed to the common factor suffered from worse performance once the crisis set in.

Due to the fact that hedge funds are largely unregulated, there is little direct information about hedge funds’ investment strategies and risk exposures. Fortunately, available data on hedge funds’ returns represent a valuable source of information allowing inference on hedge funds’ commonality. In this paper, we conduct an empirical analysis of hedge fund returns between January 1994 and June 2009 with a database of about 6,400 hedge funds, aiming to (i) measure the degree of hedge funds’ commonality, (ii) identify its potential driving factors, and (iii) characterize the risk exposure of funds with different degrees of commonality. We contribute to the literature by using a large sample of individual hedge funds to identify the driving factors of hedge funds’ commonality and by investigating the risk profiles of the corresponding funds both before and during the recent financial crisis. Identifying the major driving factor of commonality allows us to assess whether hedge funds provided diversification benefits to the financial system, an aspect that has not received much attention in the literature to date.

We proceed in three steps. In the first step, we measure the commonality in hedge fund returns using Principal Component Analysis (PCA), in particular using the proportion of variation in the data set explained by the first principal component. We find three broad patterns prior to 2007: commonality increased between January 1996 and August 1998, declined thereafter, and rose again almost two-fold between May 2002 and December 2006. Next, we measure the commonality in the returns of 12 risk factors

that have been frequently used in the literature to model hedge funds' risk exposure (Fung and Hsieh (2004), Bondarenko (2007*b*), Sadka (2010) and Pojarliev and Levich (2011)). We ask whether the rise in commonality between 1996 and 1998, as well as between 2002 and 2006, can be related simply to increased commonality in the returns of 12 risk factors. For the latter period, the answer is negative: the commonality in the returns of 12 risk factors did not change or decreased. Moreover, market volatility also declined in this period. This makes the period between 2003 and 2006 a unique setting to identify the drivers of increased commonality, beyond changing commonality in risk factors or market volatility.

In the second step, we thus focus on the period between 2003 and 2006, aiming to pinpoint factors behind the rise in hedge funds' commonality. To this end, we first need to determine the identity of the common risk factor. We do so by classifying the hedge funds into deciles based on the correlation of their returns with the first principal component. We find that hedge funds with a high degree of commonality were particularly exposed to equity-oriented risk factors. By contrast, funds with a low commonality had only a small or no exposure to equity-oriented risk factors. In addition, the exposure to emerging market equities increased almost monotonically with an increasing level of commonality. We conclude that the common factor driving a substantial proportion of hedge fund returns over this period was emerging market equities. Second, we analyze how the exposure of hedge funds to this common risk factor evolved over time and find that it increased significantly over the period from 2004 until end-2006 for funds with a high commonality. At the individual fund level, we find that 20% of the hedge funds significantly increased their exposure to emerging market equities over this period, with 80% of those funds having no significant exposure prior to 2004. This result suggests that the increase in hedge funds' exposure to emerging market equities can be considered as the main driver of the rise in hedge funds' commonality.

In the third step, we investigate the risk exposure of hedge funds in the different commonality deciles. Specifically, we examine whether funds with a high commonality have a comparable downside and illiquidity risk exposure to funds with a low commonality. While hedge fund failures are strongly related to their downside risk exposure (Liang and Park (2010)), their excessive leverage and illiquidity of their investments affect the risk of a market disruption (Khandani and Lo (2007), Stein (2009), Shleifer and Vishny (2011)). We find that both during the upmarket and the financial crisis period funds with a high commonality had a significantly higher downside risk, captured by negative skewness and semi-deviation, compared to funds with a low commonality. Moreover,

the downside risk of funds with a high commonality increased significantly more often over the period from 2004 until end-2006. As we identified emerging market equities as the common risk factor, the higher downside risk of funds with a high commonality can be regarded as a direct consequence of their greater exposure to this risk factor. As for illiquidity risk exposure, we find that hedge funds with a high commonality had a higher degree of illiquidity (i.e., the fund specific illiquidity level), captured by the return autocorrelation, compared to funds with a low commonality. Since emerging markets generally exhibit a higher degree of illiquidity than developed markets, this finding can be attributed to the fact that funds with a high commonality had a greater exposure to this risk factor, thereby providing them with an illiquidity premium. While those funds benefited from the illiquidity premium as they increased their returns, the adverse effects of illiquidity materialized in stress periods when investors were forced to liquidate their positions. Indeed, we show that hedge funds with a high commonality were affected by illiquidity in the post-Lehman period significantly more often than funds with a low commonality.¹

In sum, we provide evidence that through their investment behavior prior to 2007, hedge funds established pre-conditions for posing risks to the financial system, in particular via their exposure to common risk factors and their specific risk exposures. When such risks materialize, funds with a high risk exposure following similar strategies can trigger feedback loops involving asset prices and funding liquidity, as emphasized by Brunnermeier et al. (2009), and adverse shocks in the hedge fund sector can be further transmitted to other financial institutions, an aspect analyzed by Billio et al. (2012).

The rapid growth in the hedge fund industry over the last years and the availability of hedge fund data from commercial data providers such as Hedge Fund Research (HFR) and Lipper TASS, has led to a substantial number of theoretical and empirical papers on hedge funds. Our paper is related to two strands of the literature on hedge funds: (i) papers focusing on hedge funds' risk exposures in general and (ii) papers investigating commonality in risk exposures in particular.

In the first strand of the literature, Chan et al. (2005) develop several new risk measures for hedge funds and provide evidence that the level of systemic risk in the hedge fund industry has increased as a consequence of large capital inflows, higher

¹At the same time, we do not find evidence that high commonality funds used share restrictions to manage their liquidity risk exposures, as less than 20% of high commonality funds had a lockup provision and their redemption notice periods were not significantly different from those of low commonality funds. For an in-depth analysis of the impact of share restrictions on hedge fund performance in both crisis and non-crisis periods, see Schaub and Schmid (2013).

competition for yield among investors and increased illiquidity. Our paper shows that commonality in hedge fund returns increased significantly prior to the recent financial crisis. Boyson et al. (2010) document the existence of contagion in hedge fund returns and show that large adverse shocks to asset and hedge fund funding liquidity make contagion more likely. Akay et al. (2013) show that both funding liquidity (proxied by the TED spread and the margin requirement on S&P 500 futures relative to the level of the index) and investor panic (measured by the VIX index) play a significant role in leading to hedge fund contagion. We provide evidence that due to exposure to common risk factors, hedge funds exhibited negative returns especially after the failure of Lehman Brothers. Sadka (2010), Teo (2011), and Schaub and Schmid (2013) focus on the liquidity risk of hedge funds and Aragon and Strahan (2012) find that the market liquidity of stocks held by Lehman Brothers hedge fund clients fell more after the Lehman failure than otherwise similar stocks. Patton (2009) analyzes the market neutrality of hedge funds and finds that even among those funds being classified as “market neutral”, about 25% exhibit significant correlation with the market that investors seek to avoid. Our result that high commonality funds were strongly affected by illiquidity and negative returns confirms that a substantial proportion of hedge funds did not provide diversification benefits to investors at a time when they were needed most. Bali et al. (2012) investigate the extent to which aggregate risk measures explain the cross-sectional dispersion of hedge fund returns. They find that systematic risk has the greatest role in explaining the cross-section of future fund returns. Eling and Faust (2010) analyze the performance of hedge funds and mutual funds in emerging markets and document that hedge funds increased their equity exposure to emerging markets after 2003, which is consistent with our findings.

Papers in the second strand are most closely related to ours and include Khandani and Lo (2007), Billio et al. (2012), Adrian (2007) and Pericoli and Sbracia (2010). Khandani and Lo (2007) follow the lines of Chan et al. (2005) and further analyze the systemic risk in the hedge fund industry, focusing on the profitability of quantitative long/short equity strategies, especially during August 2007. They find that the asset growth in the long/short equity strategy, the increased leverage and the increased connectedness of hedge funds have contributed to the losses of quantitative hedge funds during this period. A particularly important factor for financial stability is the “degree of connectedness” in the hedge fund industry, which the authors measure using the absolute value of correlations between the different hedge fund indices. Adding to the work of Khandani and Lo (2007), our paper explicitly analyzes one source of the

increased commonality in hedge fund returns, the changes in exposures to specific risk factors over time. Billio et al. (2012) use principal component analysis and Granger-causality tests to measure the connectedness among the returns of hedge funds, banks, broker/dealers, and insurance companies. They find that all four sectors have become highly interrelated over the past decade. While Billio et al. (2012) measure the connectedness of four types of financial institutions, our paper focuses explicitly on hedge funds return commonality. In addition to measuring the commonality degree using the returns of individual funds and fund indices, we examine whether changes in risk factor exposures drove the increase in commonality and investigate the risk profiles of funds with different levels of commonality. Adrian (2007) focuses on the notion of similarity of hedge funds' trading strategies. This similarity is measured by the covariances and correlations of hedge fund index returns and the proportion of variance explained by the first principal component. The author concludes that the increase in correlations among hedge fund returns from 2003 onwards is due to the decline in the volatility of returns. As both covariances and volatilities of hedge fund returns are functions of the funds' risk factor exposures, our paper uses individual hedge fund and hedge fund index returns to analyze whether changes in exposures to specific risk factors drove hedge funds' return commonality.² Pericoli and Sbracia (2010) analyze the correlation between "idiosyncratic" hedge fund index returns over the period from 1995 until 2009. They find that these correlations have increased substantially with the start of the financial crisis in summer 2007. They conclude that prior to the crisis hedge funds invested in new markets such as levered loans and distressed debt and during the crisis a disorderly exit from these crowded trades led to a rise in return correlations. Compared to Pericoli and Sbracia (2010), we use a more comprehensive data set consisting of individual hedge funds including those of the multi-strategy investment category. We focus on the rise in commonality prior to the recent financial crisis, documenting that it doubled from 2003 until end-2006, and compare the risk profiles of the corresponding funds before and during the crisis.

The remainder of the paper is organized as follows. Section 2 describes the hedge

²European Central Bank (2005, 2007) similarly analyze the connectedness of hedge funds, using the term "crowding of trades", which is measured by the median of pairwise correlation coefficients of individual hedge fund returns within a given investment strategy. Pojarliev and Levich (2011) measure the crowding of trades in hedge funds following currency strategies over the period from April 2005 until March 2008, and document that carry trades became a crowded strategy towards the end of their sample period. Stein (2009) develops a theoretical model showing that the "crowded trade" effect, i.e. the inability of traders to condition their behavior on market-wide arbitrage capacity, creates a coordination problem which can in some cases push prices away from fundamentals.

fund data and the risk factors used in our analysis. Section 3 discusses the sources of “connectedness” in hedge fund returns and introduces the concept of commonality we use. It outlines how we measure commonality and how we identify its main driving factor. Section 4 investigates the risk exposure of the hedge funds in the different commonality deciles, focusing on hedge funds’ downside and illiquidity risk exposure before and during the financial crisis, and section 5 concludes.

2 Data

2.1 Hedge fund data

To investigate the commonality in hedge fund returns, we use data from Lipper TASS, one of the main databases used in academic and commercial hedge fund studies. The data set covers the period from January 1994 until June 2009 and includes a total of 13,050 funds before filtering (6,472 funds after filtering), of which 5,684 are classified as “live” and 7,366 as “graveyard”.³ The category of “graveyard” funds consists of hedge funds that stopped reporting to the database at some point during the sample period. TASS provides two types of information that are relevant for the exercise that we conduct in this paper: (i) monthly data on individual hedge fund returns net of all fees and transaction costs and on assets under management and (ii) time-invariant data on hedge 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. TASS classifies hedge 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. Based on these categories, Credit Suisse/Tremont constructs asset-weighted hedge fund style indices which are also provided in the TASS database. In our analysis we differentiate between the commonality across all investment styles using hedge fund index returns and the commonality within each style category using individual fund returns.

In contrast to mutual funds that are legally required to disclose their performance,

³The data filtering procedure consists of dropping hedge funds that belong to the investment strategies “fund of funds”, “options strategy” and “other”, report outlier returns lower (higher) than the 0.05th (99.95th) percentile of the distribution, and report non-monthly return data or have several consecutive missing values in their return series.

hedge funds are largely unregulated and therefore have to disclose only very limited data to financial authorities.⁴ The fact that hedge funds are not allowed to advertise to the public appears to create an incentive to voluntarily report information to databases such as TASS in order to attract potential investors. As a consequence of this voluntary reporting, there are natural biases in all hedge fund databases. The literature investigated survivorship bias (Fung and Hsieh 1997, Brown et al. 1999, Liang 2000), termination and self-selection bias (Ackermann et al. 1999), backfilling and illiquidity bias (Asness et al. 2001, Getmansky et al. 2004), and look ahead bias (Baquero et al. 2005). In addition, Bollen and Pool (2009) studied the distribution of hedge fund returns and found that the number of small gains exceeds the number of small losses which they interpreted as evidence of misreporting. To mitigate potential survivorship bias, we use both “live” and “graveyard” funds in our analysis.

2.2 Hedge fund risk factors

To analyze the commonality in the returns of the assets in which hedge funds have invested and to identify the drivers of hedge funds’ commonality, we use a set of 12 risk factors (summarized in Table 1) that capture a broad range of asset classes.⁵ When choosing these risk factors, we follow the approach of previous studies (see, e.g., Bollen and Whaley (2009), Buraschi et al. (2009), Patton and Ramadorai (2013)) and use the seven-factor model of Fung and Hsieh (2004). In order not to be limited to equity-oriented risk factors that focus only on U.S. equities, we use the returns on the MSCI North America index (MSCINA), MSCI Europe index (MSCIEU), MSCI Pacific index (MSCIPC), and MSCI Emerging Market index (MSCIEM). In addition, the set of factors includes three trend-following risk factors, namely the returns on portfolios of lookback straddle options on bonds (PTFSBD), currencies (PTFSFX) and commodities (PTFSCOM), and two bond-oriented risk factors, namely the monthly change in the 10-year U.S. Treasury constant maturity yield (BD10RET) and the monthly change in the Moody’s Baa yield less the 10-year U.S. Treasury constant maturity yield (BAAMTSY). In addition, we include two risk factors, which have been shown to explain a substantial proportion of hedge fund returns (see, e.g., Bondarenko (2007b), Pojarliev and Levich (2011)), the return on the Deutsche Bank G10 Currency Carry Total Return index

⁴Institutions with more than 100 million USD under management are required to disclose their holdings in stocks and a few other securities (as specified in the list of “section 13(f) securities”) to the U.S. Securities and Exchange Commission (SEC) each quarter on form 13F.

⁵Importantly, this paper only aims to explain returns ex post, and not to forecast them; for an analysis of the predictability of hedge fund returns see Wegener et al. (2010) and the literature therein.

(CARRY) and the return on a variance swap (VARSWAP).⁶ Finally, two recent papers (Sadka (2010) and Teo (2011)) have shown that liquidity risk, in the sense of market-wide liquidity as an undiversifiable risk factor, is an important determinant of hedge fund returns. We thus include the monthly innovations of the Pastor and Stambaugh (2003) liquidity measure (LIQUIDITY) as an additional risk factor.

3 Commonality in hedge fund returns

As hedge funds are important market participants, the high degree of “connectedness” of hedge funds can impact financial stability, which has been stressed in several studies (Chan et al. (2005), Garbaravicius and Dierick (2005), Khandani and Lo (2007), Adrian (2007), European Central Bank (2007), Pericoli and Sbracia (2010), Pojarliev and Levich (2011), Billio et al. (2012)).⁷ The “connectedness” of hedge funds can be attributed to the following channels: (i) exposure to the same risk factors, (ii) mutual financial linkages, (iii) funding liquidity, (iv) information contagion, and (v) investor “panic”. The first channel concerns the asset side of hedge funds’ balance sheets and simply asserts that hedge funds investing in the same or correlated assets will experience co-movements in their returns. The second channel is more linked to the liability side of hedge funds’ balance sheets and may cause correlated returns in case a common primary broker fails or tightens funding conditions, for example. Funding liquidity, information contagion and investor panic channels become particularly relevant during the times of stress (see, e.g., Akay et al. (2013)). Funding problems of hedge funds may force them to liquidate their assets, which may adversely affect prices of those assets and force more liquidations, causing further price declines. These “liquidity spirals” can impact the prices of all assets held by hedge funds, resulting in correlated returns. News of one fund’s distress can make investors update their valuations of other funds, leading to information contagion. Finally, high stress and volatility in financial markets may trigger a flight-to-safety by hedge fund investors, further aggravating adverse funding

⁶The Bloomberg ticker for the Deutsche Bank G10 Currency Carry Total Return index is DBHT10UF Index. The return on a variance swap is obtained as the difference between the realized variance over the past month and its delivery price at the beginning of the month. As the delivery price is not observable, we use the implied variance given by the VIX squared normalized to 21 trading days. The realized variance of the S&P 500 index is computed from daily index data for a given month.

⁷Having the same phenomenon in mind, terminology used in the papers differs: while Khandani and Lo (2007) and Billio et al. (2012) explicitly refer to network theory and use the term “connectedness”, Adrian (2007) refers to the “similarity of hedge fund strategies” and “co-movement”, and Garbaravicius and Dierick (2005), European Central Bank (2007), Pericoli and Sbracia (2010) and Pojarliev and Levich (2011) use the term “crowded trades”.

liquidity and return dynamics.

In this paper, we first measure the extent to which hedge fund returns are driven by common factors, which we refer to as “commonality”. We then analyze the drivers of commonality in hedge fund returns during rather tranquil times before the crisis (2003-2006). During this time period, channels (ii)-(v) appear to be less relevant as economic conditions were benign and funding conditions loose. We therefore explore the role of the exposures to the same risk factors in driving commonality.

3.1 Measuring the degree of commonality

There are several potential ways to estimate the commonality in hedge fund returns such as using the Pearson or Spearman correlation, the dynamic conditional correlation developed by Engle (2002) or copula-based dependence measures (Ignatieva and Platen (2010)). Instead of relying on one of those measures, which involves estimating the respective quantity for each pair of individual hedge funds or hedge fund indices and then aggregating them, we use the Principal Component Analysis (PCA). PCA has a major advantage in that it directly provides us with the two relevant pieces of information. First, the fraction of variance in the data set explained by each of the principal components and, second, the loadings on these components, which reflect how strong each fund’s return is associated with them.⁸

The PCA transforms the original variables into a new set of variables, the principal components, which are ordered so that the first few retain most of the variation present in all of the original variables (Jolliffe (2002)). As the first principal component is the linear combination of the original variables with maximal variance, the proportion of variation in the data set explained by this common component can be considered as the most natural measure of commonality. Thus, by definition, our measure of commonality reflects the degree of the exposure of hedge funds to the most important common factor. Another characteristic of the commonality measured based on the PCA is that it does not differentiate between long and short exposure but instead represents an absolute level of exposure. As the PCA does not provide an interpretation of the first principal component, in section 3.2, we further analyze the obtained common factor to identify its drivers.

For estimating and testing the arbitrage pricing theory (APT) of Ross (1976), it is essential to specify the number of pervasive factors in asset returns. One important

⁸While we rely on the PCA to measure commonality, we use several alternative measures as a robustness check, which yield similar results. The results are available upon request from the authors.

issue is the estimation of the appropriate number of factors which has been extensively discussed in the literature (Brown (1989), Connor and Korajczyk (1993)). In particular, Brown (1989) finds that the PCA identifies a single dominant factor in an economy in which K factors are priced and contribute equally to the returns. The first principal component in this case is a linear combination of the K factors and in this sense accurately reflects the underlying factors. It would, however, be misleading to conclude from this result that the first principal component represents only one underlying factor. For our purpose, the PCA serves as a statistical tool to estimate the degree of commonality over a specific time period and to assess whether the returns of individual funds or fund indices are strongly correlated with the common factors. To identify the risk factors which constitute the first principal component, and which may very well represent several underlying risk factors, in section 3.2, we run style regressions using portfolios formed on the basis of hedge funds' commonality degree. Thus, focusing on the first principal component in our analysis does by no means indicate the number of underlying priced risk factors in hedge fund returns.

To measure the degree of commonality in the overall hedge fund industry, we use the 10 major Credit Suisse/Tremont hedge fund indices, without the fund of funds category. As a benchmark, we also measure the commonality in the returns of the 12 risk factors presented in section 2.2. In both cases, we use a rolling window of 12 months to obtain a time-varying measure. Our sample period extends from April 1994 to June 2009. Figure 1 shows the commonality in hedge fund and risk factor returns as the proportion of variation in each data set explained by the first principal component. The overall evolution of the commonality in hedge fund returns obtained from our measure is very similar to that of the absolute correlation measure used in Khandani and Lo (2007) and the PCA measure presented in Adrian (2007).⁹

We find that, with regard to the pattern of the commonality in hedge fund returns, the sample period can be separated into three major sub-periods as shown in Figure 1. The first sub-period extends from January 1996 until August 1998 and is characterized by a strong increase in commonality, in particular in the course of the collapse of Long-Term Capital Management (LTCM). The second sub-period is from September 1998 until April 2002 and thus covers the buildup and the burst of the technology bubble and shows a decline in commonality. The third sub-period covers the upmarket period from May 2002 until December 2006 and exhibits a gradual increase in commonality.

⁹We have also measured the evolution over time of commonality using the returns of about 6,400 individual hedge funds and obtained very similar results which are available upon request from the authors.

Particularly striking is the divergence between the commonality in hedge fund and risk factor returns during the third sub-period. While the commonality in hedge fund returns increased substantially, the commonality in the returns of the 12 risk factors used to model hedge funds' risk exposure remained unchanged or decreased. This suggests that the increase in hedge funds' commonality during this sub-period is not related to a kind of "phase-locking" behavior whereby assets in which hedge funds invest suddenly become more synchronized. Our results are robust to the choice of the risk factors (eight standard asset classes of Fung and Hsieh (1997)) as well as to the length of the rolling time window (24 and 36 months).¹⁰

It is likely that over time different factors were responsible for changes in the degree of hedge funds' commonality. In the following, we focus our analysis on the third sub-period. We argue in the next subsection that this period exhibits specific characteristics which reduce the impact of some potential factors and thus makes it easier for us to narrow down the major driving factors of commonality. In addition, it is the period which exhibits the largest increase in commonality during the entire sample period, taking place gradually and over a relatively long time. Last but not least, it is directly followed by a global financial crisis and thus provides an ideal setting to study the performance of hedge funds with different degrees of commonality during a period of extreme stress.

3.2 Identification of factors driving commonality

In the previous section, we documented a significant increase in the commonality in hedge fund returns between 2003 and end-2006. A natural question that arises is which factors drove this increase in hedge funds' commonality.

To motivate our approach, it is useful to consider the linear Pearson correlation of two simple return generating processes of hedge funds. The following two equations represent simplified return generating processes of two hedge funds i and j :

$$R_{i,t} = \alpha_i + \beta_i \Lambda_t + \epsilon_{i,t}$$

$$R_{j,t} = \alpha_j + \beta_j \Lambda_t + \epsilon_{j,t}$$

where Λ_t is a systematic risk factor such as the S&P 500 to which both hedge funds have exposure, as captured by the corresponding beta coefficient. Based on these two return processes, the linear Pearson correlation of the returns of the two hedge funds is

¹⁰The results are available upon request from the authors.

given by:

$$\text{Corr}(R_{i,t}, R_{j,t}) = \frac{\beta_i \beta_j \sigma_\lambda^2}{\sqrt{\beta_i^2 \sigma_\lambda^2 + \sigma_{\epsilon_i}^2} \sqrt{\beta_j^2 \sigma_\lambda^2 + \sigma_{\epsilon_j}^2}} \quad (1)$$

where σ_λ^2 is the variance of the risk factor Λ_t and σ_ϵ^2 is the variance of the idiosyncratic error.

Computing the partial derivatives of equation (1) reveals that, all else being equal, an increase in the absolute value of the correlation between the returns of funds i and j can be due to three effects: (i) an increase in the absolute value of the beta coefficient of fund i or j , (ii) an increase in the variance of the systematic risk factor Λ , or (iii) a decrease in the variance of the idiosyncratic error ϵ_i or ϵ_j . Since we are interested in identifying the major driver of the rise in hedge funds' commonality during the upmarket period from 2003 until end-2006, a period where the overall market volatility declined, the second effect can almost be ruled out.¹¹ To examine the potential of the third effect, we regress hedge fund index returns on the 12 risk factors presented in section 2.2 and compute the variance of the obtained residuals (i.e., the idiosyncratic error) using a rolling time window. We find that the variance of the idiosyncratic error remained mostly unchanged or increased during this period. We conclude that it is unlikely that the rise in hedge funds' commonality was due to the third effect. In what follows, we thus focus on the first effect, i.e., on the increase in the absolute value of hedge funds' exposure to a common risk factor.

To measure hedge funds' exposure to a common risk factor, we rely on the PCA as it gives us loadings on the common component. The loadings reflect how strong the corresponding hedge fund is associated with the common component. We thus perform a PCA on individual hedge funds using return data from October 2003 until September 2006, which approximately corresponds to the third sub-period shown in Figure 1. Our sample includes about 1,400 hedge funds, which report return data over the entire sample period of 36 months. We then rank the hedge funds with respect to their loading on the first principal component (PC1-loading), form decile portfolios and compute the average return of these decile portfolios at each point in time over the sample period. In what follows, we refer to hedge funds belonging to decile 1 (decile 10), which have the lowest (highest) PC1-loading, as those with the lowest (highest) degree of commonality.

¹¹For example, the VIX index, an option-implied volatility index, was at very low levels during this period; the same holds true when looking at equity correlations, as measured by S&P 500 1-month correlations.

In the next step, we try to identify the common factor to which hedge funds across the decile portfolios were exposed over the period from October 2003 until September 2006. We regress the monthly excess returns $R_{d,t} - R_{f,t}$ of each decile portfolio $d = \{1, \dots, 10\}$ on the 12 risk factors described in section 2.2 in the following way.¹²

$$\begin{aligned} R_{d,t} - R_{f,t} = & \alpha_d + \beta_d^1 \text{MSCINA}_t + \beta_d^2 \text{MSCIEU}_t + \beta_d^3 \text{MSCIPC}_t + \beta_d^4 \text{MSCIEM}_t \\ & + \beta_d^5 \text{PTFSBD}_t + \beta_d^6 \text{PTFSFX}_t + \beta_d^7 \text{PTFSCOM}_t \\ & + \beta_d^8 \text{BD10RET}_t + \beta_d^9 \text{BAAMTSY}_t \\ & + \beta_d^{10} \text{CARRY}_t + \beta_d^{11} \text{VARSWAP}_t + \beta_d^{12} \text{LIQUIDITY}_t + \epsilon_{d,t}. \end{aligned} \quad (2)$$

To avoid spurious results, we follow McGuire and Tsatsaronis (2008) and Pericoli and Sbracia (2010) and instead of using the entire set of risk factors as regressors for each decile portfolio we use a stepwise regression procedure that recursively includes and excludes risk factors, and retains them only if they are at least statistically significant at the 5% level.¹³

The results shown in Table 2 reveal several interesting aspects. First, decile portfolios with a high commonality are mostly exposed to equity-oriented risk factors and to the variance risk factor, while decile portfolios with a low commonality have only a small or no exposure to equity-oriented risk factors. The negative exposure of hedge funds to the variance risk factor supports the findings of Bondarenko (2007a), who argues that hedge funds earn about 7% annually by shorting the variance risk. Second, the magnitude of the exposure to the MSCI Emerging Market index increases almost monotonically with the increasing commonality. Put differently, hedge funds with a high degree of commonality (decile 10) have a much higher long-exposure to emerging market equities than funds with a low degree of commonality (decile 1). Third, the proportion of variation in hedge fund returns explained by our set of risk factors increases with an increasing commonality. This finding indicates that hedge funds with a low (high) degree of commonality tend to follow relative-value (directional) investment strategies which are less (more) correlated to market risk factors. Fourth, in contrast to Sadka (2010) and Teo (2011), we do not find a significant loading on the liquidity

¹²This procedure is similar to the one employed by Fung and Hsieh (1997) who use the PCA and hedge funds most highly correlated with these principal components to extract five dominant investment style factors.

¹³The results using all 12 regressors, presented as a robustness check in Table 3, are qualitatively similar.

factor.¹⁴ This could be due to the fact that the Pastor and Stambaugh (2003) liquidity measure is based on order flow of stocks traded on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX),¹⁵ while the investment strategies of hedge funds are considered to be much more diverse.¹⁶

These results are qualitatively confirmed through the decomposition of the hedge funds belonging to each decile portfolio into the 10 major TASS investment strategies as reported in Table 4. While the high commonality decile portfolio (decile 10) consists mostly of hedge funds from the Long/Short Equity Hedge, the Multi-Strategy and the Emerging Markets category, the low commonality decile portfolio (decile 1) is a lot more diverse, mostly consisting of hedge funds from the Equity Market Neutral, the Long/Short Equity Hedge, the Fixed Income Arbitrage and the Managed Futures category. The proportion of hedge funds belonging to equity-oriented investment strategies, in particular to the Long/Short Equity Hedge category, rises with an increasing degree of commonality.

Overall, our findings suggest that the common factor in hedge fund returns identified by the PCA over the period from 2003 until end-2006 was an emerging market equity-oriented risk-factor. As emerging market equities were delivering high returns over this period, it is perhaps not surprising that hedge funds were largely exposed to this risk factor in order to deliver high returns to their investors. The negative exposure of hedge funds to the variance risk factor does not contradict this interpretation. As hedge funds can obtain the negative exposure to the variance risk both directly through trades in variance swaps and other derivatives and indirectly by employing relative-value and event-driven arbitrage strategies, it is difficult to infer the employed trading strategy from this finding. In any case, shorting the variance risk during this period with a declining volatility provided hedge funds with an additional risk premium and thus appears reasonable.

After having broadly identified the common factor that explains a large proportion of hedge fund returns during the period from 2003 until end-2006, we now study whether, and to what extent, the exposure of hedge funds to this risk factor varied over time. We

¹⁴We do find a significant positive liquidity loading for funds with a low degree of commonality (decile 1) using the stepwise regression, but it turns out to be not significantly different from zero when including all risk factors in the regression.

¹⁵The same holds true for the Acharya and Pedersen (2005) and the Sadka (2006) measures also used in the two aforementioned papers.

¹⁶A different concept is the asset-specific liquidity characteristic (i.e., the liquidity level), which is difficult to measure for hedge funds since their portfolio holdings are not available. Getmansky et al. (2004) propose to use the return serial correlation as a proxy for fund-specific liquidity levels, which we use in section 4.2 to infer the level of illiquidity in the different commonality deciles.

thus perform the same stepwise regression for each decile portfolio as outlined before, but this time using a rolling estimation approach with a 36-month rolling window. The resulting time-varying beta coefficients of the MSCI Emerging Market index are plotted in Figure 2. They reveal, first, the differences in the overall degree of exposure to emerging market equities between the different decile portfolios, thus confirming results from Table 2. Second, and more importantly, the graph shows that the long-exposure of the deciles with a high commonality (decile 9 and 10) increased substantially from 2004 until end-2006. We also investigate the evolution of the beta coefficient of the MSCIEM risk factor at the individual fund level and find that 20% of the hedge funds significantly increased their exposure to emerging market equities over this period, with 80% of those funds having no significant exposure prior to 2004.¹⁷ The results are in line with Eling and Faust (2010) who find that hedge funds reporting to be active in emerging markets increased their exposure to equities in emerging Asia and emerging Europe from 2003 onwards. They also mention that the high explanatory power of their emerging market model may be a result of many hedge funds following a long-only investment strategy. As we have broadly identified emerging market equities as the common component of hedge fund returns during the upmarket period from 2003 until end-2006, the increase in the beta coefficient of the MSCIEM risk factor can be considered as the major factor that has driven the increase in commonality from 2004 until end-2006.

If emerging market equities were indeed the major risk factor driving hedge fund returns over this period, as suggested by the previous analysis, then regressing hedge fund returns on this common risk factor and computing the residuals would remove the majority of the variation in fund returns. We thus regress the return series of each decile portfolio separately on each of the 12 risk factors using a 36-month rolling estimation window and compute the residuals. Then we perform a PCA on both the raw returns of the decile portfolios and on the obtained residuals to compare the two measures of commonality. The results shown in Figure 3 reveal that we obtain a lower degree of commonality during the period from 2004 until end-2006 only when using the equity-oriented risk factors in the style-type regressions. But only in the case of the MSCIEM risk factor the degree of commonality does not increase from 2004 onwards. Overall, we interpret these findings as a strong evidence that the increase in the exposure to emerging market equities over the period from 2004 until end-2006 has been the major driver of the rise in hedge funds' commonality over this period.

¹⁷The results are available upon request from the authors.

4 Commonality and risk exposure

We now characterize in more detail the risk exposure of hedge funds in the different commonality deciles. The question we address is whether funds following rather different investment strategies (low commonality) have a comparable risk profile to those funds following more similar strategies (high commonality). This is an important aspect because funds with a similar strategy having at the same time a high risk exposure have a potential to trigger powerful feedback loops involving asset prices and funding liquidity once the risk materializes (Brunnermeier et al. (2009)). We focus on two types of risk exposure: downside risk exposure and illiquidity risk exposure.

4.1 Downside risk exposure

As outlined by the Financial Stability Forum (2007), hedge fund failures cause credit losses to their counterparties such as prime brokers and banks, which may in turn adversely affect their function as financial intermediaries (e.g., to channel credit to the real economy). The distress risk of a hedge fund is directly related to its downside or tail risk exposure (Liang and Park (2010)). Brunnermeier and Pedersen (2009) show that even small speculator losses can lead to higher margins, rapid asset sales and reduction in mark-to-market wealth, which in turn may lead to additional losses and potential spillovers to other asset classes. To quantify the tail risk exposure of hedge funds from the different commonality deciles, we use the following downside risk measures: semi-deviation, Value-at-Risk, expected shortfall, and tail risk in returns. These measures were shown to have a considerable explanatory power for the cross-sectional variation in hedge fund returns and for hedge fund failures (Bali et al. (2007), Liang and Park (2007, 2010)).

Semi-deviation, proposed by Estrada (2000) as an alternative risk measure to the beta, considers standard deviation solely over negative outcomes and is of interest because investors only dislike downside volatility. It is defined as

$$\text{Semi-deviation}_t = \sqrt{E_t\{\min[(R_t - \mu), 0]^2\}},$$

where R_t denotes the return at time t and μ is the average return.

Value-at-Risk (VaR) is one of the most widespread tools used by financial institutions to measure market risk. If $R_{t+\tau}$ denotes the portfolio return during the period between t and $t + \tau$, $F_{R,t}$ denotes the cumulative distribution function (CDF) of $R_{t+\tau}$

conditional on the information available at time t , and $F_{R,t}^{-1}$ is the inverse function of $F_{R,t}$, then the portfolio VaR as of time t is given by

$$VaR_t(\alpha, \tau) = -F_{R,t}^{-1}(\alpha),$$

where α refers to the confidence level $1-\alpha$ and τ is the time horizon. In our analysis, we use a 95% confidence level ($\alpha = 0.05$) and a time horizon τ of one month. We estimate the VaR using the Cornish-Fisher (1937) expansion (see Liang and Park (2007) for details).

Expected shortfall (ES) is the expected loss greater than or equal to the VaR . It is given by

$$ES_t(\alpha, \tau) = -E_t[R_{t+\tau} \mid R_{t+\tau} \leq -VaR_t(\alpha, \tau)].$$

We estimate the 95% ES by first computing the 95% VaR as described above and then taking the average of the returns less than or equal to this value. As in the case of the VaR , we multiply the resulting value by minus one to avoid confusion.

Tail risk (TR) measures the deviation of losses larger than or equal to the VaR from the mean. It is defined as

$$TR_t(\alpha, \tau) = \sqrt{E_t[(R_{t+\tau} - E_t(R_{t+\tau}))^2 \mid R_{t+\tau} \leq -VaR_t(\alpha, \tau)]}.$$

As in the case of the ES, we estimate TR based on the Cornish-Fisher VaR .

In addition, we consider the skewness in returns as a measure of downside risk. Chen et al. (2001) investigate factors that help to forecast skewness in the returns of individual stocks. They find that negative skewness is most pronounced in stocks that have experienced an increase in trading volume and positive returns. The authors argue along the lines of the stochastic bubble model of Blanchard and Watson (1982) that negative skewness reflects the expectation of the burst of a previously formed bubble and the associated large negative returns. This is consistent with the findings of Bates (1991), who interprets the negative skewness in S&P 500 index futures prior to August 1987 as fears of a market crash.

We now examine the relationship between commonality in hedge fund returns and funds' downside risk. In the first step, we compute various summary statistics of the returns of each decile portfolio, including the downside risk measures presented above, as well as risk-adjusted performance measures. We consider the following performance measures: the Sharpe ratios, alphas, information ratios (the t -statistics of alphas, which

takes into account the estimation error in alphas, as in Kosowski et al. (2006)) and R -squareds (used in Titman and Tiu (2011)). The latter three measures are derived from a regression of decile portfolio excess returns on those of the 12 risk factors summarized in Table 1. Instead of performing a rolling PCA to continuously update the composition of the deciles, we use decile portfolios that are formed on the basis of a PCA over the period from October 2003 until September 2006 as described in section 3.2. They reflect the dispersion in the commonality of hedge funds during a period where the overall degree of hedge funds' commonality was high. We investigate the return characteristics of these decile portfolios in two different market regimes, namely during the upmarket period from October 2003 until June 2007 and during the financial crisis period from July 2007 until June 2009. To test the statistical significance of the differences in the summary statistics between decile portfolio 10 (high commonality) and decile portfolio 1 (low commonality), we use a bootstrap approach (see appendix for details).

Results are reported in Table 5. Panel A shows that during the upmarket period, decile portfolio 10 had a significantly higher average return and a significantly higher standard deviation than decile portfolio 1.¹⁸ As the standard deviation of decile portfolio 10 was more than three times as high as that of decile portfolio 1, while the return was only twice as high, the Sharpe ratio of decile portfolio 10 was significantly lower than that of decile portfolio 1. Similarly, funds in the highest commonality decile had lower alphas, lower information ratios and higher R -squareds compared to funds in the lowest commonality decile. The difference between high and low commonality funds became particularly pronounced during the financial crisis (see Panel B). Decile portfolio 10 had a significantly lower average return, higher standard deviation and lower Sharpe ratio compared to decile portfolio 1. The difference in alphas increased by a factor of 10 compared to the pre-crisis period. Moreover, while funds with a low commonality were still able to generate a positive alpha during the crisis, funds with a high commonality had a negative alpha.

Interestingly, decile portfolio 10 had a negative skewness while decile portfolio 1 had a positive skewness during the upmarket period, with the difference being statistically significant. Following Bates (1991), we interpret the negative skewness in the high commonality portfolio (decile 10) as an indicator of crash expectations. In section 3.2, we found that hedge funds belonging to decile 10 had a strong exposure to emerging market equities during the upmarket period from 2003 until end-2006. As

¹⁸As the first principal component represents the linear combination of the original variables with maximal variance, the standard deviation of the returns rises by construction with an increasing PC1-loading.

emerging market equities increased substantially over this period, one could argue that the negative skewness in the returns of decile portfolio 10 may reflect the expectation of the burst of a potentially formed equity market bubble and the resulting negative returns. In addition, the downside risk of decile portfolio 10 during the upmarket period, captured by semi-deviation, Value-at-Risk, expected shortfall, and tail risk, was significantly higher than that of decile portfolio 1. Panel B shows that during the financial crisis, the downside risk of decile portfolio 10, as measured by semi-deviation, Value-at-Risk and expected shortfall, was significantly higher than that of decile portfolio 1.

In the second step, we compute the same summary statistics but this time using the returns of the individual hedge funds in each decile. This procedure intends to make sure that our main results are not simply a spurious effect of using decile portfolios in the study. To be included in the analysis, every hedge fund needs to have at least 24 monthly observations. We then compute the summary statistics separately for each fund and take the median of all funds in a given decile as the final measure. The results reported in Table 6 are similar to those of the decile portfolios. During the upmarket period, hedge funds in the highest commonality decile had a significantly higher average return, higher R -squared, lower skewness and higher downside risk compared to funds in the lowest commonality decile.¹⁹ During the financial crisis period, high commonality funds delivered a significantly lower return, and performed significantly worse according to all risk-adjusted measures compared to low commonality funds. They also had a significantly higher downside risk according to all four risk measures we use.

In the third step, we investigate whether the downside risk of hedge funds increased with the rise in commonality from 2004 until end-2006. We select all funds in a given decile that have observations over the entire period from February 2002 until December 2006. For each of these funds, we compute the skewness and the semi-deviation for two subsamples, first over the 24 months ending in January 2004 and second over the 24 month ending in December 2006. To test the statistical significance of the differences between both subsamples, we use a bootstrap approach. The results are reported in Table 7. Panel A shows that in the high commonality decile (decile 10) 24.36% of funds faced a significant increase in negative skewness from January 2004

¹⁹While we do not find statistically significant differences in the median alphas and information ratios before the crisis, these differences are statistically significant when looking at the right tail (e.g., the 75th percentile) of the cross-sectional distribution of alphas and their t -statistics, with high commonality funds exhibiting lower alphas and lower information ratios. Results are available upon request from the authors.

until December 2006, while in the low commonality decile (decile 1) the corresponding share of funds was 11.69%. The ratio of the two shares equals 2.08 and is significantly higher than 1, implying that the share of funds with an increase in negative skewness was significantly higher in the high commonality decile. The results are even more pronounced when semi-deviation is used to capture downside risk. Panel B reveals that the share of hedge funds with a significant increase in semi-deviation from January 2004 until December 2006 was 30.77% in the high commonality decile (decile 10) and 6.40% in the low commonality decile (decile 1). The ratio of the two shares equals 4.74 and is significantly higher than 1.

In sum, hedge funds with a high degree of commonality had a significantly higher downside risk than funds with a low degree of commonality both during the upmarket and the financial crisis period. Additionally, over the period from January 2004 until December 2006, funds with a high degree of commonality exhibited an increase in downside risk significantly more often than funds with a low degree of commonality. We attribute the higher downside risk of funds with a high degree of commonality to their greater emerging market exposure.

4.2 Illiquidity risk exposure

Hedge funds may also pose risks to other financial institutions through disrupting market functioning, which is a consequence of their role as key players in certain markets. If they are suddenly forced to liquidate their positions, this is likely to cause a sharp deterioration in market liquidity. The more illiquid their portfolio, the larger the price impact of a forced liquidation, which can erode funds' risk capital very quickly. To gauge the illiquidity risk exposure of hedge funds' investments, we use the first-order autocorrelation coefficient as proposed by Getmansky et al. (2004) and Khandani and Lo (2011). The economic rationale for this measure is that in an informationally efficient market, price changes must be unforecastable if they fully incorporate the information of all market participants. However, as a consequence of various market frictions, serial correlation arises in asset returns which cannot be exploited by trading strategies due to the presence of these frictions. Thus, the degree of serial correlation can be regarded as a proxy for the illiquidity exposure of the corresponding asset.²⁰

To examine the relationship between commonality in hedge fund returns and funds'

²⁰We have also performed the analysis using the Getmansky et al. (2004) smoothing parameter and found results to be very similar to those based on the autocorrelation (the correlation between the two measures is equal to -0.80 in our sample). Results are available upon request from the authors.

illiquidity risk, we proceed in the same way as for the downside risk. In the first step, we compute the 1st-order autocorrelation of the returns of the decile portfolios and of the individual funds in each decile. The results that cover the upmarket period from October 2003 until June 2007 and the financial crisis period from July 2007 until June 2009 are reported in Table 8. We find that in both periods the difference in illiquidity between the high and the low commonality decile portfolio was not statistically significant. However, when analyzing the individual hedge funds in each decile, we find that funds in the highest commonality decile (decile 10) had a higher degree of illiquidity than funds in the lowest commonality decile (decile 1) in both periods. In particular, during the upmarket period from October 2003 until June 2007, the median autocorrelation of the funds in decile 10 was 0.16, while it was 0.07 in decile 1. During the financial crisis period from July 2007 until June 2009, the median autocorrelation of the funds in decile 10 was 0.31, while it was 0.17 in decile 1. In both periods, the difference in autocorrelation was significantly positive, implying that hedge funds with a higher commonality had a higher degree of illiquidity.²¹ This result is not surprising. According to our findings in section 3.2, hedge funds in the high commonality decile had a strong exposure to emerging market equities. Since emerging market equities generally exhibit a higher illiquidity than developed market equities (see, e.g., Lesmond (2005) and Bekaert et al. (2007)), hedge funds investing in this asset class also have a higher degree of illiquidity.²²

As the adverse effects of illiquidity only materialize when investors are forced to liquidate their positions, we investigate in the second step the extent to which the illiquidity in the different deciles increased after the collapse of Lehman Brothers in September 2008. We thus aim to directly test the impact of an asset price shock on the liquidity of the respective portfolio in relation to its degree of commonality. Following Adrian (2007), we expect that the larger the degree of commonality in hedge fund returns, the higher the risk of liquidity drying up in the corresponding markets when hedge funds have to simultaneously close out their positions. Our analysis proceeds

²¹Schaub and Schmid (2013) document that funds with higher illiquidity (proxied by share restrictions) had provided an illiquidity premium for investors in the pre-crisis period. During the crisis, more illiquid funds experienced a relatively poor performance, indicating that the pre-crisis illiquidity premium turned into an illiquidity discount.

²²We also analyzed the characteristics of funds across the commonality deciles to see whether their share restrictions differ. We find that high commonality funds have one of the lowest percentages of funds with a lockup provision (as for their redemption notice periods, those are not significantly different from low commonality funds). This finding indicates that high commonality funds did not use share restrictions to manage their liquidity risk exposures (finding similar to Teo (2011), Sadka (2006, 2010)).

as follows. We select all hedge funds in a given decile that have observations over the entire period from November 2007 until June 2009. We split the sample in two subsamples which cover the 10 months before and after the Lehman collapse. For each hedge fund in a given decile, we then compute the return autocorrelation separately for both subsamples and determine how many funds in each decile faced a significant illiquidity in the post-Lehman sample.

The results are reported in Table 9. Panel A shows that in the highest commonality decile (decile 10) 13.64% of funds had a significant illiquidity in the post-Lehman period only, as measured by the 1st-order autocorrelation, while in the lowest commonality decile (decile 1) the share of funds was 5.26%. The ratio of the two percentages equals 2.59 and is not significantly higher than 1, implying that the share of funds facing illiquidity in the post-Lehman period was not significantly different in both deciles. However, when comparing the share of funds in the different deciles, it seems that the majority of funds with a significant degree of illiquidity in the post-Lehman period were in deciles with a higher degree of commonality (deciles 6-10). Thus, in Panel B, we report the results for two groups of deciles, namely the lower commonality deciles (deciles 1-5) and the higher commonality deciles (deciles 6-10). It turns out that in deciles with a higher commonality (deciles 6-10) 20.54% of funds had a significant illiquidity in the post-Lehman period, while the share of funds in the low commonality deciles (deciles 1-5) was only 11.71%, with the ratio of these shares being significantly higher than 1. Our results suggest that hedge funds with a high degree of commonality were affected by illiquidity in the post-Lehman period significantly more often than funds with a low degree of commonality.

5 Conclusion

The recent financial crisis revealed that connectedness of financial institutions is an important determinant of financial stability. In this paper, we have studied the connectedness of hedge funds arising from the commonality in their returns and analyzed the risk exposure of hedge funds with different degrees of commonality. Commonality is measured using Principal Component Analysis (PCA), in particular by the proportion of variation in the data set explained by the first principal component.

We find that the commonality in hedge fund returns increased significantly over the period from 2003 until end-2006. Hedge funds with a high commonality were particularly exposed to equity-oriented risk factors, while funds with a low commonality had

only a small or no exposure to equity-oriented risk-factors. Most importantly, funds' exposure to emerging market equities increased almost monotonically with an increasing level of commonality. Moreover, funds with a high commonality had a higher downside risk, captured by negative skewness and semi-deviation, and a higher illiquidity risk, captured by return autocorrelation, than funds with a low commonality. In the post-Lehman period, hedge funds with a high commonality were affected by illiquidity significantly more often than funds with a low commonality.

Based on our empirical analysis, we conclude that during the upmarket period from 2003 until end-2006 hedge funds substantially increased their investment into assets with a high downside and illiquidity risk exposure to provide investors with a higher return and attract new capital. As a consequence, the commonality in hedge fund returns increased and during the subsequent financial crisis those funds were affected disproportionately by illiquidity and exhibited negative returns.

Due to their high commonality, those funds did not provide the diversification benefits to the financial system and to investors that hedge funds are generally considered to offer. Our findings underscore hedge funds' risk potential stemming from exposure to common risk factors. Such increased exposure deserves careful monitoring, as it could pose a threat to the stability of the entire financial system, once risks materialize.

A Bootstrap approach

In order to test the statistical significance of the differences of various summary statistics between decile 10 (high commonality) and decile 1 (low commonality), we use a bootstrap approach. Since our statistics are based on hedge fund returns, which are subject to short sample sizes, serial correlation, volatility clustering, and non-normality, a block-bootstrap appears most appropriate. We follow Kosowski et al. (2006), Fung et al. (2008) and Patton (2009), and use the stationary bootstrap of Politis and Romano (1994) which allows for weakly dependent correlation over time. Subsequently, we describe the procedure used for each analysis in section 4.

Summary statistics of decile portfolio returns

To test the statistical significance of the differences in the summary statistics between decile portfolio 10 (high commonality) and decile portfolio 1 (low commonality), as reported in Table 5, we resample the return series of each decile portfolio using 10,000 bootstrap replications. For each bootstrap sample and each decile portfolio, we then compute the respective summary statistic (i.e. the mean, standard deviation, skewness, etc.). Subsequently, we compute the high-low difference for each bootstrap sample. The resulting distribution of the high-low difference can be used to obtain p -values. To test whether the high-low difference of the alpha, the alpha's t -statistic and the R^2 is statistically significant, we use residual resampling as in Kosowski et al. (2006).

Summary statistics of individual hedge fund returns across deciles

To test the statistical significance of the differences in the median of the summary statistics between decile 10 (high commonality) and decile 1 (low commonality), as reported in Table 6, we resample the return series of each hedge fund in a given decile using 1,000 bootstrap replications per fund. For each bootstrap sample and each hedge fund, we then compute the respective summary statistic (i.e. the mean, standard deviation, skewness, etc.). Subsequently, for each bootstrap sample, we compute the median of the respective summary statistic using all hedge funds in a given decile. We finally compute the high-low difference of the median for each bootstrap sample. The resulting distribution of the high-low difference can be used to obtain p -values. To test whether the high-low difference of the median of the alpha, the alpha's t -statistic and the R^2 is statistically significant, we use residual resampling as in Kosowski et al. (2006).

Increase in downside risk across deciles

To test whether a hedge fund faced a significant increase in downside risk, i.e. in negative skewness or semi-deviation, over the period from January 2004 until December 2006, as reported in Table 7, we proceed as follows. First, we resample the return series of each hedge fund in a given decile using 1,000 bootstrap replications per fund independently for two sub-periods: period 1 over the 24 months ending in January 2004 and period 2 over the 24 months ending in December 2006. For each bootstrap sample and each hedge fund, we then compute the respective downside risk measure and the difference between both sub-periods. Based on the resulting distribution, for each hedge fund, we test whether the change in downside risk was significantly positive. For each decile, we then obtain a proportion of hedge funds that faced a significant increase in downside risk. To test whether the proportion of funds in decile 10 is significantly different from that in decile 1, we resample the two corresponding vectors consisting of zeros and ones using 1,000 bootstrap replications each (Efron and Tibshirani (1993)). For example, in the case of decile 1 shown in Panel A of Table 7, this is a vector consisting of 9 ones (representing the funds with a significant increase in downside risk) and 68 zeros (representing the funds with no significant increase in downside risk). For each bootstrap sample, we then compute the ratio of the proportions of funds with a significant increase in downside risk in decile 10 relative to that in decile 1. The resulting distribution of the high/low ratio can be used to obtain p -values.

Illiquidity risk exposure across deciles

To test the statistical significance of the differences in the return autocorrelation between decile 10 (high commonality) and decile 1 (low commonality), as reported in Table 8, we apply the same procedure used for the summary statistics of decile portfolio returns and for the individual hedge fund returns, respectively.

Illiquidity risk in pre- and post-Lehman period

To test whether the proportion of hedge funds with a significant illiquidity in the post-Lehman period in decile 10 (high commonality) was significantly different from that in decile 1 (low commonality), as reported in Table 9, we proceed as follows. For each hedge fund in a given decile, we estimate the return autocorrelation and its significance in the 10 months before (pre-Lehman period) and in the 10 months after (post-Lehman period) the collapse of Lehman Brothers in September 2008. For each decile, we then

obtain a proportion of hedge funds that faced a significant autocorrelation in the post-Lehman period only. To test whether the proportion of funds in decile 10 is significantly different from that in decile 1, we apply the same procedure used for the increase in downside risk across deciles.

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Table 1: Hedge fund risk factors

This table summarizes the 12 risk factors used in our analysis to model hedge funds' risk exposure. The equity-oriented risk factors are obtained from Datastream, the trend-following risk factors from David Hsieh's website, the bond-oriented risk factors from the website of the Federal Reserve Board, and the additional risk factors from Bloomberg and from Lubos Pastor's website.

Equity-oriented risk factors	
MSCINA	Return on the MSCI North America index
MSCIEU	Return on the MSCI Europe index
MSCIPC	Return on the MSCI Pacific index
MSCIEM	Return on the MSCI Emerging Market index
Trend-following risk factors	
PTFSBD	Return on portfolios of lookback straddle options on bonds
PTFSFX	Return on portfolios of lookback straddle options on currency
PTFSCOM	Return on portfolios of lookback straddle options on commodity
Bond-oriented risk factors	
BD10RET	Monthly change in the 10-year U.S. Treasury constant maturity yield
BAAMTSY	Monthly change in the Moody's Baa yield less the 10-year U.S. Treasury constant maturity yield
Additional risk factors	
CARRY	Return on the Deutsche Bank G10 Currency Carry Total Return index
VARSWAP	Return on variance swap
LIQUIDITY	Monthly innovations in the Pastor and Stambaugh (2003) liquidity measure

Table 2: Beta coefficients of risk factors across decile portfolios - stepwise regression

This table reports the coefficient estimates of regressions of monthly excess returns of each decile portfolio on the 12 risk factors summarized in Table 1. The decile portfolios are formed on the basis of the loadings on the first principal component of each hedge fund obtained from a PCA over the period from October 2003 until September 2006. Decile portfolio 1 (10) thus consists of hedge funds with a low (high) degree of commonality. To avoid spurious results, a stepwise regression procedure is used that recursively includes and excludes risk factors, and retains them only if they are at least statistically significant at the 5% level. The sample period extends from October 2003 until September 2006. Standard errors are reported in parenthesis.

Risk factor	Decile portfolio									
	1 Low	2	3	4	5	6	7	8	9	10 High
Equity-oriented risk factors										
MSCINA	-0.169 (0.025)					0.232 (0.083)		0.178 (0.084)		
MSCIEU					0.116 (0.053)					
MSCIPA		0.082 (0.019)	0.076 (0.031)							
MSCIEM			0.097 (0.023)	0.157 (0.018)	0.157 (0.031)	0.216 (0.037)	0.287 (0.037)	0.331 (0.020)	0.378 (0.022)	0.342 (0.018)
Trend-following risk factors										
PTFSBD										
PTFSFX		0.011 (0.005)				0.018 (0.007)				
PTFSCOM										

Table 2: (continued)

Risk factor	Decile portfolio									
	1 Low	2	3	4	5	6	7	8	9	10 High
Bond-oriented risk factors										
BD10RET						1.260 (0.538)	1.416 (0.464)	1.581 (0.511)	1.324 (0.420)	
BAAMTSY										
Additional risk factors										
CARRY										
VARSWAP			-0.464 (0.222)	-0.519 (0.248)	-1.255 (0.291)	-1.113 (0.289)	-1.109 (0.255)	-1.006 (0.280)	-0.949 (0.231)	
LIQUIDITY	2.614 (1.163)									
adj. R^2	0.57	0.45	0.72	0.72	0.81	0.87	0.89	0.90	0.91	0.92
N	36	36	36	36	36	36	36	36	36	36

Table 3: Beta coefficients of risk factors across decile portfolios - regression including all risk factors

This table reports the coefficient estimates of regressions of monthly excess returns of each decile portfolio on the 12 risk factors summarized in Table 1. The decile portfolios are formed on the basis of the loadings on the first principal component of each hedge fund obtained from a PCA over the period from October 2003 until September 2006. Decile portfolio 1 (10) thus consists of hedge funds with a low (high) degree of commonality. Coefficients being statistically significant at the 5% level are in bold. The sample period extends from October 2003 until September 2006. Standard errors are reported in parenthesis.

Risk factor	Decile portfolio									
	1 Low	2	3	4	5	6	7	8	9	10 High
Equity-oriented risk factors										
MSCINA	-0.139 (0.058)	0.098 (0.066)	-0.023 (0.081)	0.097 (0.090)	0.021 (0.096)	0.178 (0.123)	0.096 (0.120)	0.075 (0.100)	0.115 (0.112)	0.080 (0.089)
MSCIEU	0.025 (0.047)	-0.055 (0.053)	0.044 (0.065)	0.023 (0.073)	0.074 (0.077)	0.082 (0.100)	0.096 (0.097)	0.061 (0.081)	0.032 (0.091)	0.028 (0.072)
MSCIPA	0.025 (0.028)	0.100 (0.032)	0.080 (0.038)	0.059 (0.043)	0.034 (0.046)	0.002 (0.059)	0.003 (0.057)	0.016 (0.048)	-0.008 (0.053)	0.050 (0.042)
MSCIEM	-0.044 (0.031)	-0.023 (0.035)	0.060 (0.042)	0.063 (0.047)	0.146 (0.050)	0.188 (0.065)	0.254 (0.063)	0.269 (0.053)	0.324 (0.059)	0.279 (0.047)
Trend-following risk factors										
PTFSBD	0.009 (0.011)	0.017 (0.013)	-0.018 (0.015)	-0.013 (0.017)	-0.015 (0.018)	-0.031 (0.023)	-0.022 (0.023)	-0.014 (0.019)	-0.025 (0.021)	-0.003 (0.017)
PTFSFX	0.000 (0.005)	0.007 (0.005)	0.008 (0.006)	0.009 (0.007)	0.009 (0.007)	0.019 (0.010)	0.016 (0.009)	0.009 (0.008)	0.011 (0.009)	0.003 (0.007)
PTFSCOM	0.007 (0.006)	0.005 (0.007)	0.009 (0.009)	0.009 (0.010)	-0.003 (0.011)	0.017 (0.014)	0.006 (0.013)	-0.003 (0.011)	-0.001 (0.012)	-0.007 (0.010)

Table 3: (continued)

Risk factor	Decile portfolio									
	1 Low	2	3	4	5	6	7	8	9	10 High
Bond-oriented risk factors										
BD10RET	-0.066 (0.422)	0.511 (0.479)	-0.285 (0.584)	-0.202 (0.650)	0.392 (0.692)	-0.000 (0.894)	0.673 (0.871)	0.473 (0.726)	0.525 (0.812)	0.528 (0.643)
BAAMTSY	-0.362 (0.925)	-0.801 (1.050)	0.013 (1.281)	-0.580 (1.425)	-0.640 (1.517)	1.018 (1.959)	0.398 (1.910)	-1.241 (1.592)	-1.480 (1.780)	-1.897 (1.410)
Additional risk factors										
CARRY	-0.008 (0.042)	0.108 (0.047)	0.024 (0.058)	0.021 (0.064)	-0.029 (0.068)	-0.049 (0.088)	-0.033 (0.086)	-0.100 (0.072)	-0.115 (0.080)	-0.092 (0.063)
VARSWAP	0.144 (0.165)	-0.165 (0.188)	-0.294 (0.229)	-0.455 (0.255)	-0.658 (0.271)	-1.226 (0.350)	-1.076 (0.341)	-1.065 (0.285)	-1.020 (0.318)	-0.874 (0.252)
LIQUIDITY	2.101 (1.446)	-0.273 (1.642)	-0.515 (2.004)	1.202 (2.228)	2.012 (2.373)	1.441 (3.064)	1.353 (2.987)	0.705 (2.490)	-0.691 (2.783)	-0.161 (2.204)
adj. R^2	0.53	0.52	0.68	0.71	0.80	0.85	0.88	0.90	0.90	0.93
N	36	36	36	36	36	36	36	36	36	36

Table 4: Decomposition of decile portfolios into TASS styles

This table shows the percentage share of the hedge funds in each decile portfolio belonging to the 10 major TASS investment strategies. The decile portfolios are formed on the basis of the loadings on the first principal component of each hedge fund obtained from a PCA over the period from October 2003 until September 2006. Decile portfolio 1 (10) thus consists of hedge funds with a low (high) degree of commonality.

TASS style (in %)	Decile portfolio									
	1 Low	2	3	4	5	6	7	8	9	10 High
Long/Short Equity Hedge	24.1	24.6	28.4	39.4	31.9	41.8	53.5	50.4	50.7	48.2
Global Macro	7.8	12.0	5.0	0.7	5.0	2.1	1.4	5.7	4.9	3.5
Event Driven	5.0	8.5	5.0	12.0	12.8	19.1	11.3	12.8	12.7	7.1
Convertible Arbitrage	2.8	4.2	7.1	4.9	10.6	3.5	1.4	4.3	2.8	0.0
Managed Futures	10.6	9.9	14.2	11.3	9.9	14.2	12.7	3.5	2.8	0.7
Fixed Income Arbitrage	11.3	15.5	9.9	10.6	3.5	2.8	1.4	0.7	0.0	1.4
Equity Market Neutral	27.0	12.7	14.9	6.3	6.4	5.0	3.5	7.1	6.3	6.4
Dedicated Short Bias	4.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Multi-Strategy	5.7	9.9	10.6	12.0	12.8	7.1	7.7	9.2	15.5	24.8
Emerging Markets	1.4	2.8	5.0	2.8	7.1	4.3	7.0	6.4	4.2	7.8

Table 5: Summary statistics of decile portfolio returns

This table shows various summary statistics of the monthly returns of each decile portfolio for two different periods. The decile portfolios are formed on the basis of the loadings on the first principal component of each hedge fund obtained from a PCA over the period from October 2003 until September 2006. Decile portfolio 1 (10) thus consists of hedge funds with a low (high) degree of commonality. Panel A shows the statistics for the upmarket period from October 2003 until June 2007, while Panel B shows the results for the financial crisis over the period from July 2007 until June 2009. The reported summary statistics include the mean (Mean), standard deviation (SD), Sharpe ratio (SR), the alpha from a regression of decile portfolio excess returns on those of the 12 risk factors summarized in Table 1 (Alpha), the t -statistic of the alpha (t -stat), the adjusted- R^2 corresponding to the risk factor regression (R^2), skewness (Skew), semi-deviation (SEM), Value-at-Risk (VaR), Expected Shortfall (ES) and Tail Risk (TR). As in Liang and Park (2007), we multiply the original Value-at-Risk number by minus one to avoid confusion. Thus, Value-at-Risk and Expected shortfall are usually positive in this paper. In the lower part of each panel, we also report the difference in the respective statistic between the high commonality decile (decile 10) and the low commonality decile (decile 1), and the corresponding p -value obtained from a bootstrap approach.

Decile	Mean	SD	SR	Alpha	t -stat	R^2	Skew	SEM	VaR	ES	TR
Panel A: 10/2003 - 6/2007 (T=45)											
1 Low	0.56	0.49	1.14	0.43	5.23	0.60	0.47	0.32	0.15	0.22	0.05
2	0.72	0.53	1.35	0.56	6.02	0.55	-0.20	0.38	0.17	0.28	0.06
3	0.79	0.80	0.99	0.41	3.24	0.64	-0.41	0.59	0.57	1.05	0.29
4	0.71	0.93	0.76	0.26	2.11	0.70	-0.31	0.69	0.86	1.07	0.09
5	0.89	1.21	0.74	0.26	1.90	0.80	-0.46	0.91	1.19	1.80	0.17
6	1.04	1.79	0.58	0.53	4.17	0.84	-0.44	1.34	2.03	2.72	0.32
7	1.12	1.92	0.59	0.39	2.52	0.88	-0.43	1.45	2.17	2.68	0.19
8	1.11	1.80	0.62	0.37	2.40	0.88	-0.53	1.37	2.01	2.69	0.20
9	1.14	2.01	0.57	0.21	1.34	0.88	-0.48	1.53	2.32	3.12	0.39
10 High	1.13	1.83	0.62	0.31	2.16	0.91	-0.66	1.40	2.10	2.91	0.63
High-Low	0.58	1.34	-0.52	-0.12	-3.07	0.31	-1.13	1.08	1.95	2.68	0.58
p -value	0.03	0.00	0.03	0.29	0.07	0.00	0.00	0.00	0.00	0.00	0.00
Panel B: 7/2007 - 6/2009 (T=24)											
1 Low	0.64	0.62	1.02	0.66	3.93	0.16	0.19	0.41	0.31	0.78	0.00
2	0.01	1.18	0.00	-0.11	-0.95	0.82	-0.02	0.83	1.87	2.35	0.00
3	0.20	1.57	0.13	0.45	3.43	0.74	-0.13	1.08	2.34	3.05	0.25
4	-0.34	1.87	-0.18	0.00	-0.02	0.41	-0.94	1.42	3.72	5.87	0.00
5	-0.34	2.27	-0.15	-0.21	-1.10	0.72	-0.01	1.55	3.96	5.03	0.00
6	-0.32	2.51	-0.13	-0.19	-0.70	0.66	0.00	1.71	4.34	5.25	0.00
7	-0.27	2.64	-0.10	0.07	0.31	0.76	0.17	1.75	4.36	5.31	0.00
8	-0.40	3.56	-0.11	-0.03	-0.15	0.90	0.01	2.47	6.03	7.51	0.39
9	-0.40	3.21	-0.12	-0.25	-1.50	0.85	-0.16	2.28	5.66	6.73	0.07
10 High	-0.82	3.92	-0.21	-0.37	-2.01	0.94	-0.19	2.78	7.24	8.87	0.20
High-Low	-1.46	3.30	-1.23	-1.03	-5.93	0.78	-0.38	2.37	6.94	8.08	0.20
p -value	0.03	0.00	0.00	0.00	0.00	0.00	0.28	0.00	0.00	0.00	0.70

Table 6: Summary statistics of individual fund returns across deciles

This table shows various summary statistics of the monthly returns of the individual hedge funds in each decile for two different periods. The deciles are formed on the basis of the loadings on the first principal component of each hedge fund obtained from a PCA over the period from October 2003 until September 2006. Decile 1 (10) thus consists of hedge funds with a low (high) degree of commonality. We compute the summary statistics separately for each hedge fund with at least 24 monthly observations and take the median of all funds in a given decile as the final measure. The number of hedge funds in each decile used to compute the statistics is denoted by N. Panel A shows the statistics for the upmarket period from October 2003 until June 2007, while Panel B shows the results for the financial crisis over the period from July 2007 until June 2009. The reported summary statistics include the mean (Mean), standard deviation (SD), Sharpe ratio (SR), the alpha from a regression of individual hedge fund excess returns on those of the 12 risk factors summarized in Table 1 (Alpha), the t -statistic of the alpha (t -stat), the adjusted- R^2 corresponding to the risk factor regression (R^2), skewness (Skew), semi-deviation (SEM), Value-at-Risk (VaR), Expected Shortfall (ES) and Tail Risk (TR). As in Liang and Park (2007), we multiply the original Value-at-Risk number by minus one to avoid confusion. Thus, Value-at-Risk and Expected shortfall are usually positive in this paper. In the lower part of each panel, we also report the difference in the respective statistic between the high commonality decile (decile 10) and the low commonality decile (decile 1), and the corresponding p -value obtained from a bootstrap approach.

Decile	N	Mean	SD	SR	Alpha	t -stat	R^2	Skew	SEM	VaR	ES	TR
Panel A: 10/2003 - 6/2007 (T=45)												
1 Low	141	0.56	1.57	0.37	0.34	1.12	0.07	0.18	1.05	1.63	2.62	0.32
2	142	0.65	1.66	0.41	0.37	1.18	0.11	0.17	1.10	1.71	2.52	0.36
3	141	0.67	1.63	0.41	0.36	0.94	0.13	-0.03	1.13	1.97	2.83	0.33
4	142	0.68	1.69	0.40	0.27	0.79	0.16	-0.07	1.22	1.97	2.88	0.44
5	141	0.79	1.89	0.42	0.26	0.79	0.25	-0.10	1.35	2.21	3.27	0.39
6	141	0.91	2.17	0.44	0.31	0.94	0.34	-0.04	1.52	2.48	3.87	0.43
7	142	0.94	2.52	0.45	0.30	0.67	0.44	0.02	1.84	2.59	4.01	0.49
8	141	0.95	2.16	0.45	0.38	1.04	0.49	-0.14	1.60	2.48	3.51	0.41
9	142	0.99	2.21	0.48	0.29	0.92	0.58	-0.14	1.64	2.50	3.77	0.46
10 High	141	0.84	1.64	0.53	0.32	1.26	0.72	-0.41	1.24	2.02	3.05	0.43
High-Low		0.28	0.07	0.16	-0.02	0.14	0.65	-0.59	0.18	0.39	0.43	0.10
p -value		0.00	0.34	0.00	0.23	0.73	0.00	0.00	0.05	0.05	0.11	0.08
Panel B: 7/2007 - 6/2009 (T=24)												
1 Low	58	0.80	3.04	0.28	0.68	1.42	0.29	-0.17	1.90	3.74	5.62	0.00
2	59	0.45	3.10	0.15	0.26	0.59	0.23	-0.16	2.33	3.87	5.87	0.32
3	73	0.34	3.74	0.14	0.46	0.86	0.39	-0.23	2.53	5.43	7.76	0.10
4	59	0.12	3.77	0.04	0.21	0.39	0.39	-0.26	2.85	5.86	7.80	0.28
5	63	0.13	4.27	0.05	0.02	0.03	0.48	-0.04	2.88	6.56	8.48	0.13
6	84	0.17	4.40	0.06	-0.18	-0.28	0.42	-0.47	3.36	8.01	10.37	0.15
7	68	0.23	4.55	0.06	0.10	0.17	0.48	-0.24	3.17	6.48	8.62	0.13
8	60	-0.23	3.96	-0.06	-0.42	-0.91	0.57	-0.35	2.90	7.06	9.44	0.20
9	78	-0.20	4.06	-0.06	-0.18	-0.35	0.59	-0.44	3.10	6.78	9.43	0.31
10 High	111	-0.47	3.59	-0.14	-0.26	-0.72	0.72	-0.56	2.69	6.70	8.41	0.44
High-Low		-1.27	0.55	-0.42	-0.94	-2.14	0.44	-0.39	0.78	2.96	2.79	0.44
p -value		0.00	0.24	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00

Table 7: Increase in downside risk across deciles

This table shows the share of hedge funds in each decile that faced a statistically significant increase in negative skewness (Panel A) and semi-deviation (Panel B) over the period from January 2004 until December 2006. The deciles are formed on the basis of the loadings on the first principal component of each hedge fund obtained from a PCA over the period from October 2003 until September 2006. Decile portfolio 1 (10) thus consists of hedge funds with a low (high) degree of commonality. For each hedge fund in a given decile with a sufficient number of observations, we compute the skewness and semi-deviation for two subsamples, first, over the 24 months ending in January 2004 and, second, over the 24 months ending in December 2006. We then test the statistical significance of the differences in downside risk between both subsamples using a bootstrap approach. Finally, for each decile, we determine the number of funds that faced a significant increase in the respective downside risk measure. In the lower part of each panel, we also report the ratio of the percentage of funds that faced an increase in downside risk in the high commonality decile (decile 10) to the percentage in the low commonality decile (decile 1), and the *p*-value obtained from a bootstrap approach.

Decile	Funds with a significant increase in downside risk	Total number of funds	Percent
Panel A: Negative skewness			
1 Low	9	77	11.69
2	13	85	15.29
3	11	86	12.79
4	9	83	10.84
5	10	79	12.66
6	14	79	17.72
7	14	92	15.22
8	21	96	21.88
9	17	92	18.48
10 High	19	78	24.36
High/Low ratio			2.08
<i>p</i> -value			0.02
Panel B: Semi-deviation			
1 Low	5	77	6.49
2	9	85	10.59
3	10	86	11.63
4	14	83	16.87
5	15	79	18.99
6	10	79	12.66
7	16	92	17.39
8	31	96	32.29
9	30	92	32.61
10 High	24	78	30.77
High/Low ratio			4.74
<i>p</i> -value			0.00

Table 8: Illiquidity risk exposure across deciles

This table shows the 1st-order autocorrelation estimates of the returns of each decile portfolio and the median of the autocorrelation estimates of the individual hedge funds in each decile for two different periods. The deciles are formed on the basis of the loadings on the first principal component of each hedge fund obtained from a PCA over the period from October 2003 until September 2006. Decile 1 (10) thus consists of hedge funds with a low (high) degree of commonality. To estimate the autocorrelation coefficient of the individual hedge funds, only funds with at least 24 monthly observations are used. We estimate the autocorrelation coefficient separately for each fund in a given decile and take the median of all funds in this decile as the final measure. The number of hedge funds in each decile used to estimate the autocorrelation is denoted by N. Panel A shows the results for the upmarket period from October 2003 until June 2007, while Panel B shows the results for the financial crisis over the period from July 2007 until June 2009. In the lower part of each panel, we also report the difference in the autocorrelation between the high commonality decile (decile 10) and the low commonality decile (decile 1), and the corresponding *p*-value obtained from the stationary bootstrap of Politis and Romano (1994).

Decile	Autocorrelation of decile portfolios	N	Median autocorrelation of individual funds
Panel A: 10/2003 - 6/2007 (T=45)			
1 Low	0.31	141	0.07
2	0.29	142	0.11
3	0.18	141	0.10
4	0.19	142	0.07
5	0.23	141	0.15
6	0.18	141	0.08
7	0.17	142	0.11
8	0.21	141	0.16
9	0.20	142	0.16
10 High	0.18	141	0.16
High-Low	-0.13		0.09
<i>p</i> -value	0.11		0.00
Panel B: 7/2007 - 6/2009 (T=24)			
1 Low	0.16	56	0.17
2	0.30	58	0.12
3	0.35	70	0.22
4	0.24	59	0.20
5	0.31	63	0.27
6	0.14	83	0.19
7	0.24	66	0.19
8	0.43	59	0.26
9	0.33	78	0.29
10 High	0.35	109	0.31
High-Low	0.19		0.14
<i>p</i> -value	0.09		0.00

Table 9: Illiquidity risk in pre- and post-Lehman period

This table shows the share of hedge funds in each decile that faced a significant illiquidity, as measured by the 1st-order autocorrelation, in the post-Lehman period but not in the pre-Lehman period. The deciles are formed on the basis of the loadings on the first principal component of each hedge fund obtained from a PCA over the period from October 2003 until September 2006. Decile 1 (10) thus consists of hedge funds with a low (high) degree of commonality. For each hedge fund in a given decile with a sufficient number of observations, we estimate the return autocorrelation for two subsamples, first, over the pre-Lehman period from November 2007 until August 2008 and, second, over the post-Lehman period from September 2008 until June 2009. We then determine the share of funds that faced a significant autocorrelation in the post-Lehman period only. Panel A shows the results for each decile individually, while Panel B shows the results for two groups of deciles, the lower commonality deciles (deciles 1-5) and the higher commonality deciles (deciles 6-10). In the lower part of each panel, we also report the ratio of the percentage of funds with a significant illiquidity in the post-Lehman period in the high commonality decile(s) (decile 10 / deciles 6-10) to the percentage in the low commonality decile(s) (decile 1 / deciles 1-5), and the *p*-value obtained from a bootstrap approach.

Decile	Number of funds with significant illiquidity		Total number of funds	Percent
	pre-Lehman period	post-Lehman period only		
Panel A: All deciles				
1 Low	0	1	19	5.26
2	0	2	25	8.00
3	0	4	25	16.00
4	0	1	19	5.26
5	2	5	23	21.74
6	0	5	35	14.29
7	1	4	19	21.05
8	1	6	21	28.57
9	0	5	15	33.33
10 High	0	3	22	13.64
High/Low ratio				2.59
<i>p</i> -value				0.29
Panel B: Lower versus higher deciles				
1-5 Low	2	13	111	11.71
6-10 High	2	23	112	20.54
High/Low ratio				1.75
<i>p</i> -value				0.04

Figure 1: Commonality in hedge fund and risk factor returns

This figure shows the evolution over time of the commonality in the returns of the 10 major TASS hedge fund strategies (solid line) and in the returns of the 12 risk factors, summarized in Table 1, used to model hedge funds' risk exposure (dashed line). Commonality is measured by the proportion of variance in each data set explained by the first principal component. To obtain a time-varying measure of commonality, we use a rolling window of 12 months.

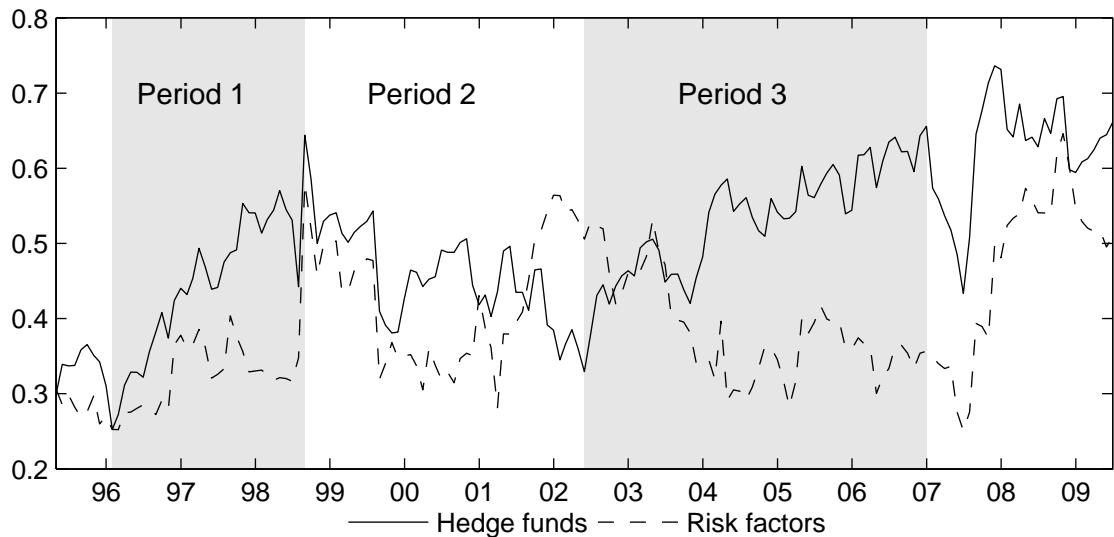


Figure 2: Time-varying beta coefficient of the MSCIEM risk factor

This figure shows the evolution over time of the beta coefficients of the MSCI Emerging Market index (MSCIEM) for specific decile portfolios. To obtain time-varying beta coefficients, we use stepwise regressions of the corresponding decile portfolio returns on the 12 risk factors summarized in Table 1 with a 36 months rolling window. Due to the stepwise regression approach only beta coefficients being statistically significant at the 5% level are shown in the figure.

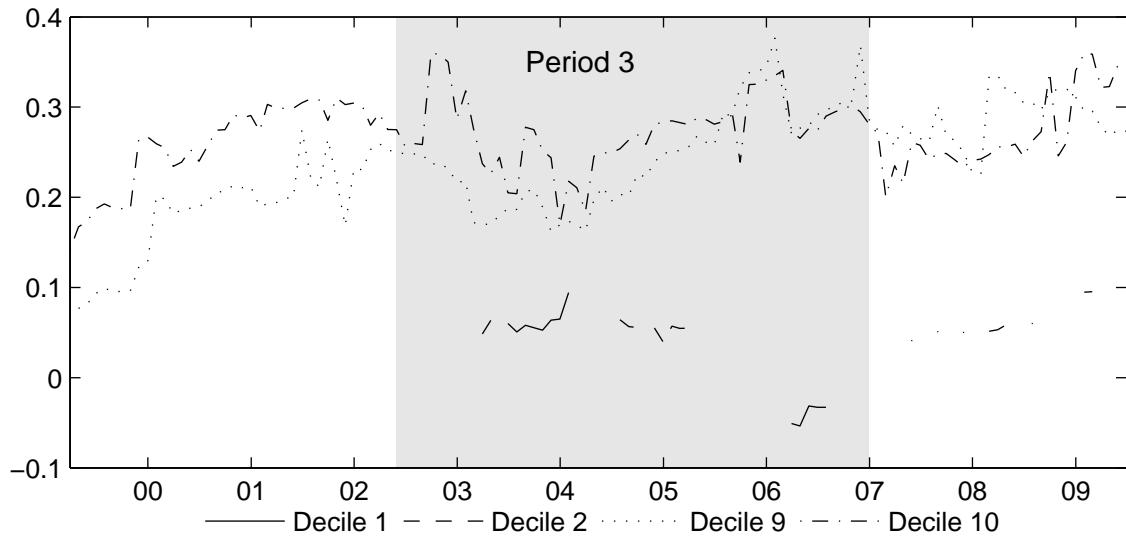


Figure 3: Commonality in hedge fund returns using raw returns and residuals

This figure shows the evolution over time of the commonality in hedge fund returns using the raw returns of the decile portfolios (solid line) and the residuals from a 36 months rolling stepwise regression of the decile portfolio returns on each of the 12 risk factors, summarized in Table 1, (dashed line). Commonality is measured by the proportion of variance in each data set explained by the first principal component. To obtain a time-varying measure of commonality, we use a rolling window of 24 months.

