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Zeno Adams
EBS University

Roland Füss
EBS University

Reint Gropp
EBS University and ZEW

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Spillover Effects among Financial Institutions: A State-Dependent Sensitivity Value-at-Risk (SDSVaR) Approach

Zeno Adams[†], Roland Füss[‡], and Reint Gropp[§]

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[†] Zeno Adams, Union Investment Chair of Asset Management, EBS Business School, EBS Universität für Wirtschaft und Recht, D-65189 Wiesbaden, Germany, Phone: +49 (0)611 7102 1215, Fax: +49 (0)611 7102 10 1215, Email: zeno.adams@ebs.edu.

[‡] Roland Füss, Union Investment Chair Asset Management, EBS Business School, EBS Universität für Wirtschaft und Recht, D-65189 Wiesbaden, Germany, Phone: +49 (0)611 7102 1227, Fax: +49 (0)611 7102 10 1227, Email: roland.fuess@ebs.edu.

[§] Corresponding author: Reint Gropp, Chair of Financial Economics and Taxation, EBS Business School, EBS Universität für Wirtschaft und Recht, D-65189 Wiesbaden, Germany, Phone: +49 611 7102 1234; Fax: +49 611 7102 10 1234; Email: reint.gropp@ebs.edu.

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Abstract

In this paper, we estimate a system of quantile regressions for four sets of major financial institutions (commercial banks, investment banks, hedge funds and insurance companies) using daily data. Our state-dependent sensitivity value-at-risk (SDSVaR) approach enables us to quantify the size and duration of risk spillovers among financial institutions as a function of the state of financial markets (tranquil, normal, volatile). We show that while small during normal times, equivalent shocks lead to considerable spillover effects in volatile market periods. The results highlight that estimates on spillover magnitudes that do not condition on the state of financial markets may substantially over- or understate spillover effects. We show that investment banks and, especially, hedge funds play a major role in the transmission of shocks to the other financial institutions. Given our high frequency data, we can trace out the spillover effects over time in a set of impulse response functions and find that they reach their peak after 10 to 20 days. Finally, the evidence provides further support for the notion that different hedge fund styles tend to converge during crisis times.

Keywords: Contagion; state-dependent sensitivity value-at-risk (SDSVaR); quantile regression; financial institutions; hedge funds

JEL-Classification: *G*01, *G*10, *G*24

"Continued focus on counterparty risk management is likely the best course for addressing systemic concerns related to hedge funds".

Ben S. Bernanke (2006)

1 Introduction

From a regulatory perspective, one of the most important lessons from the 2007/2009 financial crisis may be that systemic risk and spillover effects are significantly underestimated in most widely used risk measures and that standard risk measurement instruments, such as value-at-risk (VaR), need to be adjusted to adequately reflect overall risk.[1]

In this paper, we propose a state-dependent sensitivity (SDS) VaR for quantifying the spillover effects among systemically important financial institutions. Our model explicitly accounts for the effects of different market states (tranquil, normal, and volatile) on the magnitude of risk spillovers. Further, we model the simultaneity that arises from the feedback effects of interdependent financial institutions. In particular, we apply two-stage least squares to a quantile regression setting to obtain consistent coefficient estimates. We perform this analysis in a system of four sets of financial institutions (commercial banks, investment banks, insurance companies, and hedge funds), in which each type of financial institution is represented by an index of several financial firms.

A recent paper by Billio, Getmansky, Lo, and Pelizzon (2010) empirically investigates the interconnectedness among financial institutions using monthly data. They find insurance companies, banks, brokers, and hedge funds have become highly interrelated over the past decade. Commercial banks and insurers are estimated to have a more significant impact on hedge

[1] In line with literature, we define systemic risk as the risk that the failure of a participant to meet its contractual obligations may in turn cause other participants to default with a chain reaction leading to broader financial difficulties (BIS, 1994)

funds and investment banks than vice versa. Their systemic risk measures contain predictive power to identify financial crisis periods. In contrast, we propose a systemic risk measure that is based on different core variables (value-at-risk measures instead of returns), and uses different methodological concepts. Our study is the first that provides empirical estimates of the size of intra-month spillover effects from hedge funds to other financial institutions.

Boyson, Stahel, and Stulz (2010) apply quantile regression for binary dependent variable models in order to measure contagion effects among hedge fund styles. Similarly, Chan, Getmansky, Haas, and Lo (2006) and more recently Billio, Getmansky, and Pelizzon (2009) propose a regime switching framework to estimate the probabilities of switching to a "systemic risk regime". The joint distribution of hedge fund returns is studied by Brown and Spitzer (2006) who measure the dependence structure between hedge fund strategies using copulae. While the first two studies estimate the effects on state probabilities rather than the size of the spillover effects, the latter study provides estimates on the tail-dependence structure without presenting empirical estimates of the magnitude of potential risk spillovers.[2]

Our empirical results suggest that shocks to hedge funds result in significant spillovers to investment banks and to insurance companies. Commercial banks exhibit statistically significant spillover effects to investment banks and insurance companies, but the economic magnitude is much smaller relative to the spillovers from hedge funds. Specifically, we show that, during market distress, a one percent increase in the value-at-risk of the hedge fund industry leads to a 0.6% increase in the VaR of investment banks and a 0.3% increase in the VaR of insurance companies. In contrast, again during market distress, a one percent increase in the value-at-risk of commercial banks results in a 4.1% increase in the VaR of insurance companies and a 4.0%

[2] In fact, the general belief in 2005 was that "current state-of-the-art methods do not allow us to capture the systemic risk component of a hedge fund's position" (see Danielsson, Taylor, and Zigrand, 2005).

increase in the VaR of investment banks.[3] Spillovers during calm times are small and generally statistically not significant. In summary, the results emphasize the importance of controlling for different states of the economy when estimating spillover effects.

The paper complements a growing literature that examines the potential transmission channels between financial institutions in general and from hedge funds to the financial system in particular. The majority of the related literature examines contagion and systemic risk in the banking sector. The main findings on systemic risk generating factors are thereby the growth in credit risk transfers (Hakenes and Schnabel, 2010; Altunbas, Gambacorta, and Marquez-Ibanez, 2010), investor sentiments (Shleifer and Vishny, 2009; Hott, 2009), and the interaction of liquidity shortages and solvency problems among banks (Diamond and Rajan, 2005).[4] Gropp, Lo Duca and Vesala (2009), and Gropp and Moerman (2004), as well as Hartmann, Straetmans, and De Vries (2006) show that distress in one banking system transmits across national borders to other banking systems. Brownlees and Engle (2010) and Acharya, Pedersen, Philippon, and Richardson (2010) propose marginal expected shortfall (MES) and systemic expected shortfall (SES) as a measure of systemic risk and an indicator of financial crises. Thereby, high levered firms show higher MES, whereas the impact of leverage differs across market states. Broker-Dealers are identified as the most systemically relevant sector.

Implications of financial fragility for the real economy are analyzed by Campello, Graham, and Harvey (2010) who find evidence that constrained firms bypass attractive investment opportunities and are forced to sell more assets to fund their operations. Furthermore, sectors that

[3] Throughout the study we will refer to a "one percentage increase". Note, however, that the value-at-risk is measured in percentage *points* so that a one percentage increase actually means an "increase by one percentage point".

[4] One interesting aspect of the study by Hott (2009) is that uninformed "mood investors" may create a price bubble even in the absence of speculation.

are highly dependent on external financing also suffer the greatest adverse impact on value added during banking crises (Kroszner, Laeven, and Klingebiel, 2007).[5]

A few recent studies also provide evidence of contagion in the insurance industry. Allen and Gale (2005) argue that the considerable growth in the transfer of credit risk across sectors of the financial system has lead to a shift in risk from the banking sector to the insurance sector. Fenn and Cole (1994) investigate the contagion effects among life insurance companies when major insurance companies report significant write downs of their portfolios. Negative wealth effects on shareholders of other insurance companies are shown to be particularly strong if the write downs refer to junk bonds or commercial mortgages.

Until recently the literature generally seemed to agree that hedge funds are systemically important and that this importance is likely to increase even more so in the future (Danielsson, Taylor, and Zigrand (2005), Garbaravicius and Diereck (2005), Kambhu, Schuermann, and Stiroh (2007), and Chan, Getmansky, Haas, and Lo (2006) among others).

As opaque and highly leveraged investment partnerships, hedge funds have received prominent attention as a potential source of contagion, a transmission channel of risk between different financial institutions and potential amplifiers of systemic risk in financial markets. If highly leveraged hedge funds are forced to liquidate large position at fire-sale prices, counterparties sustain heavy losses. This may lead to further defaults or threaten systemically important institutions not only directly as counterparties or creditors but also indirectly through asset price adjustments (Bernanke, 2006).

[5] Another implication of these findings is that full diversification may in fact not be desirable. Although it reduces each institution's individual probability of failure it also increases the probability of systemic risk (see Wagner, 2010).

Our results are complementary to studies that are confined to estimating the average impact on the response variable like, e.g., Halstead, Hegde, and Klein (2005), who use an event study approach to estimate contagion effects from hedge funds during the LTCM crisis in 1998, or Ding, Getmansky, Liang, and Wermers (2009), who investigate fund flows during periods of financial distress.[6] Furthermore, for the spillover effects at the disaggregated hedge fund strategy level, our results confirm the findings of the recent literature on the interrelation among hedge funds. For instance, Brunnermeier and Pedersen (2008) find that market liquidity and funding liquidity are interrelated. In particular, hedge funds provide liquidity to otherwise illiquid markets as long as access to credit is easy. However, traders are concerned about margin calls and avoid high margin positions when funding liquidity dries up. At that point, prices are more driven by funding liquidity considerations rather than by movements in fundamentals.

Our approach is most closely related to Adrian and Brunnermeier's (2010) CoVaR approach. However, we focus on spillover effects among financial institutions, rather than the contributions of financial institutions to systemic risk. We furthermore apply a more flexible methodology that allows for the fact that spillovers are determined simultaneously and explicitly measures the spillover effects during a crisis. Finally, the quantile regression setup and the dynamic structure of the model were inspired by Engle and Manganelli's (2004) CAViaR model. Our SDSVaR model is an indirect approach to measuring spillover risk. Relevant determinants such as leverage, liquidity and hedge funds' asset holdings are not available, so that we cannot *explain* the causes of risk spillovers. On the other hand, measuring risk through daily value-at-risk also has some advantages. All risk relevant shocks are likely to be reflected in an institutions value-at-risk. We can therefore also capture risks that arise from complex relationships among

[6] In these studies the response variable is abnormal stock market returns and hedge fund flows, respectively. The response variable in our study is the value-at-risk of different financial institutions and hedge fund strategies.

financial institutions. For instance, in an article from August 9th 2007, The Economist addresses the complex relationship between the three major prime brokers (Goldman Sachs, Morgan Stanley, and, at that time, Bear Stearns) and hedge funds. Investment banks that own corporate bonds may use the swap market to hedge against corporate defaults. But if hedge funds take the other side of the swap and at the same time depend on loans from the same bank, the spillover risk between the bank and the hedge fund increases.

The remainder of this paper is organized as follows. The next section describes the SDSVaR approach of modeling contagion risk conditional on the state of the economy. In section three we discuss the general implications of this model in a static setting using the full sample range but also present the dynamic development in the spillover estimates in a one-step-ahead forecast setting. We furthermore show how impulse response functions can be used to illustrate the dynamics of risk spillovers. In section four we analyze the risk spillovers, at a disaggregated level, of hedge fund strategies. Some concluding remarks are drawn in Section 5. Since transparency and representativeness are a major concern when working with financial data in general and hedge funds in particular, we provide a detailed appendix on data source, index constituents and representativeness. Thus, our empirical findings concerning the spillover effects from the hedge fund index are likely to be close but generally somewhat lower than what could be expected if a truly representative hedge fund index was available.

2 A State-Dependent Sensitivity VaR Model (SDSVaR)

Value-at-risk (VaR) is a risk measure with the appealing property of expressing the risk in only one number. Its intuitive interpretation and regulatory importance has led to general acceptance and wide application for internal and external purposes. From a statistical standpoint, estimation of the VaR requires adequate modeling of the time-varying distribution of returns.[7] In the past, a vast variety of different approaches have been applied, including GARCH (Bollerslev, 1986), extreme value theory (Danielson and De Vries, 2000), conditional autoregressive VaR (Engle and Manganelli, 2004), and simulation based methods (Barone-Adesi and Giannopoulos, 2000). The 2007/2009 financial crisis, however, has further highlighted the importance of accounting for the dependence of a VaR measure of one financial institution *i* on the VaR of some other institution *j* and, perhaps, on the VaR of the entire financial system.[8]

To derive the SDSVaR approach, we start with the standard value-at-risk of a single type of financial institution. The value-at-risk is the estimated loss of a financial institution that, within a given period (usually 1 to 10 days), will be exceeded with a certain probability θ (usually 1% or 5%). Thus, the 1-day 5% VaR shows the negative return that will not be exceeded within this day with a 95% probability,

$$prob\left[return_t < -Var_t \middle| \Omega_t\right] = \theta \,. \tag{1}$$

Recently, Adrian and Brunnermeier (2010) propose CoVaR as a measure for the contribution of a financial institution to systemic risk. This conditional VaR measure incorporates the additional risk in financial institution i caused by institution j being in distress. If the focus is on macroprudential bank regulation, institution i is taken to be the financial system. A substantial difference between institution j's CoVaR and its VaR measure then indicates significant

[7] In the multivariate VaR context, additional attention has to be devoted to the tail dependencies of the joint density of returns.

[8] We will refer at several points in this paper to the term "financial institution" but this generally corresponds to an index of single companies, representing each type of institution (commercial banks, insurance companies, investment banks, and hedge funds).

contribution of this institution to general systemic risk and should result in higher capital surcharges for this institution.

The CoVaR uses the same conceptual approach as VaR, i.e. $prob\left[return_t < -CoVar_t \left|\Omega_t\right.\right] = \theta$, however, includes in the information set Ω_t not only the own past return history, i.e. $\Omega_t\left(VaR\right) = \left\{r_{i,t-1}, r_{i,t-2}, \ldots, r_{i0}\right\}$, but also the VaR of another institution *j*:

$$\Omega_t\left(CoVaR\right) = \left\{r_{i,t-1}, r_{i,t-2}, \ldots, r_{i0}, VaR_{j,t}\right\}. \tag{3}$$

Using quantile regression, the CoVaR is estimated by regressing the θ-% quantile of the return distribution on a constant and VaR_j. The CoVaR between institutions *i* and *j* is then given by the fitted values from this regression:

$$CoVaR_{i,j} = \hat{R}_{i,\theta}\left|VaR_j\right. = \hat{\alpha} + \hat{\beta} \cdot VaR_j, \tag{4}$$

where R_i is the time series of institution *i* returns. Adrian and Brunnermeier (2010) extend Equation (4) by adding a set of lagged regressors M_{t-1} that capture liquidity risk, market risk, and credit risk, thus generating a flexible risk measure that reacts sensitively to the underlying return process.[9] In Equation (4) the spillover coefficient $\hat{\beta}$ is an average over all states of the economy. In this paper, we examine whether β, which measures the spillover intensity of VaR_j on VaR_i, depends on the state of the economy. We hypothesize that during normal market times β may be of little economic significance, while the spillover effect becomes very important during times of financial distress.

[9] The estimating equation in Adrian and Brunnermeier (2010) is $CoVaR_t^{system,j} = \alpha^{system,j} + \beta^{system,j} M_{t-1} + \gamma^{system,j} VaR_t^j$, where the regressor set M_{t-1} consists of weekly financial market variables such as liquidity spread and stock market volatility and $CoVaR_t^{system,j}$ is measured with the returns of the entire financial system.

We propose a two-step approach to estimate the spillover coefficients β. In contrast to the CoVaR model of Adrian and Brunnermeier (2010), which relies on quantile regression to model the distribution of returns (see Koenker and Bassett, 1978; Koenker, 2005), the SDSVaR proposed in this paper models the distribution of the value-at-risk, not the returns. Since the 5% quantile of the return distribution is defined to be the value-at-risk, estimation of the CoVaR model requires setting the quantile θ to 5% or 1%. In contrast, we obtain the value-at-risk in a preceding step which enables us to regress over the whole range of VaR quantiles.[10] Thus, while the 5% quantile of the return distribution is the value-at-risk, low quantiles of the VaR distribution constitute the VaR during times of financial distress. The former is necessary to obtain the desired risk measure but it is the latter that introduces state dependency into the model.

The first step in our model setup is to estimate the VaRs of all systemically relevant financial institutions separately:

$$VaR_m = \mu_{m,t} + z\sigma_{m,t} . \tag{5}$$

with $\mu_{m,t}$ as the mean of institution *m* at time *t*. In the following we consider four financial institutions so that *m* = *i*, *j*, *k*, and *l*. It has become practice to model $\sigma_{m,t}$ by extracting the conditional standard deviation from a GARCH model (Kuester et al., 2006). This will account for the time-varying volatility of returns and leads to substantial improvements in the sensitivity of the VaR to changes in the return process. We will therefore follow this practice.[11]

[10] In fact, we estimate Equation (6) over a range of 16 quantiles with $\theta = \{0.05, 0.125, 0.1875, 0.25, 0.3125, 0.375, 0.4375, 0.5, 0.5625, 0.625, 0.6875, 0.75, 0.8125, 0.875, 0.9375, 0.99\}$.

[11] For most of our return series the volatility responds more strongly to negative return changes than to positive ones. To capture this fact we applied the asymmetric Exponential GARCH(1,1) of Nelson (1991). As a

In a second step, VaR_m now becomes the dependent variable and is modeled by its own lag and the VaR measures of the other three related institutions. For simplicity, we present the VaR in Equations (6a)-(6b) in terms of institution *i* but the expressions extends directly to institutions *j*, *k*, and *l*.

$$VaR_{i,t,\theta} = \alpha_\theta + \beta_{1,\theta} VaR_{j,t} + \beta_{2,\theta} VaR_{k,t} + \beta_{3,\theta} VaR_{l,t} + \beta_{4,\theta} VaR_{i,t-1} + u_{i,t} \,. \tag{6a}$$

Equation (6a) is estimated in a system of four equations that also includes a line for $VaR_{j,t,\theta}$, $VaR_{k,t,\theta}$, and $VaR_{l,t,\theta}$, respectively. The method of estimation is two-stage quantile regression.[12] This method is suitable for capturing the simultaneity in the VaR spillovers and their quantification during different states of the market. We identify the system by assuming that the own lag $VaR_{i,t-1}$ only affects the *VaR* of institutions *i*. Hence, controlling for contemporaneous spillover effects from the other three sets of institutions, there is no additional spillover effect of the lagged *VaR* of the other institutions. At the same time all four coefficients for the own lagged VaRs (e.g., $\beta_{4,\theta}$ in Equation (6a)) are statistically significant and therefore constitute valid instruments to identify the system (Wooldridge, 1999). The fitted values of Equation (6a) constitute the SDSVaR of institution *i*, $SDSVaR_{i|j,k,l}$:

$$SDSVaR_{\{i|j,k,l\},t,\theta} = \hat{\alpha}_\theta + \hat{\beta}_{1,\theta} VaR_{j,t} + \hat{\beta}_{2,\theta} VaR_{k,t} + \hat{\beta}_{3,\theta} VaR_{l,t} + \hat{\beta}_{4\theta} VaR_{i,t-1} \tag{6b}$$

Note that the coefficient vector $\mathbf{\Delta}'_{\mathbf{\theta}} = \left(\hat{\alpha}_\theta, \hat{\beta}_{1,\theta}, \hat{\beta}_{2,\theta}, \hat{\beta}_{3,\theta}, \hat{\beta}_{4,\theta} \right)$ in (6b) depends on the state of the economy. When using financial institutions or industry aggregates, the quantiles of the VaR can be interpreted as reflecting the state or condition of financial markets. Thereby, high quantiles

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robustness check we also computed the VaR series in Equation (5) using the asymmetric slope version of Engle and Manganelli's (2004) CAViaR model and obtain similar empirical results throughout this study.

[12] See Powell (1983) for the derivation of the statistical properties of this estimator.

correspond to tranquil market periods and low quantiles to situations of financial distress. When modeling spillover risk it seems natural that VaR measures are interdependent among financial institutions and that a set of observed VaR measures at a given day are determined simultaneously. To address the bias that is introduced by this simultaneous framework, we adapt the methodology from two-stage least squares to our quantile regression setting. This additional effort is rewarded with consistent estimates that account for the fact that the VaRs of interdependent financial institutions are determined simultaneously.

We interpret SDSVaR (i) as an extended value-at-risk model that accounts for the spillover or contagion risk that is caused by related financial institutions, and (ii) as an approach to explicitly reveal the size of the spillover risk through coefficients that vary over time as well as over different states of the economy.

Equation (6a) contains the following variables:

The value-at-risk of financial institution j, k, and l: These variables can be the VaRs of related institutions or the aggregate VaR measure of the whole system. The coefficients of interest are $\mathbf{B}'_{\boldsymbol{\theta}} = \left(\beta_{1,\theta}, \beta_{2,\theta}, \beta_{3,\theta}, \beta_{4,\theta}\right)$ which are estimated conditional on the quantile, θ. For large values of θ, the entries in $\mathbf{B}_{\boldsymbol{\theta}}$ estimate the risk spillovers of institution *j*, *k*, and *l* on institution *i* during tranquil market periods. Similarly, small values of θ will result in a $\mathbf{B}_{\boldsymbol{\theta}}$ that indicates the amount of contagion during periods of financial distress.

The lagged value-at-risk of institution i: Most VaR estimates reveal a strong autoregressive structure. This term controls for this fact and ensures that the main coefficients of interest, $\mathbf{B}_{\boldsymbol{\theta}}$, are not biased by a possible correlation between $VaR_{i,t-1}$ and contemporaneous VaR measures of other financial institutions.

3 Measuring Spillover Effects among Financial Institutions

3.1 Data

The subprime crisis of 2007/2009 spread from mortgage-backed securities and CDOs to commercial banks and on to hedge funds and investment banks.[13] Credit risk has furthermore shifted from commercial banks to insurance companies (Allen and Gale, 2005). Consequently, we investigate the following four financial institutions using daily data for the time period 04/02/2003 to 12/31/2010 (2,023 observations).[14]

1. *Commercial Bank Index (26 institutions)*: An index for the U.S. commercial banking sector. Constituents are taken from Acharya, Pedersen, Philippon, and Richardson (henceforth APPR) (2010). Note that the index contains also a few large banks such as Citigroup and Bank of America. We are aware of the fact that many large banks including Bank of America, Citigroup, JP Morgan, and Deutsche Bank generate income from both, commercial and investment banking. Accordingly the classification of these institutions contains some degree of arbitrariness. We show below that the empirical results in this study, appear to be unaffected by any overlaps between the two groups. The index weights are estimated with principal component analysis
2. *Insurance Company Index (31 institutions)*: The constituents for this index are also taken from APPR (2010). Index weights are estimated with principal component analysis.
3. *Investment Bank Index*: The investment bank index was created from the main 8 publicly listed investment banks. We used again principal component analysis for generating the index weights.

[13] See Brunnermeier (2008) for a comprehensive discussion of these linkages.

[14] A detailed description of all variables is given in Appendix A.

4. *Hedge Fund Index*: The Hedge Fund Research Equally Weighted Strategies Index is comprised of all eligible hedge fund strategies.[15] The HFRX index family is an investable index based on information derived from managed accounts for single hedge funds with the longest real track record, i.e. the maximal numbers of observations. The composite as well as the style indices cover the most liquid and largest single hedge funds in terms of assets under management (AUM). Because the return data are not self-reported, self selection bias is not an issue. Furthermore, the index has not been calculated back (backfilling bias) and does not suffer from survivorship bias. The HFRX Equally Weighted Index contains 47 hedge funds and, although similar, is not fully representative of the overall hedge fund universe. A detailed discussion of the differences and their implications for our empirical findings follows in Appendix B. In short, we compare monthly return distributions and time series properties of the HFRX index and a truly representative index. The HFRX index closely follows the development of an index derived from a hedge fund universe. Thus, although the HFRX index may be contaminated with a measurement error, the bias from using the HFRX is likely to be small.

3.2 Static SDSVaR Estimation

In this section, we present the results for estimating Equation (6). We are particularly interested in the spillover coefficient vector $\mathbf{B}_{\mathbf{\theta}}$. The estimation uses the sample period from 04/02/2003 to 12/31/2010 (2,023 observations) in order to cover tranquil, normal, and volatile

[15] Another potential candidate for a composite index is the HFRX Global Hedge Fund Index. The empirical results using the Global Hedge Fund index are similar and yield the same qualitative conclusions.

market periods. We choose the 75% quantile for tranquil market conditions, the 50% quantile for normal market conditions, and the 12.5% quantile for conditions of financial distress.[16]

Figure 1 shows the slopes of the spillover coefficient for different quantiles. While we discuss all spillover coefficients below, in the upper panel of Figure 1 we exemplarily present the effects from changes in the aggregate hedge fund VaR on the VaR of investment banks in order to demonstrate the importance of permitting different coefficients during different phases of the market.[17]

<< Figure 1 about here >>

The solid black regression line shows the spillover coefficient of Equation (4) as implied by the CoVaR model of Adrian and Brunnermeier (2010). Note how the slope of this line shows some average spillover effect but slopes are estimated to be much flatter during tranquil market periods (lighter dashed lines) and much steeper during volatile market phases (darker dashed lines). The CoVaR model would estimate the slope of the spillover effects from the hedge funds' VaR to the VaR of investment banks to be about 0.09. This corresponds to the straight black line in the lower panel of Figure 1.[18] If we interpret this situation as normal market conditions, it is

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[16] The choice of specific quantiles introduces a certain degree of arbitrariness in our model. During tranquil market times risk spillovers are generally close to zero so that the choice of a specific upper quantile has no significant effect on the results. It is also plausible to choose the 50%-quantile for normal market times. Our empirical results, however, react more sensitively to quantile changes for volatile market periods. In this context, the choice of the 12.5%-quantile reflects the trade-off between measuring the tails of the VaR distribution where the largest spillovers occur and an increasing exposure to outliers due to a decreasing number of observations. In section 3.4 we therefore present the changes on the results from using a 15% and a 10%-quantile model.

[17] Similar pictures can be seen for other combinations of financial institutions. The scatter plot above, however, is most suitable for demonstrating the effects of state dependencies. Furthermore, our empirical results in the next section suggest that shocks from the hedge fund industry are of particular importance.

[18] This slope estimate is based on a regression of the investment banking sector's VaR on a constant, the VaR of hedge funds and some control variables (see Equation 6). In contrast, the two-dimensional scatter plot

striking to see the slope of this coefficient to be almost three times higher during market conditions of financial distress. Similarly, the spillover effects are close to zero during tranquil markets.

In order to obtain a more general view of the SDSVaR model, Equation (6) is estimated as a system for all of the four financial institutions (insurance companies, commercial banks, investment banks and hedge funds) and for three different market states (tranquil, normal, and volatile). Table 1 shows the results for the spillover coefficients and the autoregressive term from Equation (6). The main interest lies in the spillover coefficients from institutions j, k, and l to institution i, $\mathbf{B}_{\boldsymbol{\theta}}$. Shocks are originating from the financial institutions denoted in the columns of the table and subsequently spill over to the institution denoted in the rows of the table. For instance, an increase in the VaR of hedge funds by one percent increases the VaR of investment banks by 0.053% during normal market periods. During a crisis this spillover effect is estimated to be 0.604%, i.e. more than 11 times higher.[19] Ignoring state dependency as in the case of the CoVaR model from Equation (4) therefore leads to substantial underestimation of spillover effects.

<< Table 1 about here >>

Table 1 shows that shocks to hedge funds also have some effect on the VaR of insurance companies, and to some extent on commercial banks. Hedge funds and investment banks show

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corresponds to a simple regression with only one regressor and is used to highlight the importance of state-dependency rather than showing the results from our estimation equation.

[19] It should be noted that the standard errors from this two-stage procedure are generally larger than their simple quantile regression counterparts. Standard errors increase (i) because of the imperfect correlation between the endogenous variables and their instruments and (ii) because of the multicollinearity that arises from the fact that endogenous variables are replaced by (different) linear combinations of the same variables. Standard errors are estimated using a residual bootstrap with 500 replications.

some degree of interdependence. During volatile market periods, a one percent increase in the VaR of investment banks leads to a 0.01% increase in the VaR of hedge funds. Every percentage point increase in the VaR of hedge funds in turn has feedback effects in the order of 0.604%. In terms of spillover coefficient size, however, we conclude from Table 1 that hedge funds play a major role in the transmission of financial shocks to other financial institutions.

Table 1 also shows the coefficients of the autoregressive term which are estimated to be close to one.[20] Note that although VaR measures are known to move wildly during crisis periods, the autoregressive structure is actually stronger during this time.[21]

One interpretation for the findings in Table 1 may be that when major prime brokers experienced financial distress in 2008/2009, hedge funds were the first to be affected by margin calls and a tightening of credit availability.[22] This had a significant negative impact on the funding and the asset side of hedge funds during market downturn. As a consequence, risk spillovers among hedge funds arose and affected the entire hedge fund industry. Because hedge

[20] In the presence of serially correlated disturbances the inclusion of a lagged dependent variable leads to biased coefficient estimates. Inspection of the regression residuals showed only little or no autocorrelation with values generally below 0.15.

[21] Some coefficients are estimated to be slightly above one. This might raise some concerns about the stationarity properties of the VaR series. An economic interpretation would be that if, over a period of time, each day is dominated by negative returns, the VaRs of financial institutions respond by turning more negative each day. What is typically observed, however, are return series showing alternating patterns of negative and positive changes so that negative shocks with lag coefficients above one are followed by positive shocks with coefficients below one. Thus, after a shock, the VaR quickly returns to more stable environments rather than increasing indefinitely. Finally, the VaR is directly tied to the return series which in turn is stationary.

[22] To give an example, in an article from the 23rd October 2008 The Economist reports that "In Europe many funds found that the assets they pledged as collateral in return for financing from Lehman have become trapped in the bankruptcy process as administrators strain to work out which assets genuinely belong to clients. Worse still, many assets have simply disappeared, thanks to a standard industry practice called "rehypotecation", in which prime brokers use clients' collateral to raise financing of their own."

funds and banks are interconnected, the failure of hedge funds leads to capital losses among investment banks (Klaus and Rzepkowski, 2009).

We also find that commercial banks increasingly affect insurance companies moving from tranquil to volatile market periods. These results are in line with Allen and Gale (2005) who state that credit risk has been considerably transferred from the banking sector to insurance companies.

Finally, we measure the amount of systemic risk in each state by summing up the spillover coefficients over the institutions.[23] While this figure does not have a natural unit of measurement, it can be used to compare (i) the amount of risk that each financial institution contributes to overall risk, and (ii) the amount of systemic risk within each market state. We estimate systemic risk to be 1.106 during volatile periods which is almost ten times higher than the value during tranquil periods. It is also interesting to note that more than 90 percent of total systemic risk stems from hedge funds, largely coming from the large effect of hedge funds on the VaR of investment banks.

3.3 Dynamic SDSVaR Estimation

In this section, we estimate the SDSVaR as a series of one-step-ahead forecasts using a rolling window of 500 trading days. This requires estimating the SDSVaR for different quantiles and selecting the quantile model that best represents the economic conditions at time *t*. For instance, a SDSVaR model with coefficient estimates that correspond to the lower tail of the VaR_i distribution is applied during times of financial distress. In this situation, a forecast

[23] Spillover coefficients are additive because the SDSVaR explicitly controls for the effects of all other institutions and also account for any potential feedback effects among institutions.

incorporates the "coefficients of the crisis" rather than some average measure which may not be representative of the dependence structure during this time.[24]

Panel A of Figure 2 shows the SDSVaR for investment banks with spillovers from insurance companies, commercial banks, and the hedge fund industry for the period 02/28/2005 to 12/31/2010 (1,525 observations).[25] For comparison, the graph also shows the performance of the CoVaR model. While both, the CoVaR and the SDSVaR are very similar during calm market periods, the CoVaR is less sensitive to extreme risk during downward markets. In contrast to other common VaR methods, such as the normal VaR, however, both VaR models react to changes in the underlying return process and indicate a high level of risk during the crisis period of 2008 and the first half of 2009.[26] In this respect, the SDSVaR is also quite similar to established flexible VaR measures, such as the GARCH-VaR or the CAViaR model of Engle and Manganelli (2004). In fact, recent studies show that these univariate VaR models are already very efficient so that room for improvements is marginal at best (Kuester et al., 2006). The contribution of the SDSVaR model to the body of existing VaR techniques is that (i) it explicitly reveals the magnitude of the spillover at time *t*, and (ii) it provides useful information for

[24] The short memory in the autoregressive structure of the SDSVaR model lends itself to one-step-ahead forecasts whereas multi-step-ahead forecasts will quickly loose in efficiency. The forecast performance will also depend on the stability of the current economic condition. As shown below, the quantile selection procedure in fact does not lead to erratic "quantile hopping" so that the error of selecting the wrong quantile for the forecast remains small (see Panel B of Figure 2).

[25] Note that a foregoing training sample is required to obtain the necessary information for estimating the first entry in the series of spillover coefficients. The estimation period therefore does not start in 4/02/2003 as before but 500 days later.

[26] See for instance Berkowitz and O'Brien (2002) for a comparison of GARCH VaR and normal VaR.

scenario analysis in asking questions such as “how will a shock to the hedge fund industry affect a certain asset class or a group of financial institutions?”[27]

<< Figure 2 about here >>

Panel B of Figure 2 shows the changes in spillover coefficients $\mathbf{B}_{\theta}$ and their corresponding 95% error bands for a rolling 500 trading day window. From left to right, this panel shows the risk spillovers from insurance companies, commercial banks, and hedge funds on the VaR of investment banks. In line with our previous findings investment banks are only marginally affected by insurance companies and commercial banks but react strongly to changes in the VaR of hedge funds. For these institutions risk spillovers remain close to zero during tranquil market periods and are generally below 0.5 for normal market phases. During crisis periods, however, the magnitude of risk spillovers increases markedly with coefficients for the lower 12.5% quantile being often more than twice the size of the spillovers during normal market phases. The two standard deviation error bands show that the effects are also significant during most of the sample period. Note that the backward looking 500 day rolling window causes the coefficients to react with a lag. For instance, coefficient estimates that are based on a sample window with its 500th observation in the first half of 2008 reflect the time before investment banks were in distress. However, coefficients will start to respond to the new circumstances as the crisis period becomes a significant part of the rolling window. Thus the peak of the hedge fund spillovers visible in 2009 in fact reflects occurrences from the second half of 2008 when the investment banks were first hit by the financial crisis.

[27] We will answer these kinds of questions in subsection 3.4 below when we model the dynamic effects of a one time shock using impulse response functions from a simultaneous four equation system.

The left graph of Panel C shows the development of the *R*-squared of the SDSVaR equation. While most common VaR measures tend to perform less well during periods of financial distress (Berkowitz and O'Brien, 2002), the amount of total variation explained by the SDSVaR model actually increases as more information concerning the spillover variables becomes available.

One-step-ahead forecasts are constructed using coefficients that can change on a daily basis, thus creating an additional source of uncertainty. Although this "quantile hopping" can in principle lead to very erratic forecast behavior, Panel A in Figure 2 demonstrates that the series of one-step-ahead forecasts accurately follows the development of the return process over time. To strengthen this argument, the right graph of Panel C shows the quantiles selected by the model.[28] In the period before 2007, only medium and upper quantiles are used for forecast construction, whereas low quantiles are selected for the period of the financial crisis. Note that the variability in the quantiles decreases strongly during this period so that any quantile selection error is reduced during this time.

3.4 Feedback Effects and Persistence of Risk Spillovers

The risk spillover estimates from the preceding section marked the responses of financial institutions within the same day. If Institutions are in fact interdependent and shocks are persistent it would seem reasonable (i) to expect reactions to the initial shock to last over a longer time period and (ii) to observe feedback effects among financial institutions. In this section, we address this issue by employing impulse response functions that show the dynamic behavior of a system of SDSVaRs in the presence of a one time shock to one financial

[28] Quantiles are selected on the whole sample rather than the rolling window. In order to determine market conditions adequately it is desirable to include a large time window that covers all market phases.

institution. Figure 3 shows the impulse response functions for tranquil, normal, and volatile market conditions. This corresponds to θ being equal to the 75%, the 50%, and the 12.5% quantiles of institution *i*'s value-at-risk distribution over the period 04/02/2003 to 12/31/2010 (2,023 observations), respectively. The series are shocked once in the order of -1.5 times their steady state values, i.e. the VaRs' stable time paths that result after all shocks and feedback effects in the system of VaR equations has been worked out. During calm market periods, none of the shocks to the VaR measures of any of the four financial institutions leads to significant spillovers to the VaRs of other institutions. This supports our hypothesis that risk spillovers only take place under distressed market conditions but do not pose a threat to the whole system when financial markets are in a stable condition.

<< Figure 3 about here >>

As we proceed towards more volatile market conditions, we can to some extent observe risk spillovers from commercial banks to insurance companies. The most striking effects, however, come from shocks to the hedge fund industry. They decrease the VaR measures of all other institutions even under market conditions in which shocks in other industries remain unnoticed. During times of extreme volatility, however, shocks from hedge funds have substantial effects on all of the remaining three institutions. The largest impact can be observed for the VaR of the investment bank sector, for which the response is estimated to be more than half the size of the initial shock to the hedge fund industry. In fact, for very low quantiles the crisis coefficients do not lead back to a steady state so that the responses are explosive. This simply reflects the fact that if, over a period of time, each day would be dominated by extreme negative shocks, the VaRs of financial institutions would respond by turning more negative each day. We therefore return to the normal market state coefficients after the day of the shock.

We believe this setting to be reasonable. Even during a financial crisis extreme negative shocks only occur over a few days but generally lead to volatility clustering containing also positive returns. This also has implications for commercial banks' shock response over time. Since risk spillovers from hedge funds are estimated to be the largest for commercial banks during normal market times, shocks in the banking sector are more persistent with only about 50% of the initial shock being adjusted after two months. Note that part of the response of insurance companies is likely to be due to their exposure to both, hedge funds and commercial banks. Finally, the four graphs at the bottom of Figure 3 also show the effects of a 15% and a 10%-quantile model represented as upper and lower borders of the shaded bands around the 12.5%-quantile estimates. The width of those bands suggests that the choice of a specific quantile may have some effect on the estimates for commercial banks but has only little effect on the results from the other three institutions.

Our estimates concerning the duration of spillover effects also help to resolve an apparent conflict with other recent findings. For instance, Billio, Getmansky, Lo, and Pelizzon (2010) find the returns of commercial banks and insurers to have a more significant impact on the returns of hedge funds and investment banks than vice versa. However, the authors estimate spillover effects that occur *between* months. The majority of the spillover effects in our model, however, are effective *within* one month. These intra-month effects remain unobservable to empirical studies based on a monthly frequency.

4 Hedge Fund Styles and Financial Institutions

While many studies focus on the interrelationship between hedge funds and other financial institutions, a number of authors have also emphasized the high "degree of connectedness" among different hedge fund strategies (see e.g. Khandani and Lo, 2007). In this context, the relationship between market liquidity and funding liquidity is regarded as one key component. For instance, Brunnermeier and Pedersen (2009) show that hedge funds are an important source of market liquidity if funding liquidity is high, but traders are less willing to hold high margin positions once funding liquidity declines. King and Maier (2009) stress excessive leverage in combination with herding behavior as an important source of intra hedge fund spillovers. With high leverage, even moderate price swings can force hedge funds to liquidate positions in order to meet margin calls. In this section, we therefore analyze how VaR adjusts by accounting for spillover effects at a disaggregated level, i.e. at the hedge fund style level. We use a similar data set as in our empirical estimations above with daily data from the beginning of the HFR hedge fund strategy series, 04/02/2003, to 12/31/2010 (2,023 observations). We follow the HFR classification and use the strategies equity hedge (EH), event driven (ED), relative value arbitrage (RV), and global macro (GM). Panel A of Table 2 shows the response of financial institutions to the four hedge fund strategies while Panel B shows a network diagram that highlights the increased interconnectedness among hedge fund strategies during financial crises.

<< Table 2 about here >>

In line with our previous results, the spillover effects are small and close to zero for tranquil market periods. During normal market conditions, most of the coefficients are still below 0.04. These estimates are likely to result if one would ignore differences due to changing market conditions. The most striking results are again visible for the coefficient estimates during volatile market periods. In particular, the event driven, the relative value, and the global macro strategy show substantial spillovers to all three financial institutions, often with coefficient values being roughly ten times the size of their normal condition counterparts.

Panel B shows a network diagram of risk spillovers among different hedge fund strategies where the connecting line width is proportional to the spillover size.[29] From this panel we find some evidence for a higher degree of connectedness during volatile market periods as event driven, equity hedge, and global macro seem to be more interrelated during this time. Therefore, we find evidence for the increasing convergence of hedge fund strategies and the impact of crowding among hedge funds.[30] Both of these effects are ignored in traditional risk measures.

5 Conclusion

In this paper, we propose a state-dependent sensitivity value-at-risk (SDSVaR) which measures spillover effects in a simultaneous equation system conditional on the state of the economy. We estimate a system of quantile regressions for four sets of major financial institutions (commercial banks, investment banks, hedge funds and insurance companies) using daily data. Conditioning on the state of financial markets (tranquil, normal, volatile), we find the size and duration of risk spillovers among financial institutions to change substantially between market phases. While risk spillovers are small during normal times, equivalent shocks lead to considerable spillover effects during crisis times. For instance, during normal market times, a one percentage point increase in the VaR of hedge funds is estimated to increase the VaR of investment banks by 0.05 percentage points. The same shock, however, increases the VaR of the investment bank industry by 0.6 percentage points during times of financial distress.

[29] Since most spillovers are bidirectional, the line width is computed as the sum of the two spillover coefficients and is only drawn for positive sums.

[30] Note that in contrast to Khandani and Lo (2007) who measure interdependency using linear correlation coefficients, our spillover coefficients control for the effects of other institutions and capture the non-linearity that is present in the tails of the VaR distribution.

Our empirical results further show that, again during market distress, a one percent increase in the value-at-risk of the hedge fund industry leads to a 0.3% increase in the VaR of insurance companies. Using a set of impulse response functions, we trace out the responses of the same shocks over time and find that they reach their peak after 10 to 20 days. Finally, we provide empirical support for the notion that hedge funds tend to become more interconnected during times of financial distress.

Accordingly, the main conclusions from our empirical results are that hedge funds play an important role as transmission channels and amplifiers of systemic risk. To our knowledge, we are thus the first to quantify the intra-month spillover effects from hedge funds to the rest of the financial system. Furthermore, we have shown that controlling for different market states is crucial for obtaining reliable spillover estimates.

Although our SDSVaR model is useful for measuring and quantifying spillover effects, it does not *explain* the mechanisms underlying the estimated spillovers. In his testimony for the U.S. House of Representatives Lo (2008) emphasizes that in order to construct specific measures that are sufficiently practical and encompassing to be used by policymakers, hedge funds may be required to provide more transparency on a confidential basis to regulators, e.g. leverage, liquidity, counterparties and holdings.

Still, our SDSVaR approach constitutes a powerful policy tool for quantifying short-term risk spillovers and contagion effects among financial institutions. It may help regulators to identify the systemically most relevant financial institutions in the financial system. Finally, the SDSVaR provides useful information to investors during crisis times by revealing substantial interdependencies among financial institutions that would otherwise remain unobservable in standard approaches that do not explicitly control for state dependency.

Appendix A: Index Creation and Constituent List

The data in this study is obtained from Thomson Financial Datastream. For hedge funds we use the original investable indices provided by Hedge Fund Research (HFR) but create own for commercial banks, insurance companies, and investment banks. For commercial banks and insurance companies we take the constituent list used in Acharya, Pedersen, Philippon, and Richardson (henceforth APPR) (2010), from which we slightly deviate. For instance, we classify JP Morgan as an investment bank, while this company is classified as a commercial bank in APPR (2010). We are aware of the fact that many large banks including Bank of America, Citi Group, JP Morgan, and Deutsche Bank generate income from both, commercial and investment banking. As we find little evidence for risk spillovers between these two groups, however, any overlaps appear to be of minor relevance for the results in this study. For the investment bank index we use eight of the largest institutions. The price series for Lehman Brothers is set to zero at 09/15/2008 when Lehman filed for bankruptcy. The Bear Stearns series equals zero after 05/19/2008. The index constituents and the corresponding Datastream Mnemonics are listed in Table A.1.

Table A.1: Aggregated Series/Indices and Datastream Mnemonics

Commercial Banks (26)			
Bb&T	992305	Regions Finl.	951051
Bank Of America	923937	Suntrust Banks	922725
Citigroup	741344	Us Bancorp	951046
Comerica	922964	Wells Fargo	906195
Commerce Bcsh.	923340	Zions Bancorp.	951584
Hudson City Banc.	271662	City National	952436
Huntington Bcsh.	951068	Northern Trust	905861
Keycorp	916130	State Street	951052
M&T Bk.	951503	Synovus Finl.	510056
Marshall & Ilsley	951063	Union Bancorp	689670
Ny.Cmty.Banc.	360240	Wachovia	26611r
Pnc Finl.Svs.Gp.	944175	Washington M.	702406
Peoples United Financial	517465	Western Union	41195m
Insurance Companies (31)			
Aflac	933185	Health Net	360691
Aetna	255956	Humana	916860
Allstate	322677	Lincoln Nat.	912402
Ambac Financial	545088	Loews	922418
American Intl.Gp.	916305	Mbia	755411
Aon	922817	Marsh & Mclennan	904780
W R Berkley	906828	Metlife	286738
Berkshire Hathaway[31]	982325	Principal Finl.Gp.	14698c
Cigna	912278	Progressive Ohio	936324
Cna Financial	907737	Prudential Finl.	14861v
Chubb	916790	Torchmark	993394
Cincinnati Finl.	951545	Travelers Cos.	933974
Coventry Health Care	544665	Unitedhealth Gp.	702635
Fidelity Nat.Financial	31942e	Unum Group	741410
Genworth Financial	28367u	Wellpoint	14737p
Hartford Finl.Svs.Gp.	867871		
Investment Banks (8)			
Credit Suisse		U:CIK	
Deutsche Bank		D:DBK	

[31] This large U.S. holding company generates the majority of its profits from the insurance companies GEICO, General Re and the Berkshire Hathaway Reinsurance Group which are 100% owned by Berkshire Hathaway. The latter company provides Super-Catastrophic (re)insurance.

Goldman Sachs	U:GS
JP Morgan	U:JPM
Morgan Stanley	U:MS
UBS	S:UBSN
Bear Stearns (until 06/19/2008)	936911
Lehman Brothers (until 09/14/2008)	@LEHMQ
Hedge Funds	
HFRX Equally Weighted Strategies	HFRXEW$
HFRX Equity Hedge	HFRXEHD
HFRX Event Driven	HFRXEVD
HFRX Relative Value Arbitrage	HFRXRVR
HFRX Macro	HFRXMAC

We generate the index weights for the commercial bank, investment bank, and insurance company indices using principal component analysis.[32] If X is the TxN matrix of returns, Ω is the sample covariance matrix, and $\Omega = \Gamma\Lambda\Gamma'$ is the spectral decomposition of Ω, then the principal components of X can be obtained by

$$Y = \left(X - 1_n \overline{x}'\right)\Gamma \tag{B.1}$$

where $\left(X - 1_n \overline{x}'\right)$ is the (time) demeaned return matrix and the first column of Γ, Γ_1 contains the $Nx1$ eigenvector that corresponds to the largest eigenvalue of Ω.[33] While this eigenvector points in the general direction of the data, its corresponding eigenvalue indicates the amount of variation that is explained by the first principal component. Figure A.1 shows the investment bank index and the corresponding index weights generated from the price series of eight of the

[32] Other commonly applied constituent weights are market value weights and equal weights. The former approach assigns large weights to large financial institutions such as JP Morgan (20% on average) but assigns only small weights to companies such as Bear Stearns and Lehman Brothers (about 2% and 5% on average, respectively). In the latter approach time series with higher variance have a higher influence on the index.

[33] See Härdle and Simar (2007) for further reference. Note that in this study, we further use the correlation matrix R instead of the covariance matrix in order to prevent overweighting institutions with a higher variance.

largest investment banks. Note that at some point during 2008 Lehman Brothers and Bear Stearns drop out of the index and the weights of the remaining 6 companies are readjusted to sum to unity.

Figure A.1: Investment Bank Index

Appendix B: Properties of the HFRX Equally Weighted Hedge Fund Index

The HFRX hedge fund index is not fully representative of the entire hedge fund universe. Yet, it is the only hedge fund index that is also available on a daily frequency. In this section, we compare the distributional properties of the HFRX index with those of the entire, and thus representative, hedge fund industry. Differences in variance, asymmetry and fat tails may be used to infer the size and the direction of a possible bias from using the HFRX index. We thereby compare the return properties using *monthly* returns since our representative hedge fund index is only available at a monthly frequency. Because our empirical findings are obtained from daily data, an implicit assumption with this approach is that the relation between both return distributions that we find using monthly data also holds if we compared the return distributions using daily data.

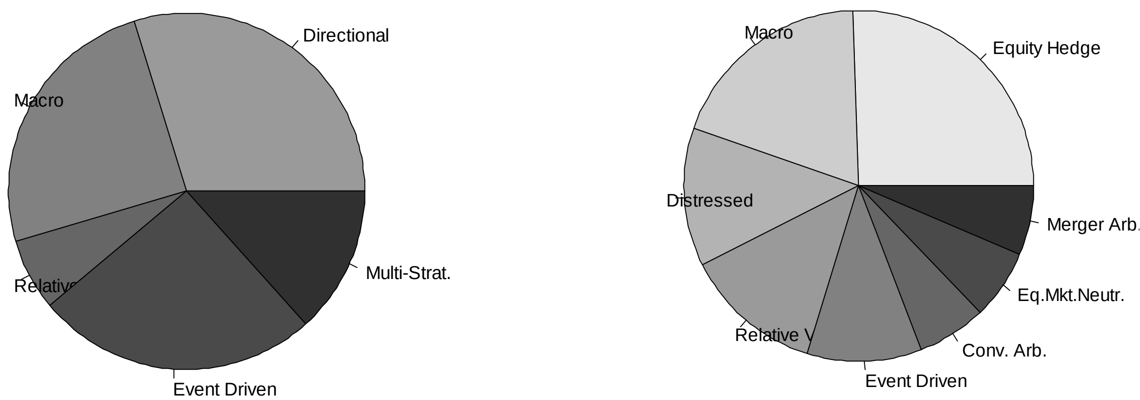
The HFRX index is an investable index. In general, investable indices suffer from the same biases (e.g., survivorship bias, instant history bias) than their non-investable counterparts. Investable indices represent passively managed fund of funds net of all fees and expenses. However, in order to avoid self-reporting bias and to reduce other biases which dominate non-investable hedge fund indices, daily data on single hedge fund basis is taken from managed accounts. In particular, the instant history bias and survivorship bias is of lower relevance due to the fact that in the case of bankruptcy or the addition of a fund the constant track record does not change. The HFRX Equally Weighted Index consists of 47 funds from all major investment strategies. This index suffers from the selection bias and only includes open funds.

In contrast the overall hedge fund universe which is taken to be a representative benchmark is represented by all operating and defunct funds that report to the TASS data base adjusted for onshore duplicates and multiple currency versions of a fund (10,556 Funds).

Panel A in Figure B.1 shows the strategy weights of the whole hedge fund industry as well as the weights in the HFRX Equally Weighted Index. Although comparison is complicated by the fact that strategy classification is not consistent over different data providers the main strategies Equity Hedge, Macro, as well as Event Driven and Distressed Securities are presented in similar proportions in both indices. Panel B in figure B.1 shows some descriptive statistics and distribution plots of the equally weighted indices constructed from the TASS and HFRX constituents, respectively. In terms of asset under management (AUM), funds in the HFRX index are on average larger than funds from the TASS database. However, because variation of AUM values among funds is substantial, the *t*-test cannot reject the null hypothesis of equal means (t = 1.36). The same applies for funds' age. The annualized mean return values of the HFRX index are higher than in the TASS index. The HFRX return distribution however exhibits slightly more extreme returns which are also reflected in higher minimum and maximum values and excess kurtosis. Thus, the distributional characteristics in the left tail are similar but somewhat more pronounced than in the total hedge fund universe. If we consider the TASS index to be representative of the hedge fund industry, the observed risk spillovers to other financial institutions have therefore been achieved with less extreme returns.

Figure B.1: Comparison of the HFRX Index with the Total Hedge Fund Universe (2003–2009)

Panel A: Representative and HFRX Equally Weighted Index Strategy Weights



Panel B: Descriptive Statistics and Distribution

	HFRX	*TASS*
Median AUM	*146m*	*17m*
Mean AUM	*877m*	*117m*
Age [years]	*13.78*	*14.67*
Mean return	*11.52%****	*6.01%*
Min return	*-0.072*	*-0.061*
Max return	*0.047*	*0.036*
Volatility	*6.65%*	*6.04%*
Skewness	*-1.37*	*-1.31*
E-Kurtosis	*4.202*	*2.77*
Jarque-Bera	*91.37****	*52.86****

development over time. Thus, if the use of the HFRX index introduces a bias it is likely to be small.

Table B.1: HFRX Investable Equally Weighted Hedge Fund Index and Hedge Fund Strategies

Equally Weighted Index
The HFRX Equally Weighted Hedge Fund Index is comprised of all eligible hedge fund strategies; including but not limited to convertible arbitrage, distressed securities, equity hedge, equity market neutral, event driven, macro, merger arbitrage, and relative value arbitrage.
Hedge Fund Strategies
Equity Hedge
Equity Hedge strategies maintain positions both long and short in primarily equity and equity derivative securities. A wide variety of investment processes can be employed to arrive at an investment decision, including both quantitative and fundamental techniques; strategies can be broadly diversified or narrowly focused on specific sectors and can range broadly in terms of levels of net exposure, leverage employed, holding period, concentrations of market capitalizations and valuation ranges of typical portfolios. Equity Hedge managers would typically maintain at least 50%, and may in some cases be substantially entirely invested in equities, both long and short.
Event Driven
Event Driven Managers maintain positions in companies currently or prospectively involved in corporate transactions of a wide variety including but not limited to mergers, restructurings, financial distress, tender offers, shareholder buybacks, debt exchanges, security issuance or other capital structure adjustments. Security types can range from most senior in the capital structure to most junior or subordinated, and frequently involve additional derivative securities. Event Driven exposure includes a combination of sensitivities to equity markets, credit markets and idiosyncratic, company specific developments. Investment theses are typically predicated on fundamental characteristics (as opposed to quantitative), with the realization of the thesis predicated on a specific development exogenous to the existing capital structure.
Macro
Macro strategy managers which trade a broad range of strategies in which the investment process is predicated on movements in underlying economic variables and the impact these have on equity, fixed income, hard currency and commodity markets. Managers employ a variety of techniques, both discretionary and systematic analysis, combinations of top down and bottom up theses, quantitative and fundamental approaches and long and short term holding periods. Although some strategies employ RV techniques, Macro strategies are distinct from RV strategies in that the primary investment thesis is predicated on predicted or future movements in the underlying instruments, rather than realization of a valuation discrepancy between securities. In a similar way, while both Macro and equity hedge managers may hold equity securities, the overriding investment thesis is predicated on the impact movements in underlying macroeconomic variables may have on security prices, as opposes to EH, in which the fundamental characteristics on the company are the most significant and integral to investment thesis.
Relative Value
Relative Value investment managers who maintain positions in which the investment thesis is predicated on realization of a valuation discrepancy in the relationship between multiple securities. Managers employ a variety of fundamental and quantitative techniques to establish investment theses, and security types range broadly across equity, fixed income, derivative or other security types. Fixed income strategies are typically quantitatively driven to measure the existing relationship between instruments and, in some cases, identify attractive positions in which the risk adjusted spread between these instruments represents an attractive opportunity for the investment manager. RV position may be involved in corporate transactions also, but as opposed to ED exposures, the investment thesis is predicated on realization of a pricing discrepancy between related securities, as opposed to the outcome of the corporate transaction.

Source: Hedge Fund Research (HFR)

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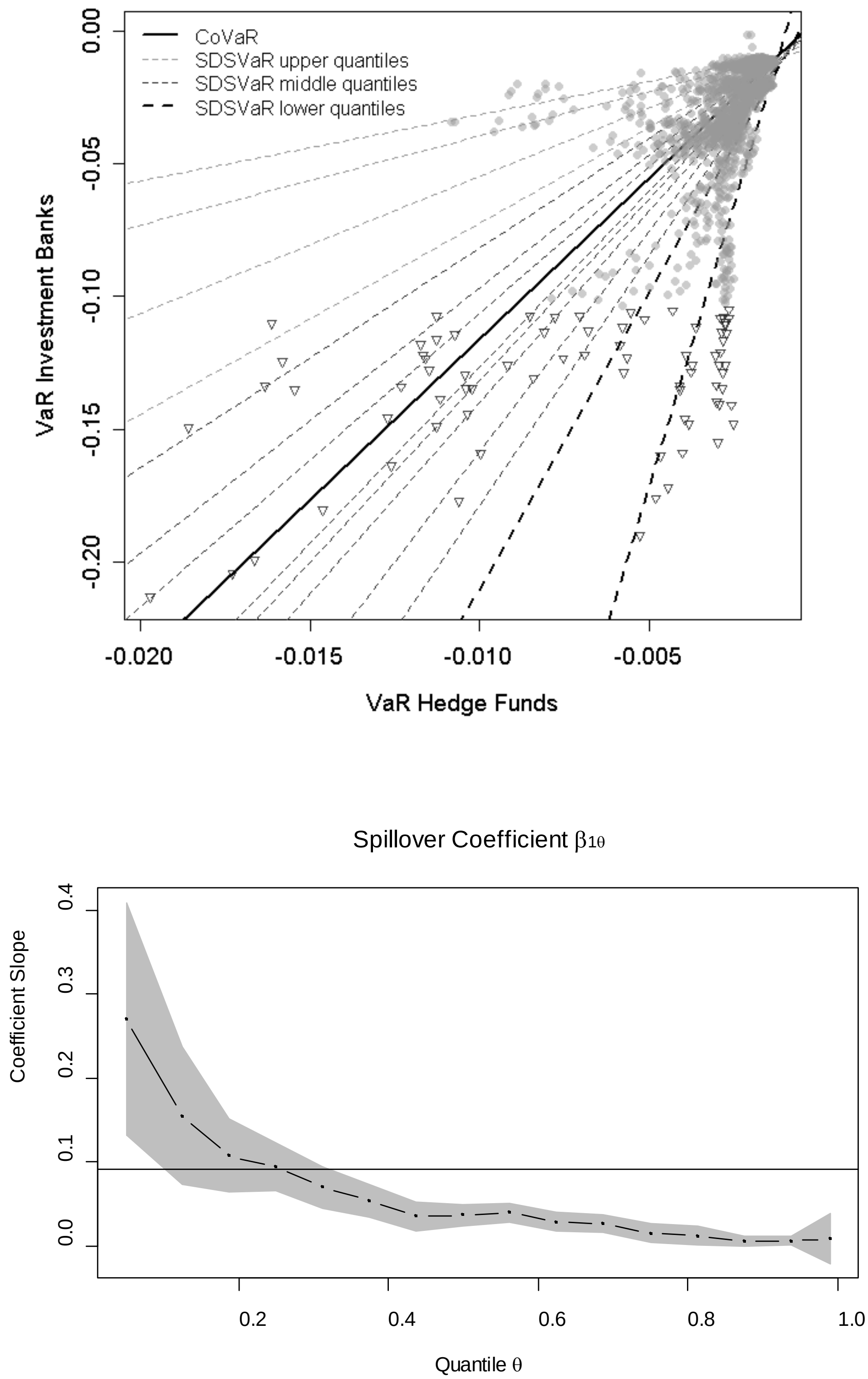
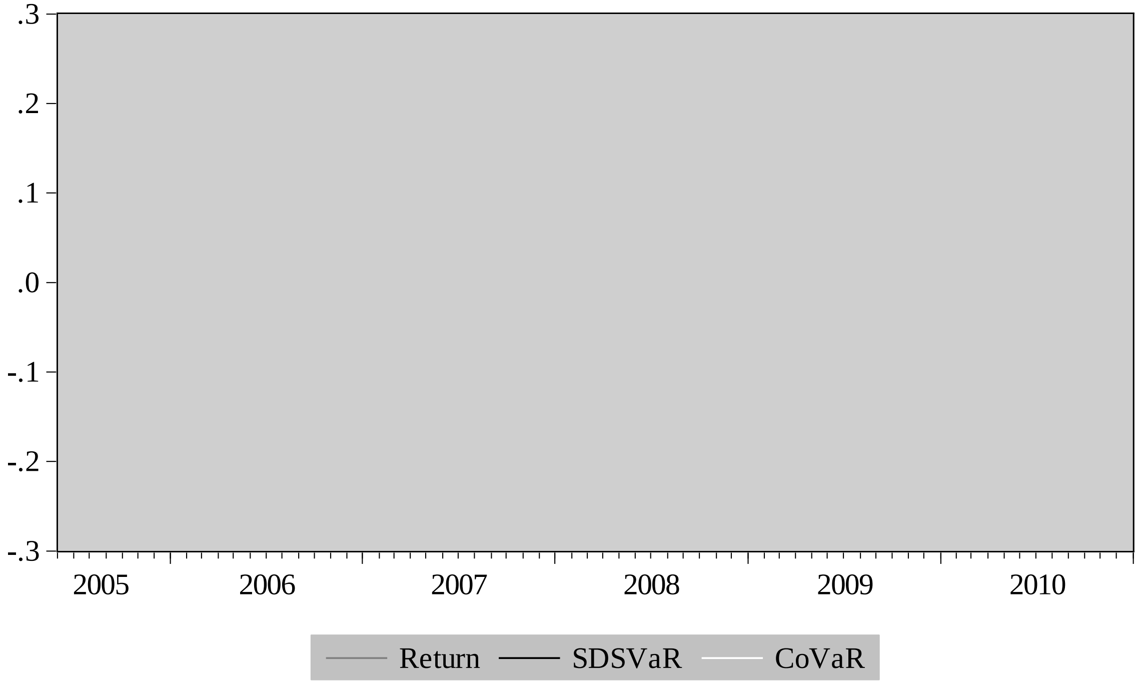
Figure 1: Value-at-Risk Scatter Plots and Quantile Effects for Selected Financial Institutions



This Figure shows the slopes of the spillover coefficient $\beta_{1\theta}$ for various quantiles θ. The coefficients show the response of the value-at-risk in the investment bank industry – denoted on the *y*-axis – to a shock originating in the hedge fund industry – denoted on the *x*-axis. For comparison, the figure also shows the average and thus state ignorant slope coefficient of a CoVaR model. Values above the 75% quantile are denoted as "upper quantiles"; values between the 12.5% quantile and the 75% quantile are denoted as "middle quantiles"; values below 12.5% are denoted as "lower quantiles". The triangles in the scatter plot denote the lowest 5% of the VaR distribution. The figure shows that ignoring different market states underestimates spillover effects during volatile markets periods and overestimates the effects during tranquil market periods.

Figure 2: Dynamic SDSVaR Model for Investment Banks

Panel A: Out-of-Sample Dynamic SDSVaR



Panel B: Time Varying Coefficients and Error Bands

Spillovers from Insurance Comp.	*Spillovers from Commercial Banks*	*Spillovers from Hedge Funds*

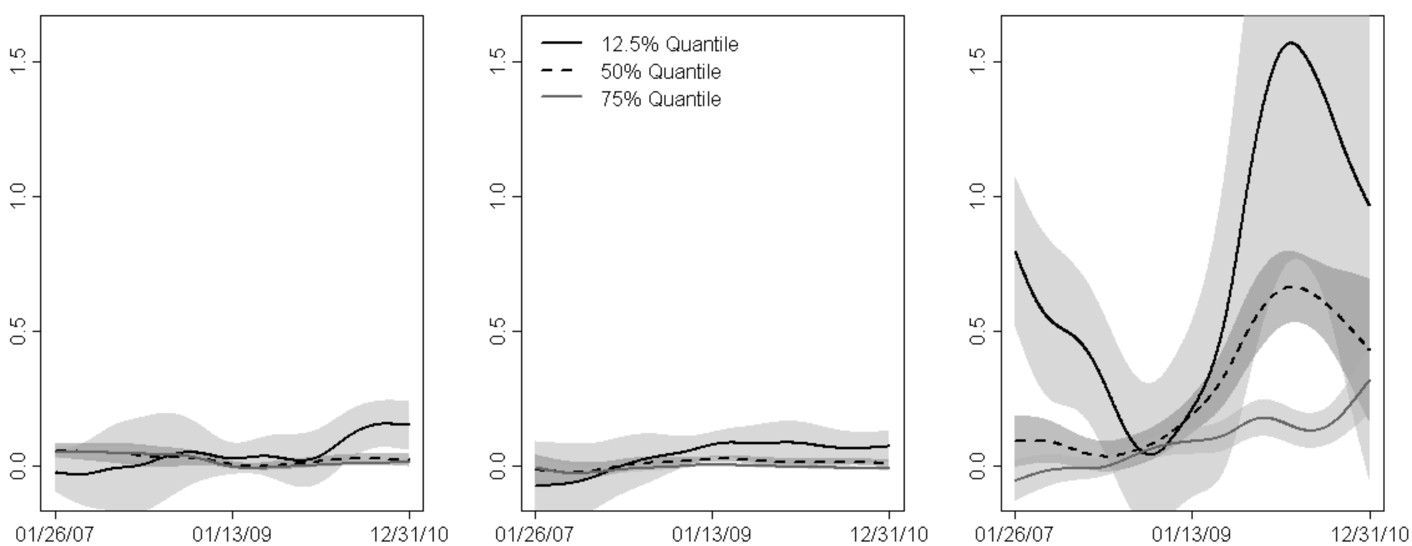
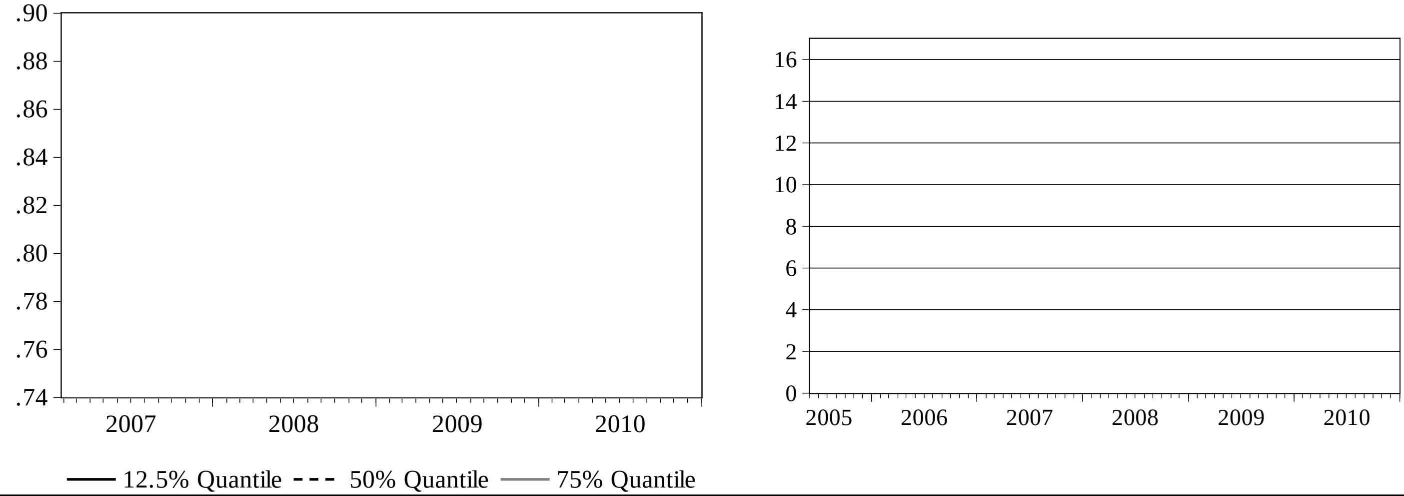


Figure 2 (continued): Dynamic SDSVaR Model for Investment Banks

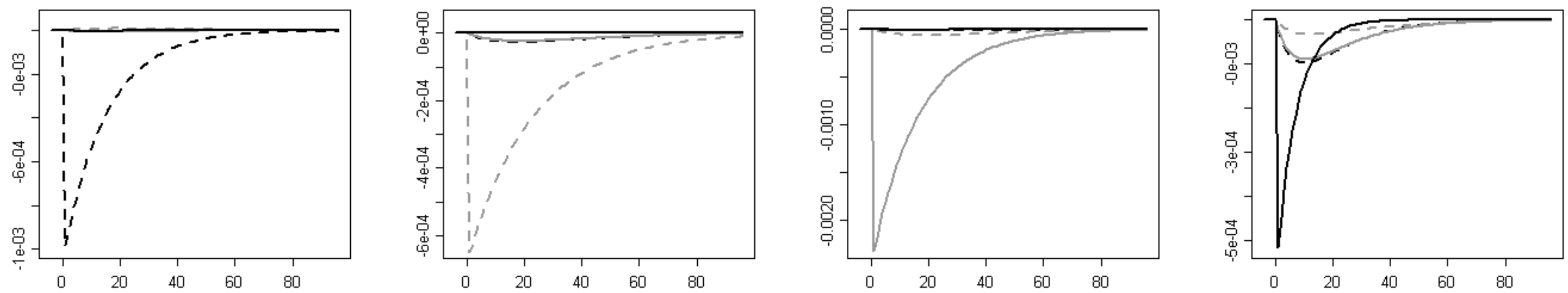
Panel C: R-squared and Quantile Jumps



This figure shows the behavior and performance of the dynamic SDSVaR model for the period 3/01/2005 – 12/31/2010 (1524 obs.). Panel A shows the series of rolling window one-step-ahead forecasts of a SDSVaR that measures the spillover effects from insurance companies, commercial banks, and hedge funds to investment banks. Panel B displays the dynamic behavior of the spillover coefficients over time for different states of the economy together with 95% confidence bands indicating the statistical significance of the estimates. The 75% quantile, the 50% quantile, and the 12.5% quantile correspond to tranquil, normal, and volatile market periods, respectively. Because of the backward looking behavior of the 500 day rolling-window the coefficients reflect the distress period in 2008 with a lag. Panel C shows the *R*-squared of the SDSVaR regression and the respective quantile that was used in estimating the reaction of the SDSVaR to a change in the VaR of hedge funds.

Figure 3: Impulse Response Functions for Tranquil, Normal, and Volatile Market Conditions

Tranquil Market Conditions: 0.75-Quantile



Volatile Market Conditions: 0.125-Quantile

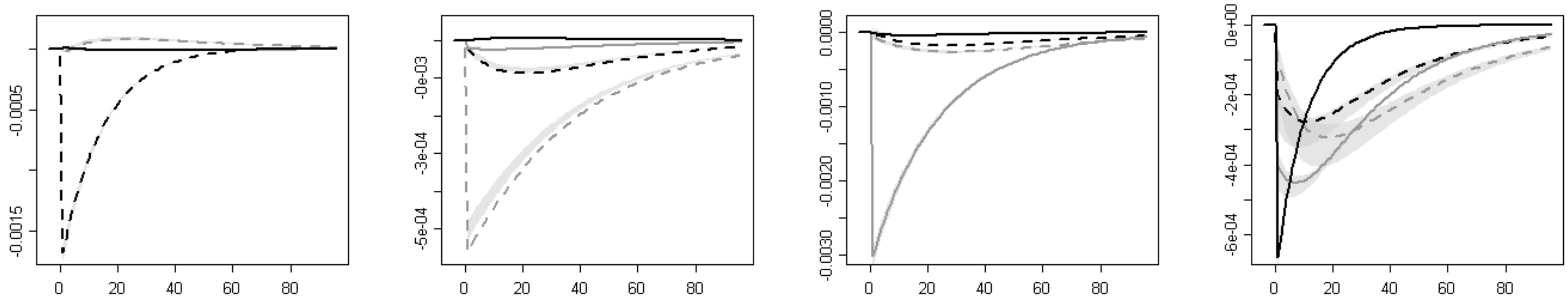


Table 1: Coefficients of the Static SDSVaR Models

from... / to...	Insurance Companies	Commercial Banks	Investment Banks	Hedge Funds	Lag
	Spillover Coefficient $\mathbf{B}_\theta$				
	Tranquil				
Insurance Companies	-	0.006***	0.000	0.047***	0.935***
Commercial Banks	-0.003*	-	0.004***	0.014*	0.957***
Investment Banks	0.001	0.005***	-	0.042***	0.940***
Hedge Funds	0.000	0.000	0.000	-	0.867***
	-0.002	0.011	0.0040	0.1030	
	Normal				
Insurance Companies	-	0.018***	0.005	0.044**	0.934***
Commercial Banks	-0.007**	-	0.007**	0.060***	0.975***
Investment Banks	0.001	0.003	-	0.053***	0.957***
Hedge Funds	0.001	-0.001*	0.001*	-	0.913***
	-0.005	0.020	0.013	0.157	
	Volatile				
Insurance Companies	-	0.041***	-0.001	0.293***	1.028***
Commercial Banks	0.009	-	0.016	0.104	1.035***
Investment Banks	-0.002	0.040***	-	0.604***	0.988***
Hedge Funds	-0.009***	0.001	0.010***	-	1.085***
	-0.002	0.082	0.025	1.001	

This Table shows the size of the coefficient estimates $\mathbf{B}_\theta$ of Equation (6b): $SDSVaR_{\{i|j,k,l\},t,\theta} = \hat{\alpha}_\theta + \hat{\beta}_{1,\theta} VaR_{j,t} + \hat{\beta}_{2,\theta} VaR_{k,t} + \hat{\beta}_{3,\theta} VaR_{l,t} + \hat{\beta}_{4\theta} VaR_{i,t-1}$ for $SDSVaR_i$. Institutions at the top of the table denote the origin of the shock while the institutions in the table rows denote the responding institution. Coefficients are estimated for tranquil, normal, and volatile market states. Market states are measured by the 75% quantile, the 50% quantile, and the 12.5% quantile of the value-at-risk distribution of the responding institution, respectively. For instance, a one percentage point increase in the VaR of hedge funds increases the VaR of investment banks by 0.053 percentage points during normal market times. The same shock, however, increases the VaR of the investment bank industry by 0.604 percentage points during volatile market phases. The estimation period is 4/02/2003 – 12/31/2010 (2,023 obs.).

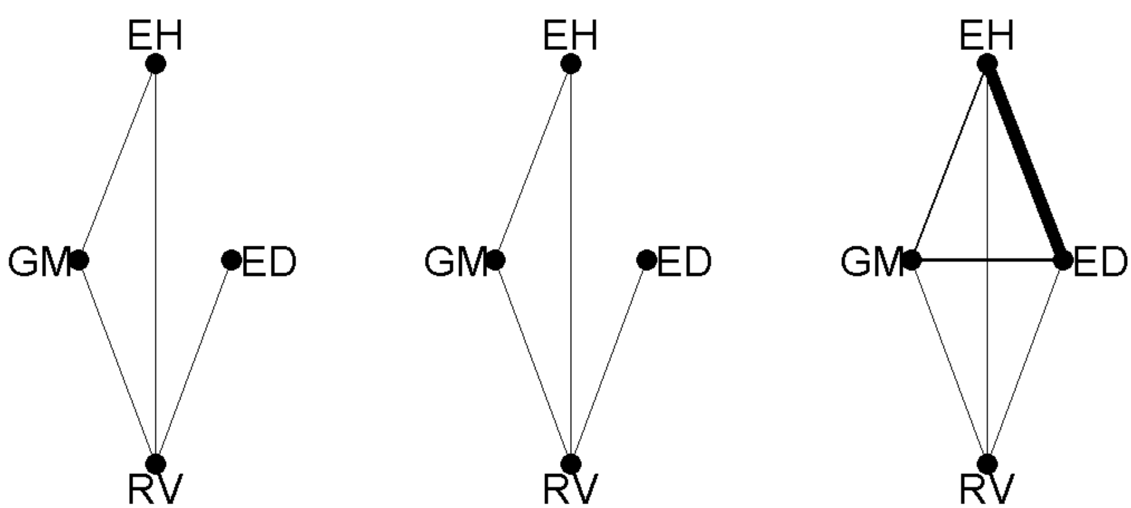
Table 2: Coefficients of the Static SDSVaR Models for Different Hedge Fund Strategies

Panel A: Risk Spillovers from Different Hedge Fund Strategies

from...	**Equity Hedge**	**Event Driven**	**Relative Value**	**Global Macro**
to...	**Tranquil**			
Insurance Comp.	0.009	0.02**	0.03***	0.009*
Commercial Banks	0.01**	0.009	0.013***	0.000
Investment Banks	0.03***	0.018**	0.004	0.008*
	Normal			
Insurance Comp.	-0.004	0.021	0.068***	0.014
Commercial Banks	0.015	0.036**	0.015	0.010
Investment Banks	0.03***	0.033**	0.031***	0.023***
	Volatile			
Insurance Comp.	0.028	0.10	0.201***	0.044
Commercial Banks	-0.117**	-0.12**	0.133***	0.139***
Investment Banks	0.091*	0.37***	0.304***	0.222***

Panel B: Interconnectedness among Hedge Fund Strategies

Tranquil	**Normal**	**Volatile**



This Table shows the size of the coefficient estimates $\mathbf{B}_{\theta}$ of Equation (6b): $SDSVaR_{\{i;j,k,l\},t,\theta} = \hat{\alpha}_{\theta} + \hat{\beta}_{1,\theta} VaR_{j,t} + \hat{\beta}_{2,\theta} VaR_{k,t} + \hat{\beta}_{3,\theta} VaR_{l,t} + \hat{\beta}_{4\theta} VaR_{i,t-1}$. Institutions at the top of the table denote the origin of the shock while the institutions in the table rows denote the responding institution. Coefficients are estimated for tranquil, normal, and volatile market states. Market states are measured by the 75% quantile, the 50% quantile, and the 12.5% quantile of the value-at-risk distribution of the responding institution, respectively. For instance, a one percentage point increase in the VaR of the global macro strategy increases the VaR of investment banks by 0.023 percentage points during normal market times. The same shock, however, increases the VaR of the investment bank industry by 0.222 percentage points during volatile market phases. The estimation period is 4/02/2003 – 12/31/2010 (2,023 obs.). Panel B shows a network diagram of the spillover coefficients among hedge fund strategies (equity hedge (EH), event driven (ED), relative value (RV), and global macro (GM)) and highlights the increase in interconnectedness among those strategies during crisis times.

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Table C.1: Coefficients of the Static SDSVaR Models based on CAViaR Estimates

from...	Spillover Coefficient $\mathbf{B}_\theta$ Insurance Companies	Commercial Banks	Investment Banks	Hedge Funds	Lag
to...	**Tranquil**				
Insurance Companies	-	0.001***	0.000	0.001	0.953***
Commercial Banks	0.000	-	0.000	0.001	0.961***
Investment Banks	0.000	0.000	-	0.002	0.946***
Hedge Funds	0.000	0.000	0.000	-	0.905***
	0.0000	0.0010	0.0000	0.0040	
	Normal				
Insurance Companies	-	0.013***	0.001	0.04***	0.95***
Commercial Banks	-0.007***	-	0.001	0.012	0.977***
Investment Banks	0.013***	0.006**	-	0.086***	0.939***
Hedge Funds	-0.002**	0.001	0.001	-	0.933***
	0.0040	0.0200	0.0030	0.1380	
	Volatile				
Insurance Companies	-	0.031***	0.008	0.132***	0.964***
Commercial Banks	0.003	-	0.011**	0.089***	0.986***
Investment Banks	0.014	0.046***	-	0.385***	0.91***
Hedge Funds	-0.002	-0.001	0.003*	-	0.967***
	0.0150	0.0760	0.0220	0.6060	

This Table shows the size of the coefficient estimates $\mathbf{B}_\theta$ of Equation (6b): $SDSVaR_{\{i|j,k,l\},t,\theta} = \hat{\alpha}_\theta + \hat{\beta}_{1,\theta} VaR_{j,t} + \hat{\beta}_{2,\theta} VaR_{k,t} + \hat{\beta}_{3,\theta} VaR_{l,t} + \hat{\beta}_{4\theta} VaR_{i,t-1}$ for $SDSVaR_i$. Institutions at the top of the table denote the origin of the shock while the institutions in the table rows denote the responding institution. The Value-at-Risk measures that enter the right-hand side of Equation (6b) have been estimated by the asymmetric slope CAViaR model from Engle and Manganelli (2004). Coefficients are estimated for tranquil, normal, and volatile market states. Market states are measured by the 75% quantile, the 50% quantile, and the 12.5% quantile of the value-at-risk distribution of the responding institution, respectively. For instance, a one percentage point increase in the VaR of hedge funds increases the VaR of investment banks by 0.086 percentage points during normal market times. The same shock, however, increases the VaR of the investment bank industry by 0.385 percentage points during volatile market phases. The estimation period is 4/02/2003 – 12/31/2010 (2,023 obs.).