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Systemic Risk, Contagion, and State-Dependent Sensitivities in Value-at-Risk Estimation: Evidence from Hedge Funds

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Working Paper
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Abstract

The occurrences of the 2007/2008 financial crisis revealed the relevance of systemic risk and contagion effects for proper risk management practice. Adrian and Brunnermeier (2009) propose a CoVaR framework by incorporating contagion and systemic risk into value-at-risk estimation. We build upon this important concept by showing that the current approach of estimating the CoVaR neglects the economic condition of the financial environment and thus cannot model the spillover intensities between two asset classes adequately. In this paper we propose a state-dependent sensitivity VaR (SDS-VaR) to show that contagion varies considerably over different market conditions. In particular, shocks to the VaR of one asset class only have a marginal impact on the VaR levels of other asset classes during normal market conditions while the same shocks lead to considerable contagion in volatile market periods. During this state of the market, hedge funds have by far the largest impact on the VaR of the financial system. Impulse response functions from this SDS-VaR measure can be used to reveal the amount of interdependencies between asset classes during market periods of financial distress which will be a highly relevant indicator for risk management purposes. The modeling of spillover effects between several financial institutions allows us to expand existing hedge fund risk factor models by a systemic risk factor.

Keywords: State-dependent sensitivity (SDS) value-at-risk; systemic risk; contagion; quantile regression; hedge funds

JEL-Classification: G10, G12

1 Introduction

From a risk management perspective one of the most important lessons from the 2007/2008 financial crisis is probably that systemic risk and spillover effects are carelessly underestimated in most current risk measures and that risk measurement instruments such as value-at-risk (VaR) are in need of proper adjustments if the level of risk is to be measured adequately.¹ Recent promising work in this direction is the working paper of Adrian and Brunnermeier (2009) who introduce CoVaR as a measure for systemic risk.² This conditional VaR measure incorporates the additional risk in asset i caused by asset j being in distress. If the focus is on macroprudential bank regulation asset i is taken to be the financial system. A substantial difference between asset j 's CoVaR and its VaR measure then indicates significant contribution of this asset to general systemic risk and should result in higher capital surcharges for this institution. From the point of view of an investor CoVaR may be useful for quantifying spillover risk between assets of a portfolio thus providing additional information concerning the tail behavior of the asset's joint distribution.

In this paper we propose a state-dependent sensitivity VaR (SDS-VaR) which builds on the CoVaR framework but estimates the spillover sensitivities conditional on the state of the economy. Our empirical results show that the contagion effects from other asset classes are negligible during tranquil and normal market conditions but become a major risk driver during turbulent market periods. Measuring the spillover sensitivities over all states of the economy

¹ In line with literature we define a crisis to be systemic in nature if many companies fail together, or if one company's failure propagates as contagion causing the failure of many other companies. See e.g., Acharya (2009).

² CoVaR stands for "contagion" or "conditional" VaR. Note that in the literature, the term "conditional VaR" or CVaR (Artzner et al., 1999) usually refers to the mathematical expectation of the return under the condition that the VaR has been exceeded. This common VaR measure however is based on the own past return history and does not condition on spillover effects from other assets.

results in an average value that is not representative of any of the economic states. Even in the context of risk management where the efficient control of capital reserves and risk budgeting plays a major role, state-dependency cannot be neglected.

The remainder of this paper is organized as follows. The next section gives a short overview of the existing approach to CoVaR estimation and proposes the SDS-VaR approach of modeling contagion risk conditional on the state of the economy. We discuss the full-sample-static and the rolling-window-dynamic properties of this model. Impulse response functions showing the dynamics in risk spillovers are presented in Section 3. Based on our previous results, we derive a systemic risk factor and enhance the hedge fund multi-factor model of Fung and Hsieh (1997) in Section 4 to render more precisely the risk premiums of hedge fund investments. Some concluding remarks are drawn in Section 5.

2 A State-Dependent Sensitivity VaR Model

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 modelling of the time-varying distribution of returns.³ In the past, a vast variety of different approaches have been applied. In the expanding literature on VaR estimation, 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) seem to dominate. Common to all methods is the fact

³ In the multivariate VaR context additional attention has to be devoted to the tail dependencies in the joint density of returns.

that the information set that is used to form the VaR estimates is confined to the past return history of the asset or portfolio under consideration. The occurrences of the 2007/2008 financial crisis, however, has sparked interest in the dependence of a VaR measure of one asset i conditional on the VaR of some other asset j and perhaps the total financial system.

The value-at-risk is the estimated loss of an asset that, within a given period (usually 1-10 days), will only be exceeded with a certain small 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,

$$\text{prob}[return_i < -Var_i | \Omega_i] = \theta. \quad (1)$$

The CoVaR has the same concept, i.e. $\text{prob}[return_i < -CoVar_i | \Omega_i] = \theta$ but differs in the information set Ω_i that is used in the estimation process. While traditional VaR measures only make use of the own past return history, i.e. $\Omega_i(VaR) = \{r_{i,t-1}, r_{i,t-2}, \dots, r_{i0}\}$ the CoVaR also includes the VaR of some other, however, related asset j :

$$\Omega_i(CoVaR) = \{r_{i,t-1}, r_{i,t-2}, \dots, r_{i0}, VaR_{j,t}\}. \quad (3)$$

The current approach of estimating the CoVaR is to use quantile regression, by regressing the θ -% quantile of the return distribution on a constant and VaR_j thus generating the VaR as the fitted values from this regression:

$$CoVaR_{i,j} = \hat{R}_{i,\theta} | VaR_j = \alpha + \beta \cdot VaR_j. \quad (4)$$

Adrian and Brunnermeier (2009) extend the basic version of Equation (4) by adding an AR(1) term in order to account for the strong autoregressive structure inherent in the time series of $CoVaR_{i,j}$. Furthermore, several firm characteristic variables such as leverage, size, and maturity

mismatch enter the equation in lagged form generating a flexible risk measure that reacts sensitively to the underlying return process.

One of the main contributions of this paper is to provide evidence that the coefficient β which measures the spillover intensity of VaR_j on VaR_i strongly depends on the state of the economy. During normal market times β will have only little economic significance while the spillover effects become very large if financial markets in general, and the VaR of asset j in particular enters a state of financial distress. This is of course completely in line with our understanding of systemic risk, which only becomes significant during a crisis period. The spillover coefficient $\hat{\beta}$ estimated with the model specification in Equation (4) or some variation thereof will be an average over all states of the economy, possibly being not even representative of any of the states. We propose a two-step approach that makes use of quantile regression. In contrast to the CoVaR model of Adrian and Brunnermeier (2009) who use quantile regression to model the distribution of returns, our SDS-VaR models the distribution of the value-at-risk. While the former model requires setting the quantile θ to 5% or 1% in order to model the VaR, our model enables us to regress over the whole range of quantiles.⁴ When using asset classes or industry aggregates the quantiles of the VaR can be interpreted as reflecting the state or condition of the economy whereby high quantiles correspond to tranquil market periods and low quantiles to situations of financial distress. Furthermore, our interpretation of a SDS-VaR model differs from the interpretation given in Adrian and Brunnermeier (2009). In their view, the $CoVaR_{i,j}$ estimated from Equation (4) measures the VaR of asset i conditional on asset j being under distress. Furthermore, the difference between $CoVaR_{i,j}$ and VaR_i is supposed to measure

⁴ In fact, we estimate equation (6) over a range of 16 quantiles with $\theta = \{0.05, 0.125, 0.1875, 0.25, 0.3125, 0.375, 0.4375, 0.5, 0.5625, 0.625, 0.6875, 0.75, 0.8125, 0.875, 0.9375, 0.99\}$

the contribution of asset j to the market risk of asset i . This interpretation, however, is misleading since VaR_j is simply used as an additional explanatory variable for modeling VaR_i . Asset j however will have a corresponding VaR level at any given point in time which in itself does not reveal any information about the financial condition of asset j .⁵ It may also be misleading to interpret the differences between $CoVaR_{i,j}$ and VaR_i as asset j 's risk contribution since both models measure the same thing: the value-at-risk.⁶ We interpret SDS-VaR (i) as an improved value-at-risk model that accounts for the spillover or contagion risk that is caused by related assets, and (ii) as an approach to explicitly reveal the size of the contagion risk through coefficients that vary over time as well as over different states of the economy.

The first step in our model setup is to estimate VaR_i and VaR_j separately:

$$VaR_k = \mu_{k,t} + z\sigma_{k,t} \quad \text{for } k = i, j. \quad (5)$$

It has become practice to model σ_t by extracting the conditional standard deviation from a GARCH(1,1) model (Kuester et al., 2006, Füss et al., 2009). This will account for the time-varying distribution of returns accurately and leads to substantial improvements in the sensitivity of the VaR to changes in the return process. We will therefore follow this practice.

In a second step, VaR_i now becomes the dependent variable in the quantile regression (see Koenker and Bassett, 1978; Koenker, 2005):

⁵ In fact, even the number of asset j 's VaR exceedances will only reveal information about the goodness of the applied VaR model but nothing about the financial condition. In contrast, only a comparison of an asset's VaR level over time is likely to display any reasonable information about its health status.

⁶ This would be like interpreting the difference between \hat{y}_1 and \hat{y}_2 as the contribution of x_2 to y , where \hat{y}_1 and \hat{y}_2 are the fitted values from the regressions $y = \alpha_{10} + \beta_{11}x_1 + \beta_{12}x_2$ and $y = \alpha_{20} + \beta_{21}x_1$, respectively. This, however, is only true for the special case that $E[u|x_1] = 0$. In particular, it would require $VaR_{j,t-1}$ to be uncorrelated with $VaR_{i,t-1}$, an assumption that is highly unlikely to hold in practice.

$$SDS - VaR_{\{i,j\},t,\theta} = \alpha_{\theta} + \beta_{1,\theta} VaR_{j,t-1} + \beta_{2,\theta} VaR_{i,t-1} + \beta_{3,\theta} |R_{i,t-1}|. \quad (6)$$

The fitted values in Equation (6) constitute the $SDS - VaR_{i,j}$ with the coefficient vector $B' = (\alpha_{\theta}, \beta_{1,\theta}, \beta_{2,\theta}, \beta_{3,\theta})$ depending on the state of the economy. Equation (6) contains the following variables:

The value-at-risk of asset j: This variable can be the VaR of a related asset or the aggregate VaR of an asset class or of the financial system. The coefficient of interest is $\beta_{1,\theta}$ which, for large values of θ , estimates the contagion of asset j on asset i during tranquil market periods. Similarly, small values of θ will result in a $\beta_{1,\theta}$ that indicates the amount of contagion during periods of financial distress. This variable may enter in lagged form depending on the speed at which information is processed by market participants.

The lagged value-at-risk of asset i: Most VaR estimates will exhibit a considerable amount of autoregressive structure. This term controls for this fact and ensures that the main coefficient of interest, $\beta_{1,\theta}$, is not biased by a possible correlation between $VaR_{i,t-1}$ and $VaR_{j,t-1}$.

The absolute return of asset i: This specification corresponds to the symmetric absolute value model in Engle and Manganelli (2004), who were the first to apply autoregressive quantile regression in a value-at-risk context. This variable measures the response to changes in the underlying returns. As positive and negative news should both increase the level of risk, the returns are taken in absolute values.⁷

⁷ Engle and Manganelli (2004) also propose a so called asymmetric slope model which controls for negative and positive return changes separately. Although this approach leads to statistically significant differences in the coefficients of this term, their increase in model performance is only marginal so that we will only consider the symmetric specification above.

2.1 Data Description

The subprime crisis of 2007/2008 spread from asset-backed securities and CDOs to commercial banks and on to hedge funds and investment banks.⁸ For the empirical analysis we therefore use the following four asset categories for the time period 04/02/2003 – 12/01/2009 (1,740 observations):

1. *Residential REIT Index* [Datastream series RITRSNA(PI)]: The subprime crisis started with the default of mortgage backed securities and collateral debt obligations. REITs are an adequate approximation since negative shocks to these financial instruments are directly reflected in the market for REITs.
2. *Commercial Bank Index* [Datastream series BANKSUS]: The commercial bank index from Thomson Reuters.
3. *Investment Bank Index*: The investment bank index was created from 25 publicly listed investment banks. We used principal component analysis for generating the index weights.
4. *Hedge Fund Index* [Datastream series HFRXEW\$]: The Hedge Fund Research Equal Weighted Strategies Index is comprised of all eligible hedge fund strategies.

All series are price indices as the dividend policy of companies would contaminate the estimation of spillover effects among asset prices.

2.2 Static SDS-VaR Estimation

In this section we will provide empirical evidence for the general direction and size of the state dependent coefficient estimates of Equation (6) in general and the spillover coefficient $\beta_{1,\theta}$ in

⁸ See for a comprehensive discussion of these linkages Brunnermeier (2008).

particular. The estimation uses the sample period from 04/02/2003 – 12/01/2009 (1,740 observations) in order to cover tranquil, normal, and volatile market periods. Although a dynamic rolling window estimation of 1-step-ahead forecasts would be preferable from a practitioner’s point of views, the static approach has the advantage of presenting all coefficients in one table and thus facilitates comparison between assets and economic states.

The need to model the contagion coefficient in a state-dependent way is demonstrated in Figure 1 which shows the slopes of this coefficient for different quantiles. The upper left panel in Figure 1 shows a scatter plot of the VaR level of commercial banks against the VaR of residential REITs while the upper right panel depicts the effects from changes in the aggregate hedge fund VaR on the VaR of investment banks.⁹

<< Figure 1 about here >>

In both graphs, the solid blue regression line shows the spillover coefficient as implied by the CoVaR model in Equation (4). This line however clearly does not capture the differences in spillover intensities for different states of the economy. For instance, the simple CoVaR model would estimate the slope of the spillover effects from the residential REITs VaR to the VaR of commercial banks to be 1.2. This corresponds to the solid red line in the lower left panel of Figure 1. If we interpret this situation as normal market conditions, it is striking to see the slope of this coefficient to almost double during market conditions of financial distress. Similarly, the spillover effects are only half the size of the simple CoVaR estimate during tranquil markets. The

⁹ Similar pictures can be seen for other asset combinations. However, the scatter plots above are most suitable for demonstrating the effects of state dependencies. Furthermore, our empirical results in the next section suggest that these are of particular importance.

lack of representativeness of the spillover coefficient of the simple CoVaR model becomes even more apparent when considering the spillovers from hedge funds to investment banks as shown in the right panel of Figure 1. In this case the spillovers are estimated to be much higher than for other assets. At the same time, the range between the high quantile effect and the low quantile effect are also much larger.

The general SDS-VaR model in Equation (6) can be estimated with a larger number of combinations of dependent and independent variables as well as different market conditions. In fact, if we choose the 75% quantile for tranquil market conditions, 50% for normal market conditions, and 12.5% for conditions of financial distress 144 coefficients and their respective significance measures have to be estimated and presented in a way that enables comparison between market conditions and coefficients.¹⁰ Panel A in Figure 2 shows a level plot of the coefficient estimates with the lower panel showing the corresponding p -values. Axis names on the left of each box denote the dependent variable while the axis labels on the bottom or top denote the respective spillover variable on the right hand side of Equation (6). The coefficient estimates are furthermore divided into tranquil, normal, and volatile market conditions. Rather than showing the exact coefficient estimate, the plot uses a color key and relative box sizes to indicate the coefficient size. This allows for quick and easy comparison of coefficients between asset classes and market conditions. Figure 2 shows that the largest coefficient is attributed to the autoregressive term with values close but generally below 1. This autoregressive structure further becomes stronger as market conditions turn bleak.

¹⁰ The number 144 is the result of 4 coefficients per equation times 4 different independent variables times 3 different spillover variables for a given independent variable times 3 different market conditions, namely tranquil, normal, and volatile.

<< Figure 2 about here >>

The main interest, however, lies in the spillover coefficient $\beta_{1\theta}$.¹¹ Although being smaller in size compared to $\beta_{2\theta}$, most of the coefficients are highly significant. Perhaps the most striking fact to derive from this figure is that the VaR spillovers from hedge funds to the other asset classes increases during periods of financial distress with the largest increase for spillovers to the investment banking industry. In contrast, the hedge fund industry itself does not seem to be much affected by shocks in any of the other asset classes. This can be explained by the fact that the financial stress experienced by major prime brokers affected hedge funds by margin calls as well as a tightening of credit availability first. This constitutes significant financial shocks on the funding and the asset side of hedge funds during market downturn. As a consequence spillovers of risk among hedge funds arise and affect the entire hedge fund industries. However, because hedge funds and banks are interconnected, the failure of hedge funds produces capital losses among banks (Klaus and Rzepkowaki, 2009). In fact, Panel B in Figure 2 reveals that the p -values for spillovers to hedge funds are insignificant. Finally, the coefficient $\beta_{3\theta}$ shows the responsiveness of the SDS-VaR to absolute changes in the return process. This effect becomes stronger (i.e. more negative) for periods of financial distress so that VaR measures seem to be more susceptible to changing market conditions during these periods.

2.3 Dynamic SDS-VaR Estimation

¹¹ Note that the color key does not use equal distances, since the distribution among the four coefficient estimates in Equation (6) varies considerably. For instance, while the autoregressive coefficient $\beta_{2\theta}$ is distributed with mean 0.96 and standard deviation 0.05, the mean value and the standard deviation of spillover coefficient $\beta_{1\theta}$ is only 0.09 and 0.15, respectively.

If the SDS-VaR was to be implemented in practice, a risk manager would realistically estimate the model in a rolling window and subsequently forecast one or more steps into the future. This requires estimating the SDS-VaR for different quantiles and selecting the model which quantile represents the economic conditions at time t . For instance, a SDS-VaR 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 incorporates the “coefficients of the crisis” rather than some average measure which may not be representative of the dependence structure during this time.¹² For instance, the empirical results from the static model indicate a higher sensitivity to shocks coming from the hedge fund industry when financial markets are in distress. Panel A of Figure 3 shows the SDS-VaR for Investment banks with spillovers from the hedge fund industry for the period 3/01/2005 – 12/01/2009. In contrast to other common VaR methods such as the normal VaR the SDS-VaR reacts sensitively to changes in the underlying return process and indicates an appropriate level of risk during the crisis period of 2008 and the first half of 2009. In this respect this model is 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.¹³ The contribution of the SDS-VaR model to the body of existing VaR techniques is that it (i) explicitly reveals the magnitude of the spillover at time t which will guide

¹² The short memory in the autoregressive structure of the SDS-VaR 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.

¹³ See for example the studies on VaR performance comparison of Kuester et al. (2006) and Füss et al. (2009).

the investor in pursuing the right hedging strategy, and (ii) provides useful information for scenario analysis in asking questions such as “how will a shock to the hedge fund industry affect a certain asset class?”.¹⁴

Panel B of Figure 3 shows the changes in coefficients and their corresponding 95% error bands for a rolling 500 trading day window. The spillover coefficient $\beta_{1,\theta}$ shows the sensitivity of the investment bank VaR to changes in the VaR of hedge funds. As market conditions change from tranquil to turbulent, the magnitude of this contagion coefficient increases markedly with spillovers for the lower 12.5% quantile of the investment bank VaR being roughly twice the size of the spillovers during more steady market phases. The two standard deviation error bands shows that this effect is also significant over the whole sample period. The coefficient $\beta_{2,\theta}$ shows that the SDS-VaR is highly autoregressive, with coefficients being generally higher during volatile market periods and for lower quantiles. These coefficients are also highly significant. Finally, the value-at-risk becomes more negative for absolute changes in the return process and this effect is again more pronounced for lower quantiles.

An interesting property of the SDS-VaR is shown in the left graph of Panel C, which denotes the development of the *R*-squared of the SDS-VaR equation. While most common VaR measures tend to perform less well during periods of financial distress, the amount of total variation explained by the SDS-VaR model actually increases as more information concerning the spillover variables becomes available.

In practical applications of the SDS-VaR model a possible point of criticism may be the fact that one-step-ahead forecasts are constructed using coefficients that possibly change on a

¹⁴ We will answer these kinds of questions in section three when we model the dynamic effects of a one time shock using impulse response functions from a 4 equation VAR system.

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 3 demonstrated that the series of one-step-ahead forecasts captured the risk in the return series efficiently. To strengthen this argument the right graph in Panel C shows the quantiles selected by the model. In the period before 2007 only medium and high quantiles were used for forecast construction, whereas low quantiles were selected during 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 Risk Spillovers in a System of Hedge Funds

3.1 Scenario Analysis with Impulse Response Functions

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 asset i 's value-at-risk distribution over the period 04/02/2003 – 12/01/2009 (1,740 observations), respectively. During calm market periods none of the shocks to the VaR measures of any of the four asset classes leads to significant spillovers to the VaRs of other asset classes.¹⁵ This supports our hypothesis that risk spillovers only take place under certain market conditions but do not pose a threat to the whole system when financial markets are in a stable condition.

<< Figure 3 about here >>

¹⁵ The series are shocked once in the order of -1.5 times their steady state values.

As we proceed towards more volatile market conditions, however, our results suggest that REITs mainly affect commercial banks and to some extent investment banks. Shocks to the VaRs of commercial banks in turn seem to impact the VaRs of the investment industry while shocks to the investment bank sector have little effect on the risk levels of other assets even in volatile market periods. The most striking effects however come from shocks to the hedge fund industry which decreases the VaR measures of REITs and commercial banks even under market conditions in which shocks from other assets remain unnoticed. During times of extreme volatility, however, shocks in this asset class have tremendous effects on all of the remaining three asset classes. The largest impact can be observed for the VaR of the investment bank sector for which the response is estimated to be even larger than the initial shock to the hedge fund VaR itself.¹⁶ In this case, a one time shock at time t will even be visible several months later.

In the model specification for the hedge funds the responding asset classes enter the SDS-VaR equation in lagged form whereas responding assets enter in contemporaneous form in all other cases. This type of specification has been selected because hedge funds are not publicly traded so that any shocks to this industry group only become noticeable through sell-side actions taken by the affected hedge fund or through news that become available to the financial system. In both cases a lag of one day seems to be reasonable.¹⁷ For instance, the impact on the

¹⁶ In fact, for very low quantiles the impact on other asset classes is estimated to reach a magnitude that causes response functions to explode, i.e. the series do not return to any long-run steady state. The graph that shows the responses to a shock in the hedge fund industry therefore does not represent the 12.5% quantile but rather the 0.375% quantile.

¹⁷ This is also supported by the fact that the impulse response functions for a shock in the hedge fund industry show only little reaction when variables enter in contemporaneous form. Note however that we did not follow this setup in the static approach above. The current preliminary results in Figure 3 come from VARs that do not contain any identifying restrictions and the lag specification might change in the future.

investment bank industry reaches its peak at about 25 trading days, at a time in which the initial shock to hedge funds has already receded.

4. Systemic Risk in Hedge Fund Factor Models

This study is at a very preliminary stage. In the near future we will use the SDS-VaR model to construct a risk factor of systemic risk for the whole financial system. We expect this systemic risk factor to be priced in a factor model for hedge funds as proposed by Fung and Hsieh (1997, 2004).¹⁸ Estimating the systemic risk factor will involve the following steps:

1. Estimate the return for the financial system using a universe of stocks, bonds, hedge funds, commodities and REIT indices. Each asset category will then enter the SDS-VaR equation $SDS - VaR_{\{i,j\},t,\theta} = \alpha_{\theta} + \beta_{1,\theta}VaR_{j,t-1} + \beta_{2,\theta}VaR_{i,t-1} + \beta_{3,\theta}|R_{i,t-1}|$ as a spillover term.
2. Compute the fitted values from $\hat{S}_{i,j,\theta,t} = \alpha_{\theta} + \hat{\beta}_{1,\theta}VaR_{j,t-1}$, thus extracting only the systemic risk component or contribution to total financial risk of the SDS-VaR of each asset category.
3. The sum of all $\hat{S}_{i,j,\theta,t}$ can be interpreted as the “immediate” systemic risk for the whole financial system. Note that this risk factor not only changes in a time dimension but also in a state dimension since different state-dependent coefficients $\hat{\beta}_{1,\theta}$ are used to estimate $\hat{S}_{i,j,\theta,t}$.
4. In order to control for the fact that (i) one time shocks to each asset class impact the financial system not only in $t+1$ but also in the following periods and (ii) shocks to one asset class also propagate to other asset classes and thus indirectly contributing to the shock in the financial

¹⁸ Fung and Hsieh (2004) use the following eight hedge fund risk factors: bonds, currencies, commodities, the trend-following risk factor according to Fung and Hsieh (2001); the two equity-oriented risk factors equity market and size spread; the two bond-oriented risk factors bond market and credit spread factor; and the emerging market index.

system, we will extend the vector autoregressive framework of Section 3 in order to estimate cumulative impacts by controlling for these interdependencies over an extended time period.

5 Conclusion

The financial market crisis of 2007/2008 has revealed fundamental shortcomings in the current framework of banking regulation. Common value-at-risk measures consider each company in isolation and do not control for risk spillovers between companies and asset classes. Recent work in this area extends the traditional VaR measures by controlling for spillover effects from other assets. The additional insights from such an estimation framework are useful for setting capital surcharges in the context of banking supervision. From a practical standpoint the knowledge of risk spillovers and their size is relevant for deciding on the right hedging strategy as well as for scenario analysis.

We propose a state-dependent sensitivity VaR model which measures spillover effects conditional on the state of the economy. The magnitude in estimated spillovers differs considerably over different states of the economy. Ignoring the state dependency in the variables leads to an average estimate of contagion that may not be representative of the actual spillovers in any of the states. In particular, our empirical results indicate only marginal spillovers risk during tranquil and normal market periods while shocks in the VaR of one asset class can lead to substantial contagion in times of financial distress. In this context hedge funds are estimated to be most relevant in generating systemic risks during turbulent market periods.

We present the dynamics of shock spillovers using impulse response functions. During volatile market periods one time shocks to the VaR of one asset can lead to significant responses in the VaRs of other assets. In line with our previous results we find that shocks to the hedge

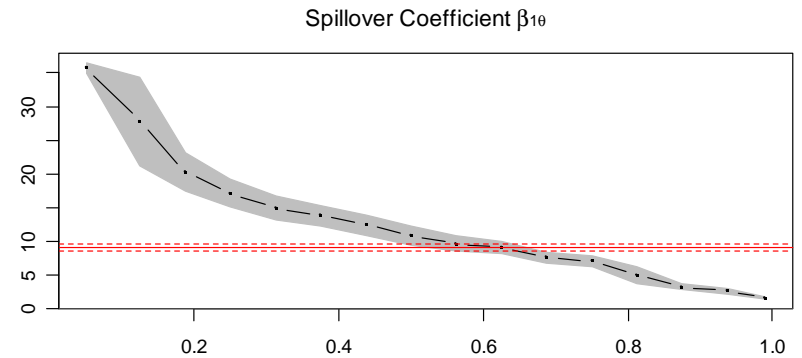
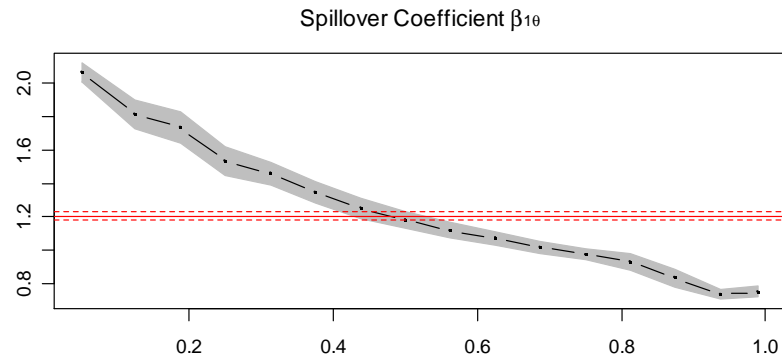
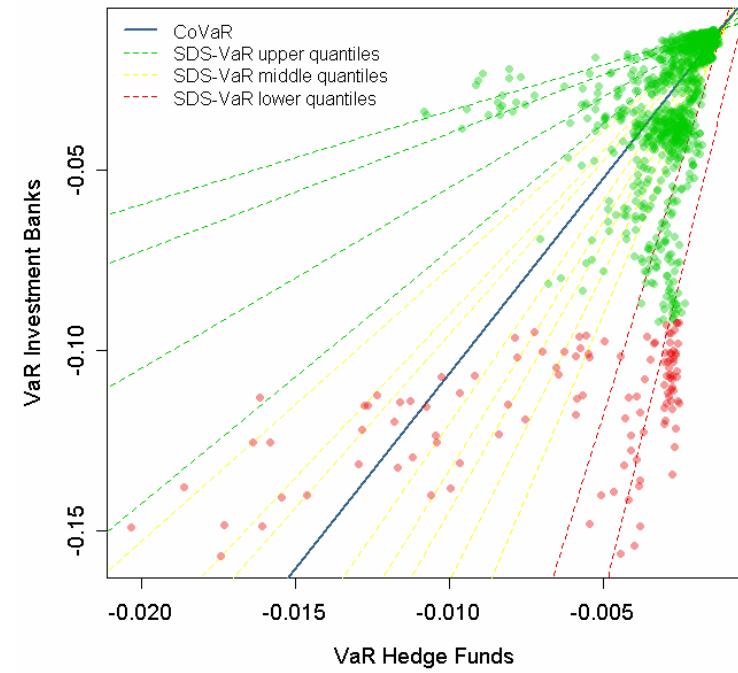
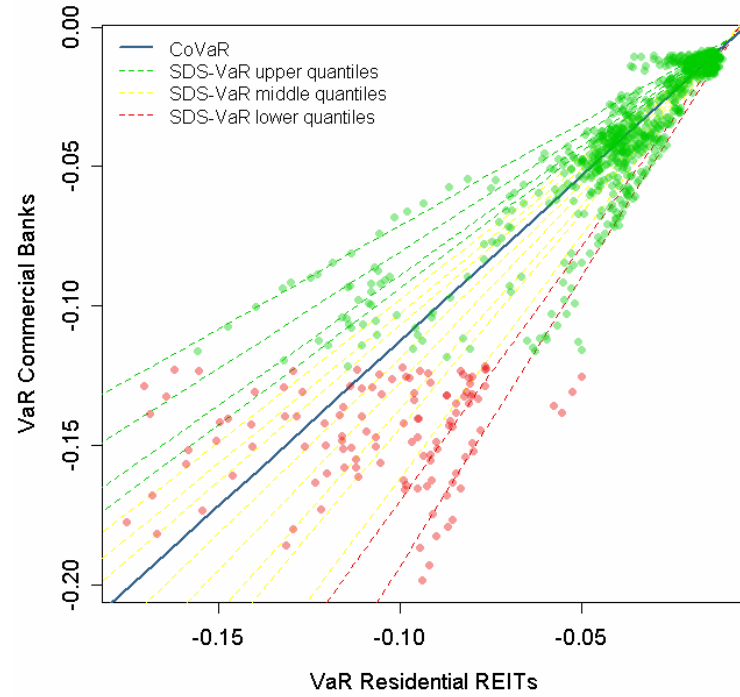
fund industry give rise to considerable VaR reactions of investment banks and other assets. In fact, one time shocks in the hedge fund VaR lead to shock reactions in the whole financial system that can be observed for several months.

References

- Acharya, Viral V. (2009). A Theory of Systemic Risk and Design of Prudential Bank Regulation. *Journal of Financial Stability* 5(3): 224–255.
- Acharaya, Viral V., and Lasse Heje Pedersen (2005). Asset Pricing with Liquidity Risk. *Journal of Financial Economics* 77(2):375–410.
- Adrian, Tobias, and Markus K. Brunnermeier (2009). CoVaR: A Method for Macroprudential Regulation. *FRB of New York Staff Report No. 348*, available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1269446
- Artzner, Philippe., Freddy Dalbaen, J.-M. Eber, and David Heath (1999). Coherent Measures of Risk. *Mathematical Finance* 9(3):203–228.
- Barone-Adesi, Giovanni, and Kostas Giannopoulos (2002), Non-Parametric VaR Techniques. Myths and Realities. *Economic Notes* 30(2):167–181.
- Bollerslev, Tim (1986). Generalized Autoregressive Conditional Heteroscedasticity. *Journal of Econometrics*, 31(3):307-327.
- Boyson, Nicole M., C.W. Stahel, and René Stulz (2009). Hedge Fund Contagion and Liquidity Shocks. *Journal of Finance*, forthcoming.
- Brunnermeier Markus K. (2008). Deciphering the Liquidity and Credit Crunch 2007-08. *Journal of Economic Perspectives* 23(1):77–100.
- Brunnermeier, Markus K., and Lasse Heje Pedersen (2009). Market Liquidity and Funding Liquidity. *The Review of Financial Studies* 22(6):2201–2238.
- Danielson, Jon, and Casper G. De Vries (2000). Value-at-Risk and Extreme Returns. *Annales D'Économie et de Statistique* 60:239–70.

- Engle, Robert F., and Simone Manganelli (2004). CAViaR: Conditional Autoregressive Value at Risk by Regression Quantiles. *Journal of Business & Economic Statistics* 22(4):367–381.
- Füss, Roland, Zeno Adams, and Dieter G. Kaiser (2009). The Predictive Power of Value-at-Risk Models in Commodity Futures Markets. *Journal of Asset Management*, forthcoming.
- Fung, William, and David A. Hsieh (1997). Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds. *Review of Financial Studies* 10(2): 275–302.
- Fung, William, and David A. Hsieh (2001). The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers. *Review of Financial Studies* 14(2):313–341.
- Fung, William, and David A. Hsieh (2004). Hedge Fund Benchmarks: A Risk-Based Approach. *Financial Analysts Journal* 60(5):65–80.
- Fung, William, and David A. Hsieh (2006). Hedge Funds: An Industry in Its Adolescence. Federal Reserve Bank of Atlanta *Economic Review* 91(Fourth Quarter):1–33.
- Kambhu, John, [Til Schuermann](#), and [Kevin J. Stiroh](#) (2007). Hedge Funds, Financial Intermediation, and Systemic Risk. FRNB [Economic Policy Review](#) 13(3):1–18.
- Khandani, Amir E., and Andrew W. Lo (2007). What Happened to the Quants in August 2007. *Journal of Investment Management* 5(4):5–54.
- Klaus, Benjamin, and Bronka Rzepkowski (2009). Risk Spillovers among Hedge Funds: The Role of Redemptions and Fund Failures, *ECB Working Paper Series No. 1112*, November.
- Koenker, Roger (2005). Quantile Regression. Cambridge University Press: Cambridge UK.
- Koenker, Roger, and Gilbert Bassett (1978). Regression Quantiles. *Econometrica* 46(1):33–50.
- Kuester, Keith, Stefan Mittnik, and Marc S. Paolella (2006). Value-at-Risk Prediction: A Comparison of Alternative Strategies. *Journal of Financial Econometrics* 4(1):53–89.

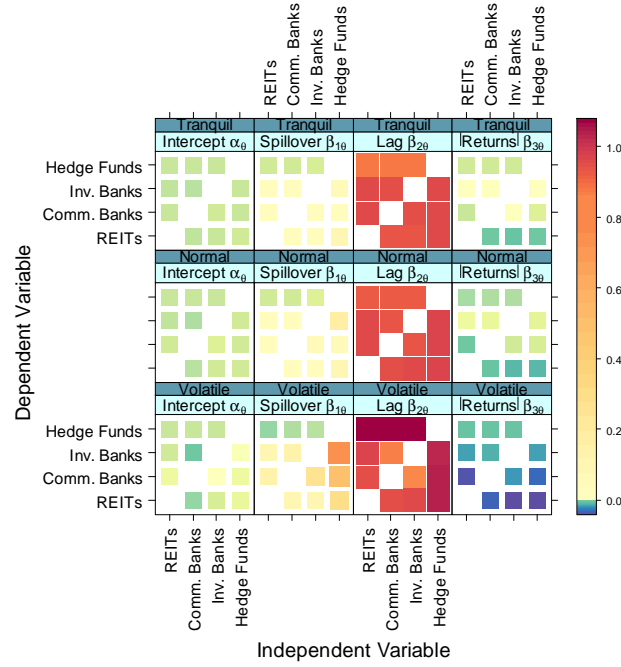
Figure 1: Value-at-Risk Scatter Plots and Quantile Effects for Selected Assets



Notes: 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 red points in the scatter plot denote the lowest 5% of the VaR distribution.

Figure 2: Coefficients and P-values of the Static SDS-VaR Models

Panel A: Coefficient Estimates



Panel B: p-Values

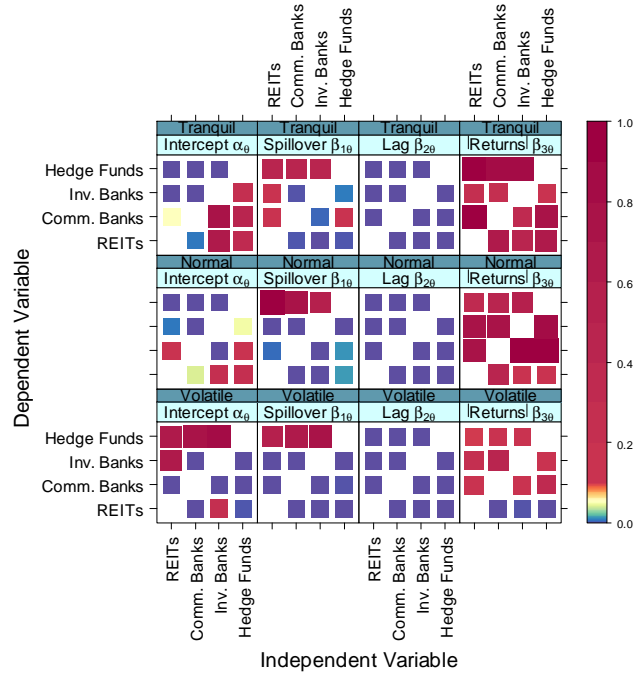
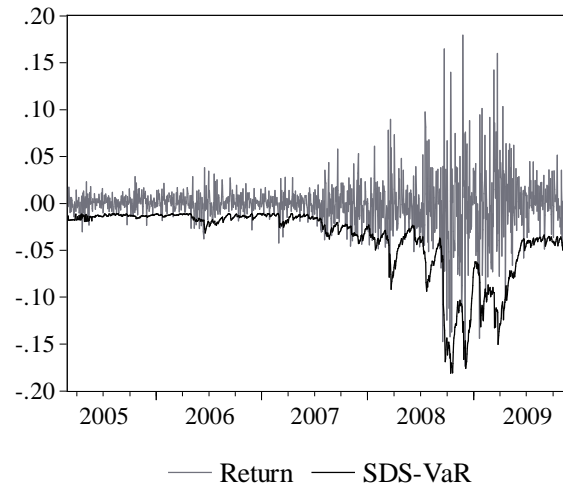


Figure 3: Dynamic SDS-VaR Model for Investment Banks with Spillovers from Hedge Funds

Panel A: Out-of-Sample Dynamic SDS-VaR

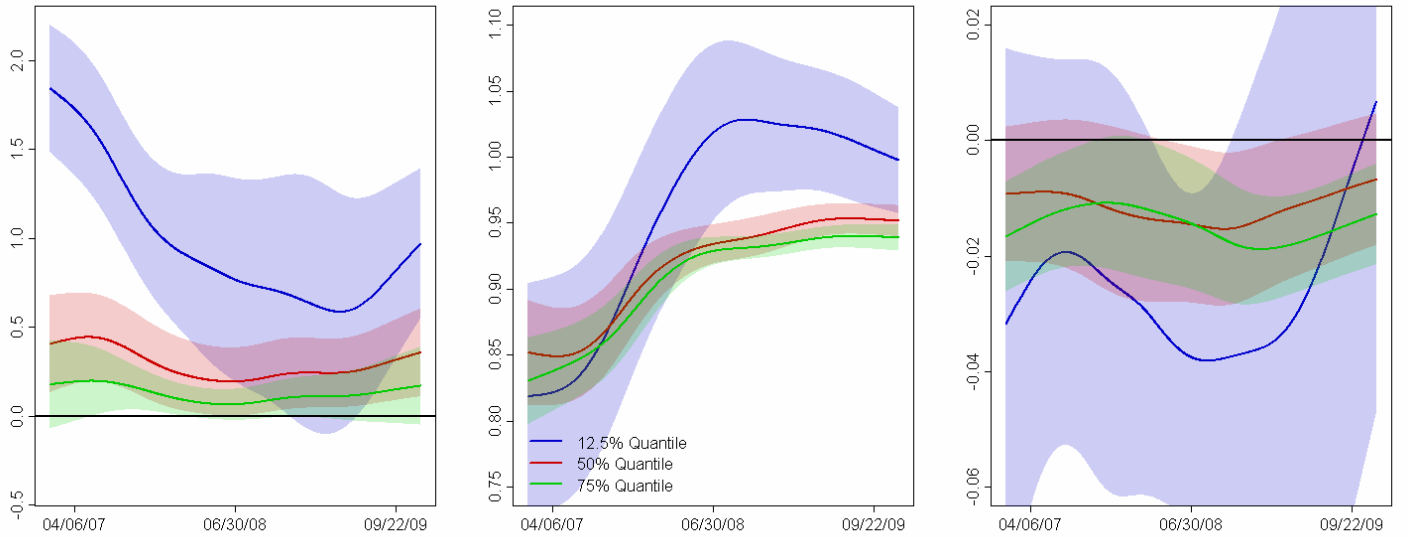


Panel B: Time Varying Coefficients and p-Values

Spillover Coefficient $\beta_{1,\theta}$

Lag $\beta_{2,\theta}$

Absolute Returns $\beta_{3,\theta}$



Panel C: R-squared and Quantile Jumps

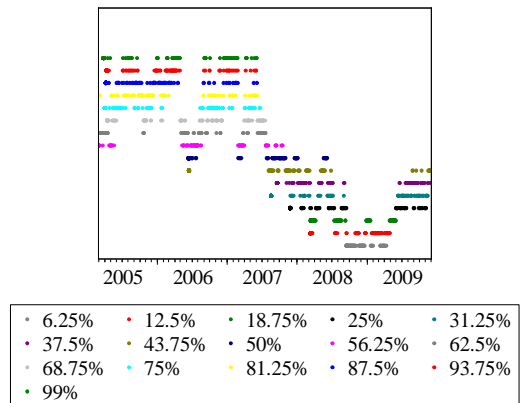
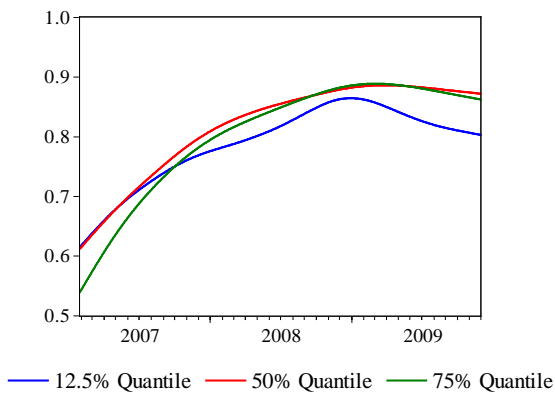
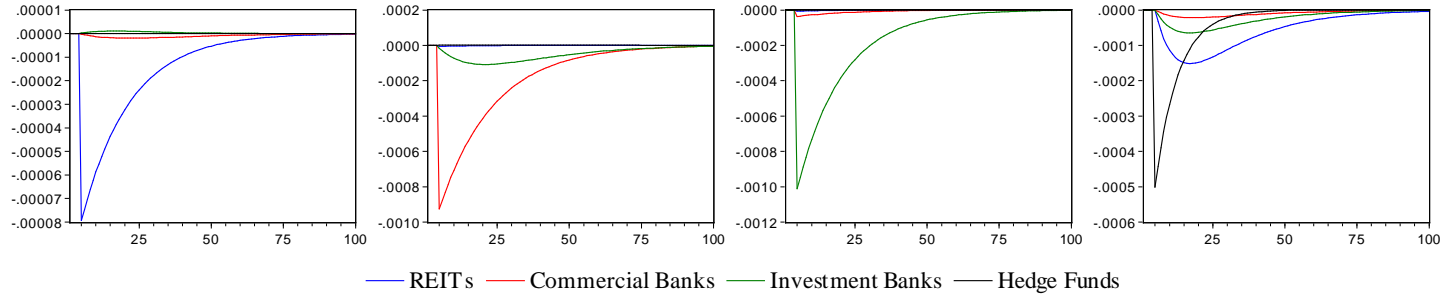
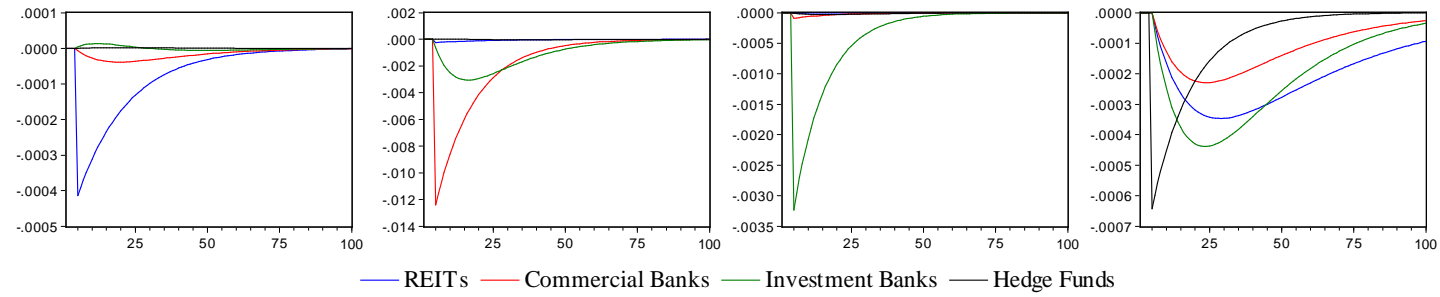


Figure 3: Impulse Response Functions For Tranquil, Normal, and Volatile Market Conditions

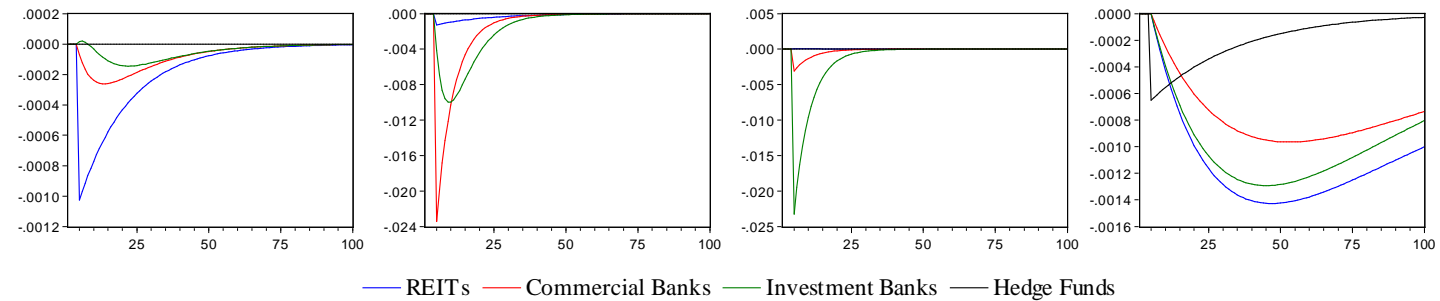
Tranquil Market Conditions: 0.75-Quantile



Normal Market Conditions: 0.5-Quantile



Volatile Market Conditions: 0.125-Quantile



Notes: The observation period ranges from 4/02/2003 to 12/01/2009 (1,740 obs.). REITs, commercial banks and investment banks enter the SDS-VaR equation without lags whereas the hedge fund index enters the equation with lag 1. For the volatile market conditions, the IRF of the hedge fund index shows the case of the 37.5% quantile because lower quantiles lead to shocked SDS-VaRs that do not return to a steady state condition.