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

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Abstract

In this paper, we develop a state-dependent sensitivity value-at-risk (SDSVaR) approach that enables us to quantify the direction, size, and duration of risk spillovers among financial institutions as a function of the state of financial markets (tranquil, normal, and volatile). For four sets of major financial institutions (commercial banks, investment banks, hedge funds, and insurance companies), we show that while small during normal times, equivalent shocks lead to considerable spillover effects in volatile market periods. Commercial banks and, especially, hedge funds appear to play a major role in the transmission of shocks to other financial institutions.

I. Introduction

> Continued focus on counterparty risk management is likely the best course for addressing systemic concerns related to hedge funds.
>
> Ben S. Bernanke (2006)

One of the important lessons from the 2007–2009 financial crisis is that systemic risk and spillover effects are significantly underestimated in most widely used risk measures and that standard risk measurement instruments, such as the value-at-risk (VaR) measure, need to be adjusted to adequately reflect overall risk. In this paper, we propose a state-dependent sensitivity VaR (SDSVaR) approach

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for quantifying risk spillovers among sets of different financial institutions.[1] We estimate a system of quantile regressions for four sets of financial institutions (commercial banks, investment banks, hedge funds, and insurance companies), in which each type of financial institution is represented by an index of several firms. In addition, our empirical model explicitly accounts for the effects of different market states (tranquil, normal, and volatile) on the magnitude of risk spillovers. We trace the time path of how shocks move through the system using impulse response functions (IRFs). The SDSVaR model explicitly reveals the magnitude of risk spillovers at time t. Moreover, in contrast to dynamic correlations, we are able to obtain the *direction* of spillovers from one set of institutions to another. Hence, the approach permits a delineation of spillover effects from shocks affecting the financial sector as a whole.

We show that while small during normal times, equivalent shocks lead to considerable spillover effects in volatile market periods. For instance, during normal market times, a 1-percentage-point increase in the VaR of hedge funds is estimated to increase the VaR of investment banks by 0.09 percentage points. The same shock, however, increases the VaR of the investment bank industry by 0.71 percentage points during times of financial distress. Similarly, during normal times a 1% increase in the VaR of commercial banks leads to a 0.01-percentage-point increase in the VaR of investment banks. In times of financial distress the spillovers from commercial banks to investment banks increases to 0.05 percentage points.

Overall, we make four main contributions to the literature. First, our two-stage quantile regression approach permits an identification of spillover effects as opposed to common shocks affecting the entire financial system. Second, we use the identification of directional shocks to document differences in their magnitude moving from tranquil to crisis times. Third, the results suggest that hedge funds may play an even more prominent role as amplifiers of systemic risk than previously thought. And fourth, the econometric approach allows us to quantify intramonth spillover effects between different sets of financial institutions.

The paper is related to Adrian and Brunnermeier's (2011) conditional value-at-risk (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 that explicitly measures the spillover effects during a crisis. The quantile regression setup and the dynamic structure of the model are inspired by Engle and Manganelli's (2004) conditional autoregressive value-at-risk (CAViaR) model.

The SDSVaR model proposed in this paper is an indirect approach to measuring spillover risk. Relevant determinants, such as direct linkages between institutions, leverage, liquidity, and hedge funds' asset holdings, are not available on a daily basis, so that we cannot *explain* the underlying economic relationships of risk spillovers. Our empirical approach comes with some limitations. Certain types of exposure between financial institutions will not be detected.

[1]We define a risk spillover as a shock in the VaR of one financial institution that is transmitted to the VaR of another financial institution.

First, our approach requires the presence of a shock in the VaR of one institution. For instance, when prime brokers tightened margin requirements for hedge funds in 2008, they most likely had an impact on the risk of hedge funds. Thus, hedge funds were exposed to investment banks, but the lack of a shock in the VaR of investment banks prevents us from measuring this type of exposure. Second, our analysis is based on daily data, which allows us to measure the immediate responses (those that occur within the same day or the next day) but leaves spillovers with a longer propagation lag undetected.[2] This means that our spillover estimates presented in the empirical part do not necessarily reflect the historically observed order with which financial institutions affected each other. Finally, certain types of exposure require investors to be informed about their presence. For instance, the exposure of many banks to American International Group (AIG) via credit default swap (CDS) contracts was basically unknown to investors and was only revealed after AIG's bailout in Sept. 2008, when a list of banks that benefited most from the rescue package was published.

On the other hand, the main spillover mechanism that has been proposed in the recent literature on systemic risk, the one we have in mind in this paper, does not require any knowledge on the side of market participants. The loss and margin spirals described in Brunnermeier and Pedersen (2009) and Brunnermeier and Oehmke (2012) generate spillovers and externalities purely through the actions and loss reactions of financial institutions. For instance, a hedge fund facing margin calls is forced to sell assets in order to raise the required cash, but the additional supply that the fund injects in the market depresses prices further, which may lead to margin calls for other financial institutions. The empirical approach used in this paper is ideally suited in such an environment. It measures the size, direction, and persistency of responses *given* a shock in one financial institution. Measuring spillovers through daily VaR has a number of other advantages. In particular, it may capture risks that arise from relationships among financial institutions that may go beyond those reflected in simple accounting variables. For instance, an article in *The Economist* (Aug. 9, 2007) describes 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. These types of spillover effects, to the extent that they are known to the market, would be fully reflected in our estimates.

The remainder of this paper is organized as follows: The next section places the paper into the literature. Section III explains our SDSVaR approach of modeling spillover effects. Section IV presents the data and the main empirical results.[3] Section V gives some concluding remarks.

[2]In a previous version of this paper, we also try measuring spillovers with monthly data. The results, however, are inconclusive. It seems that the additional observations from the daily frequency are needed to estimate spillovers in the tails of the distribution.

[3]Since transparency and representativeness are major concerns when working with financial data in general and hedge funds in particular, we provide a detailed Internet Appendix, available at www.jfqa.org, on data source, index constituents, and representativeness.

II. Previous Literature

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)). It is unlikely, however, that the systemic relevance of hedge funds is due to high leverage alone. Brunnermeier and Pedersen (2009) highlight the importance of market liquidity and funding liquidity. 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 driven more by funding liquidity considerations than by movements in fundamentals. The high exposure of hedge funds to changes in liquidity causes endogenous risk, triggered by selling pressure, to set off further downward pressure on asset prices within the financial system. This feedback loop is amplified by the risk management tools themselves, which send selling signals on the same assets in many institutions simultaneously (Danielsson and Shin (2003)).

While the literature generally tends to agree that hedge funds are systemically important and that this importance is likely to increase in the future (Danielsson, Taylor, and Zigrand (2005), Garbaravicius and Dierick (2005), Kambhu, Schuermann, and Stiroh (2007), and Chan, Getmansky, Haas, and Lo (2006), among others), our study is the first that provides empirical estimates of the size of *intramonth* spillover effects from hedge funds to other financial institutions. In this sense, we complement a recent paper by Billio, Getmansky, Lo, and Pelizzon (2012), who investigate the interconnectedness among financial institutions using monthly data. While they also find that insurance companies, banks, brokers, and hedge funds have become highly interrelated over the past decade, they focus on longer-term relationships, and they do not attempt to trace the transmission of shocks through the system of financial institutions. Using daily data, we show that the majority of the spillover effects are effective *within* 1 month, reaching their peak after 10 to 15 days. These intramonth effects remain unobservable to empirical studies based on monthly data frequency.

Methodologically, the paper is related to Cappiello, Gérard, and Manganelli (2005) and Boyson, Stahel, and Stulz (2010), who apply quantile regression for binary dependent variable models in order to measure contagion effects among hedge fund styles.[4] Similarly, Chan et al. (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.

[4]Another interesting study that seems to be relevant in our context is the recent working paper by White, Kim, and Manganelli (2010), who propose a computationally intensive generalization of Engle and Manganelli's (2004) CAViaR model.

While the first two studies estimate the effects on state probabilities rather than the size of spillover effects, the latter study provides estimates on the tail-dependence structure without presenting empirical estimates of the magnitude of potential risk spillovers.[5]

The paper also complements a growing literature that examines the actual channels of transmission between financial institutions in general and from hedge funds to the financial system in particular, an issue that we leave unexplored in this paper. However, the majority of that literature examines contagion and systemic risk within the banking sector only. 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 (2010), Hott (2009)), and the interaction of liquidity shortages and solvency problems among banks (Diamond and Rajan (2005)).[6] Gropp, Lo Duca, and Vesala (2009) and Gropp and Moerman (2004), as well as Hartmann, Straetmans, and De Vries (2007), show that distress in one banking system transmits across national borders to other banking systems. Brownlees and Engle (2011) and Acharya, Pedersen, Philippon, and Richardson (APPR) (2010) propose marginal expected shortfall (MES) and systemic expected shortfall (SES) as measures of systemic risk and indicators of financial crises. 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 are highly dependent on external financing also suffer the greatest adverse impact on value added during banking crises (Kroszner, Laeven, and Klingebiel (2007)).[7]

A few recent studies also provide evidence of contagion in the insurance industry. Allen and Gale (2007) argue that the considerable growth in the transfer of credit risk across sectors of the financial system has led 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.

Finally, our approach is complementary to studies that are confined to estimating the average impact on the response variable (e.g., Halstead, Hegde, and Klein (2005), who use an event study approach to estimate contagion effects from hedge funds during the Long-Term Capital Management (LTCM) crisis in 1998, or Ding, Getmansky, Liang, and Wermers (2009), who investigate fund flows during periods of financial distress).[8]

[5]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 et al. (2005)).

[6]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.

[7]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)).

[8]In these studies, the response variable is abnormal stock market returns and hedge fund flows, respectively. The response variable in our study is the VaR of different financial institutions and the hedge fund industry.

III. A State-Dependent Sensitivity VaR Model

Our approach requires estimating VaR measures for four financial institutions, which in turn are used as inputs in a quantile regression. This might seem unnecessarily technical, given the standard practice of measuring comovements among firms and assets with return correlations. However, return correlations are insufficient for our purpose. In order to obtain meaningful spillover estimates, one must be able to identify the direction of spillovers *from* one set of institutions *to* another and delineate them from shocks affecting all financial institutions simultaneously. Correlation coefficients, which by definition are symmetric, do not permit such identification. As a benchmark, consider Table 1, which shows the correlations of daily returns and squared daily returns (in square brackets) among the four sets of financial institutions considered in this paper for the precrisis period from April 2003 to June 2007 and the crisis period from July 2007 to July 2009.

As expected, correlation coefficients increase from the precrisis to the crisis period, at least among commercial banks, insurance companies, and investment banks. However, the increase tends to be relatively small, at least compared to some of the results we obtain below. Furthermore, the return correlations between hedge funds and the other three sets of institutions tend to decline in the crisis, which may lead one to conclude that hedge funds were innocuous in transmitting shocks in the crisis. This finding is robust to using weekly and monthly frequencies (not reported) and also holds for correlations of squared returns (i.e., nonlinear dependency (in square brackets)). Taking feedback effects into account and identifying the direction of spillover effects will let us reach very different conclusions below. Our model yields spillover effects that increase by a factor of about 7 from tranquil to volatile times and suggests a central role in the transmission of shocks of hedge funds in volatile periods.

The VaR is a risk measure with the appealing property of expressing the risk in only one number. Its intuitive interpretation and regulatory importance have led to general acceptance and wide application for internal and external purposes. From a statistical standpoint, estimation of the VaR requires adequate

TABLE 1

Return and Squared Return Correlations among Financial Institutions

Table 1 presents daily return correlations for the precrisis and the crisis period. The data series are discussed in detail in Section IV.A. Values in brackets denote correlations of squared returns.

	Insurance Companies	Commercial Banks	Investment Banks	Hedge Funds
Panel A. Precrisis Period (Apr. 1, 2003–June 29, 2007)				
Insurance companies	1			
Commercial banks	0.75 [0.53]	1		
Investment banks	0.65 [0.41]	0.71 [0.60]	1	
Hedge funds	0.43 [0.18]	0.40 [0.26]	0.59 [0.43]	1
Panel B. Crisis Period (July 1, 2007–July 31, 2009)				
Insurance companies	1			
Commercial banks	0.83 [0.68]	1		
Investment banks	0.78 [0.72]	0.75 [0.56]	1	
Hedge funds	0.28 [0.35]	0.12 [0.16]	0.38 [0.42]	1

modeling of the time-varying distribution of returns.[9] In the past, a vast variety of different approaches have been applied, including generalized autoregressive conditional heteroskedasticity (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 (2001)). 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.[10]

To derive the SDSVaR approach, we start with the standard VaR of a single type of financial institution. The VaR 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,

$$\text{(1)} \qquad prob\left[return_t < -Var_t\,|\Omega_t\right] \quad = \quad \theta.$$

Adrian and Brunnermeier (2011) 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 contribution of this institution to general systemic risk. Consequently, this should result in higher capital surcharges for systemic risk-enhancing institutions.

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

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

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

$$\text{(3)} \qquad CoVaR_{i,j} \quad = \quad \hat{R}_{i,\theta}\,|VaR_j \quad = \quad \hat{\alpha} + \hat{\beta} VaR_j,$$

where R_i is the time series of institution i returns. In order to model the condition that institution j is in distress, the returns from institution j, R_j, are replaced by the fitted values of institution j's value-at-risk, VaR_j.

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

[10]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, investment banks, hedge funds, and insurance companies).

Adrian and Brunnermeier (2011) extend equation (3) 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.[11] In equation (3), 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.

We propose a two-step approach to estimate the spillover coefficients β. In contrast to the CoVaR model of Adrian and Brunnermeier (2011), 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 VaR. This has important consequences for the interpretation of our results. In the CoVaR model, the quantile θ is set to low values such as 1% or 5%. The result is a VaR estimate from the quantiles of the return distribution. The way the VaR of one institution affects the VaR of another, that is, the spillover coefficients, are assumed to be the same whether markets go through a tranquil period or are hit by a recession. In our approach we obtain the VaR in a preceding step, which allows us to regress the VaRs over the whole range of quantiles.[12] The important point is that movements in the VaR change with the financial health of an institution. During tranquil market times, when institutions have plenty of cushions to absorb shocks, risk spillovers between financial institutions are likely to be marginal. During this market phase, the VaR is close to 0 (i.e., at high quantiles of the VaR distribution) and shows little variation. For stock prices of financial institutions, this was generally the case during the time period of 2003–2005. When the financial crisis hit in 2007, the behavior of the VaR changed dramatically. The higher risk faced in the market not only sent the VaR strongly negative (i.e., to low quantiles of the VaR distribution), but also caused the VaR to be more volatile. During this period, dormant linkages that were building up during tranquil periods became suddenly visible and led to high spillovers between institutions. By modeling different quantiles of the VaR distribution, we can measure how the response of institutions to shocks in another institution changes with the state of the market. Thus, while the 5%-quantile of the return distribution is the VaR, low quantiles of the VaR distribution constitute the VaR during times of financial distress. The former step 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, each covered by an index of several firms, separately:

[11]The estimating equation in Adrian and Brunnermeier (2011) is $R_t^{system} = \alpha^{system,j} + \beta^{system,j} R_t^j + \gamma^{system,j} M_{t-1}$, where the regressor set M_{t-1} consists of weekly financial market variables such as liquidity spread and stock market volatility, and R_t^{system} is measured with the returns of the entire financial system.

[12]We estimate system (5) for three different quantiles with $\theta = \{0.125, 0.5, 0.75\}$, where low, medium, and high VaR quantiles describe volatile, normal, and tranquil states of financial markets, respectively.

$$\widehat{VaR}_m = \hat{\mu}_{m,t} + z\hat{\sigma}_{m,t}, \tag{4}$$

with $\hat{\mu}_{m,t}$ as the mean of institution m at time t.[13] In the following we consider four financial institutions, so that $m = i, j, k$, and l. It has become practice to model $\hat{\sigma}_{m,t}$ by extracting the conditional standard deviation from a GARCH model (Kuester, Mittnik, and Paolella (2006)). This accounts 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 therefore follow this practice.[14]

In a second step, $\widehat{VaR}_m$ becomes the dependent variable and is modeled by its own lag and the VaR measures of the other three sets of institutions. In order to interpret the spillover coefficients in a causal way, the equations also include the following three control variables: the VaR of the general U.S. REIT index, the VaR of the GSCI Commodity index, and the VaR of an index of U.S. nonfinancial stocks. Although we are not interested in the coefficients of those variables, they ensure that our spillover effects are not contaminated by exposure to a common factor.

$$\begin{aligned}
\text{(5a)} \quad \widehat{VaR}_{i,t,\theta} &= \alpha_{1,\theta} + \beta_{1,\theta}\widehat{VaR}_{j,t} + \beta_{2,\theta}\widehat{VaR}_{k,t} + \beta_{3,\theta}\widehat{VaR}_{l,t} \\
&\quad + \beta_{4,\theta}\widehat{VaR}_{i,t-1} + \gamma'_{1,\theta}\mathbf{VaR_{C,t}} + u_{i,t}, \\
\text{(5b)} \quad \widehat{VaR}_{j,t,\theta} &= \alpha_{2,\theta} + \beta_{5,\theta}\widehat{VaR}_{j,t-1} + \beta_{6,\theta}\widehat{VaR}_{k,t} + \beta_{7,\theta}\widehat{VaR}_{l,t} \\
&\quad + \beta_{8,\theta}\widehat{VaR}_{i,t} + \gamma'_{2,\theta}\mathbf{VaR_{C,t}} + u_{j,t}, \\
\text{(5c)} \quad \widehat{VaR}_{k,t,\theta} &= \alpha_{3,\theta} + \beta_{9,\theta}\widehat{VaR}_{j,t} + \beta_{10,\theta}\widehat{VaR}_{k,t-1} + \beta_{11,\theta}\widehat{VaR}_{l,t} \\
&\quad + \beta_{12,\theta}\widehat{VaR}_{i,t} + \gamma'_{3,\theta}\mathbf{VaR_{C,t}} + u_{k,t}, \\
\text{(5d)} \quad \widehat{VaR}_{l,t,\theta} &= \alpha_{4,\theta} + \beta_{13,\theta}\widehat{VaR}_{j,t} + \beta_{14,\theta}\widehat{VaR}_{k,t} + \beta_{15,\theta}\widehat{VaR}_{l,t-1} \\
&\quad + \beta_{16,\theta}\widehat{VaR}_{i,t} + \gamma'_{4,\theta}\mathbf{VaR_{C,t}} + u_{l,t}.
\end{aligned}$$

We allow the vector of control variables $\mathbf{VaR_{C,t}}$ to have feedback effects with our financial institutions by modeling them in the same way, that is, the full system has another three equations for the control variables, which are omitted from

[13]The mean $\hat{\mu}_{m,t}$ can be estimated in a rolling window. In practice, however, the variation in $\hat{\mu}_{m,t}$ is dwarfed by the variation in volatility and does not contribute to the overall variation in *VaR*. For simplicity, we therefore resort to a constant overall mean.

[14]For most of our return series, volatility responds more strongly to negative return changes than to positive ones. To capture this fact we apply the asymmetric EGARCH(1,1) of Nelson (1991) with a conditional t-distribution for the error terms. As a robustness check, we also change the specification along several dimensions. We compared symmetric and asymmetric GARCH models, changed the assumptions of the error distribution, and increased the number of lags of the EGARCH model. We also estimated our VaR series using the asymmetric slope version of Engle and Manganelli's (2004) CAViaR model. The main conclusions derived in this paper are unaltered by these changes, and the spillover coefficients are similar in size. One exception was the EGARCH(2,2) specification, which led to increased spillover estimated during normal and tranquil market times, but the additional parameterization was not justified according to the Schwarz information criterion. Note also that we use VaR instead of volatility, as the former has a more direct interpretation. Technically, VaR is just a linear function of volatility, so that exactly the same spillover coefficients can be obtained using volatilities. To conserve space, we do not show the results here, however, they are available from the authors.

the presentation of system (5) to improve readability. We estimate the parameters in system (5) by two-stage quantile regression.[15] Like in the standard two-stage least squares (TSLS) approach, this method involves finding instruments for the endogenous variables on the right-hand side of the equation using ordinary least squares (OLS). The second stage, however, proceeds with estimating the parameters with quantile regression instead of OLS. We identify the system by assuming that the own lags, $\widehat{VaR}_{m,t-1}$ in equations (5a)–(5d), only affect the VaR of institutions m. Hence, our identifying assumption is that 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. All four coefficients for the own lagged VaRs, $\beta_{4,\theta}$, $\beta_{5,\theta}$, $\beta_{10,\theta}$, and $\beta_{15,\theta}$ in equations (5a)–(5d), are statistically significant at the 1% level and therefore constitute valid instruments to identify the system.[16] Equations (5a)–(5d) are the central equations in this paper, and our interest lies in the estimates of the spillover coefficients $\mathbf{B}'_{i,\boldsymbol{\theta}} = \left(\hat{\beta}_{1,\theta}, \hat{\beta}_{2,\theta}, \hat{\beta}_{3,\theta}\right)$, $\mathbf{B}'_{j,\boldsymbol{\theta}} = \left(\hat{\beta}_{6,\theta}, \hat{\beta}_{7,\theta}, \hat{\beta}_{8,\theta}\right)$, $\mathbf{B}'_{k,\boldsymbol{\theta}} = \left(\hat{\beta}_{9,\theta}, \hat{\beta}_{11,\theta}, \hat{\beta}_{12,\theta}\right)$, and $\mathbf{B}'_{l,\theta} = \left(\hat{\beta}_{13,\theta}, \hat{\beta}_{14,\theta}, \hat{\beta}_{16,\theta}\right)$, respectively.[17]

As we have motivated before, the quantiles θ of the VaR can be interpreted as reflecting the state or condition of financial markets. Note that quantile regression models the conditional quantile of the left-hand side variable, and not of the regressors. Accordingly, we estimate the spillovers conditioning on the financial health of the institution receiving the spillovers. This follows our intuition that financial institutions react more strongly to shocks when they are already weakened. The collapse of a large bank may leave other banks in the system unharmed during normal market times but can inflict substantial spillovers and distress during times of financial crisis.[18] 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 use the common approach from TSLS to replace potentially endogenous right-hand side variables by instruments obtained from lagged values. This additional effort is rewarded with consistent estimates that account for the fact that the VaRs of interdependent financial institutions are determined simultaneously.[19]

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

[16] Second-lag instruments, $\widehat{VaR}_{i,t-2}$, $\widehat{VaR}_{j,t-2}$, $\widehat{VaR}_{k,t-2}$, and $\widehat{VaR}_{l,t-2}$, are insignificant, and including them has no effect on the results.

[17] As a byproduct, the fitted values from system (5) give an extension of the common VaR measure that explicitly accounts for the spillovers from other institutions. In the following section, we briefly present this extended VaR. However, our aim in this paper is *not* to improve the effectiveness of existing univariate VaRs in capturing daily volatility processes. Existing methods are sufficiently capable of this task (see Kuester et al. (2006) for a comparison of univariate VaR measures).

[18] The VaR graphs for all four financial institutions (not shown) exhibit very similar patterns over time, so that the shock-originating institution is generally in the same market state as the shock-receiving institution. We also confirmed this finding in an expanded model that included binary variables indicating financial distress of the institutions on the right-hand side of the equation. To conserve space, we do not show the results here, however, they are available from the authors.

[19] Note that in two-stage quantile regression, like in TSLS, each equation is estimated separately. The state of the market is determined by the quantile of the left-hand side variable.

IV. Measuring Spillover Effects among Financial Institutions

A. Data

The subprime and financial crisis of 2007–2009 spread from mortgage-backed securities and collateralized debt obligations (CDOs) to commercial banks and on to hedge funds and investment banks.[20] Credit risk has furthermore shifted from commercial banks to insurance companies (Allen and Gale (2007)). According to Greenlaw, Hatzius, Kashyap, and Shin (2008), U.S. dollars (USD) 1.1 trillion of potential losses (of approximately USD 1.4 trillion total reported subprime exposure) were borne by commercial banks, investment banks, hedge funds, and insurance companies. Consequently, we investigate the following four financial institutions using daily data for the time period Apr. 2, 2003–Dec. 31, 2010 (2,023 observations).[21] The findings in this paper do not change qualitatively if we use weekly instead of daily data. However, we cannot derive reliable VaR measures from monthly data due to the absence of significant autoregressive conditional heteroskedasticity (ARCH) effects when estimating conditional volatility.

We generally use principal component analysis for the index weighting, but the results are not affected by this specific weighting approach. We reestimated the empirical results in this paper using equal weights for all four financial institutions and find very similar results. The indices of our four financial institutions are constructed as follows:

1. *Commercial Bank Index (26 institutions)*. An index for the U.S. commercial banking sector. Constituents are taken from APPR (2010). Note that the index also contains 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. However, the empirical results in this study are generally 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), and index weights are estimated with principal component analysis.
3. *Investment Bank Index (8 institutions)*. The investment bank index was created from the main eight publicly listed investment banks. We again used principal component analysis for generating the index weights.
4. *Hedge Fund Index (47 institutions)*. The Hedge Fund Research Equally Weighted Strategies Index is comprised of all eligible hedge fund strategies.[22]

[20] See Brunnermeier (2009) for a comprehensive discussion of these linkages.

[21] A detailed description of all variables is given in the Internet Appendix, available at www.jfqa.org.

[22] 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.

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.[23] 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.

B. Baseline Results

In this section, we present the results for estimating system (5). We are particularly interested in the spillover coefficient vector $\mathrm{B}_{\boldsymbol{\theta}}$. The estimation uses the sample period from Apr. 2, 2003 to Dec. 31, 2010 (2,023 observations) in order to cover tranquil, normal, and volatile 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.[24]

Figure 1 shows the slopes of the spillover coefficients for different quantiles. While we discuss all spillover coefficients below, in Graph A 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.[25]

The solid black regression line shows the spillover coefficient of equation (3) as implied by the CoVaR model of Adrian and Brunnermeier (2011). 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

[23] A detailed discussion of the differences and their implications for our empirical findings can be found in the Internet Appendix, available at www.jfqa.org.

[24] The choice of specific quantiles introduces a certain degree of arbitrariness in our model. During tranquil market times, risk spillovers are generally close to 0, 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 IV.D we therefore present the changes on the results from using a 15%- and a 10%-quantile model.

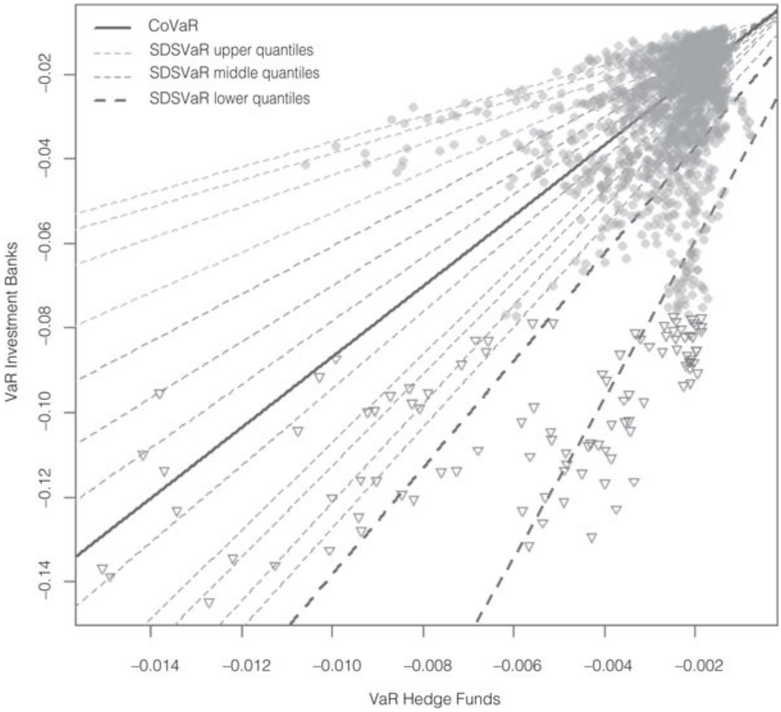
[25] Similar pictures can be seen for other combinations of financial institutions. The scatter plot in Figure 1, however, is most suitable for demonstrating the effects of state dependencies. Furthermore, our empirical results in the next section suggest that shocks from the hedge fund industry are of particular importance.

FIGURE 1

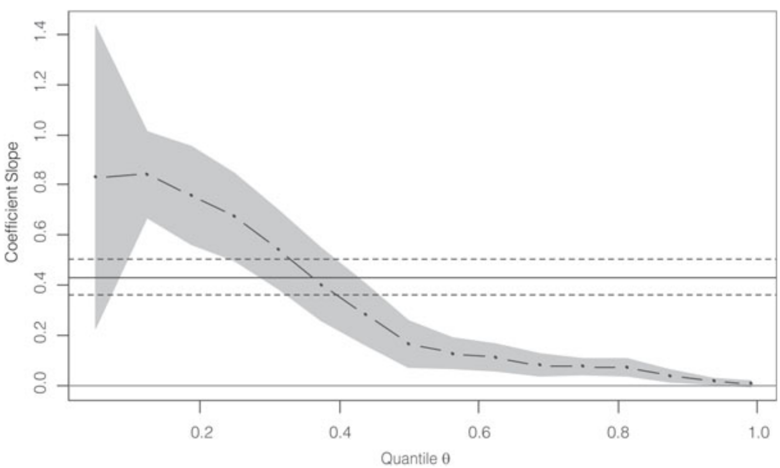
VaR Scatter Plots and Quantile Effects for Selected Financial Institutions

Figure 1 shows the slopes of the spillover coefficient $\beta_{1\theta}$ for various quantiles θ. The coefficients show the response of the value-at-risk (VaR) model in the investment bank industry (denoted on the *y*-axis) to a shock originating in the hedge fund industry (denoted on the *x*-axis). The triangles in the scatter plot denote the lowest 5% of the investment bank's VaR. For comparison, the figure also shows the average and thus state-independent slope coefficient of the CoVaR model (thick line in the upper graph and horizontal solid line with 95% confidence interval in the lower graph). In contrast, 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"; and values below 12.5% are denoted as "lower quantiles."

Graph A. CoVaR and SDSVaR Regression Slopes



Graph B. Spillover Coefficient $\beta_{1\theta}$ for Various Quantiles



black line in Graph B of Figure 1.[26] If we interpret this situation as normal market conditions, it is striking to see that the slope of this coefficient is almost three times higher during market conditions of financial distress. Similarly, the spillover effects are close to 0 during tranquil markets.

In order to obtain directional spillover effects, equations (5a)–(5d) are estimated as a system for our four financial institutions (commercial banks, investment banks, hedge funds, and insurance companies) and for the three control variables (real estate investment trusts (REITs), commodities, and nonfinancial stocks). We obtain a different set of coefficient estimates for each of the three market states (tranquil, normal, and volatile). Table 2 presents the results for the spillover coefficients and the autoregressive term from system (5). 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.[27] For instance, an increase in the VaR of hedge funds by 1% increases the VaR of investment banks by 0.087% during normal market periods. During a crisis, this

TABLE 2

Coefficients of the Static SDSVaR Models

Table 2 presents the size of the coefficient estimates $\mathbf{B}_\theta$ of equations (5a)–(5d). Institutions at the top of the table denote the origin of the shock, while the institutions in table rows denote the responding institution. Coefficients are estimated for tranquil, normal, and volatile market states. Market states are measured by the 75%-, 50%-, and the 12.5%-quantile of the value-at-risk distribution of the responding institution, respectively. For instance, a 1-percentage-point increase in the VaR of hedge funds increases the VaR of investment banks by 0.087 percentage points during normal market times. The same shock, however, increases the VaR of the investment bank industry by 0.707 percentage points during volatile market phases. The estimation period is Apr. 2, 2003–Dec. 31, 2010 (2,023 obs.). Standard errors are based on 200 bootstrap replicates and account for the fact that the regressors themselves are fitted values leading to additional uncertainty in parameter estimates. ** and * denote significance at the 1% and 5% level, respectively.

	Spillover Coefficient $\mathbf{B}_\theta$				Control Variables			
from ... to ...	Insurance Companies	Commercial Banks	Investment Banks	Hedge Funds	REITs	Commodity	Stocks	Lag
Panel A. Tranquil								
Insurance companies	—	0.006**	0.001	0.047**	−0.003**	−0.001	−0.004**	0.939**
Commercial banks	−0.003	—	0.003*	0.013**	0.000	−0.001	0.003	0.958**
Investment banks	0.012**	0.005**	—	0.062**	−0.007**	−0.002*	−0.018**	0.946**
Hedge funds	0.001	0.000	0.001*	—	0.000	−0.001	−0.002**	0.869**
Panel B. Normal								
Insurance companies	—	0.020**	0.004	0.074**	−0.008**	0.007*	−0.009	0.943**
Commercial banks	0.001	—	0.009**	0.088**	−0.007**	0.004	−0.017**	0.979**
Investment banks	0.012**	0.007**	—	0.087**	−0.007**	−0.002	−0.013**	0.957**
Hedge funds	0.003**	−0.001**	0.001**	—	0.000	−0.002**	−0.002	0.915**
Panel C. Volatile								
Insurance companies	—	0.029**	0.012	0.342**	0.013*	0.046**	−0.070**	1.039**
Commercial banks	0.047**	—	0.045**	0.278**	0.026**	0.023*	−0.111**	0.999**
Investment banks	0.044**	0.051**	—	0.707**	−0.021**	0.032	−0.098**	0.999**
Hedge funds	−0.007**	0.004**	0.007**	—	−0.001	−0.006**	−0.001	1.097**

[26]This slope estimate is based on a regression of the investment banking sector's VaR on a constant and the VaR of the other three financial institutions (see system (5)). In contrast, the two-dimensional scatter plot 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.

[27]To save space, Table 2 does not show the risk spillovers to the control variables.

spillover effect is estimated to be 0.707% (i.e., eight times higher). Ignoring state dependency as in the case of the CoVaR model from equation (3), therefore, leads to substantial underestimation of spillover effects. Note that the standard errors in Table 2 are not only determined by the sampling error in the quantile regression framework but also by the uncertainty within the VaRs themselves, which depend on the exponential GARCH (EGARCH) coefficients. To obtain correct standard errors for Table 2, we apply the maximum entropy bootstrap of Vinod and López-de-Lacalle (2009), which addresses the time-series properties within each financial institution but also retains the dependency characteristics between our four institutions. This technique is used on the raw data to produce 200 bootstrapped versions of Table 2 from which the upper and lower quantiles can be directly determined.

Table 2 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 some degree of interdependence. During volatile market periods, a 1% increase in the VaR of investment banks leads to a 0.007% 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 0.707%. 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 (2007), who argue that credit risk has been considerably transferred from the banking sector to insurance companies. In terms of spillover coefficient size, however, we conclude from Table 2 that hedge funds play a major role in the transmission of shocks to other financial institutions.

This finding should not be unexpected, as recent work directly or indirectly points to hedge funds as major contributors of systemic risk. 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. The high levels of leverage and similarity in investment strategies set off a feedback loop where adverse price moves result in liquidations (Danielsson and Shin (2003)). One interpretation for the findings in Table 2 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.[28] 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 funds and banks

[28]To give an example, *The Economist* (Oct. 23, 2008) reports, "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."

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

Note that our results do not imply that major shocks during the 2007–2009 financial crisis originated in the hedge funds industry and subsequently spread to other institutions. Indeed, anecdotal evidence suggests that some hedge fund distress was caused by increasing margins set by prime brokers. Our findings indicate, however, that shocks in the hedge fund industry (coming from prime brokers or any other source) did not stay in the hedge fund industry. Instead, and this is what seems to be a distinct feature of hedge funds, shocks to hedge funds were amplified and led to severe spillovers to other financial institutions, in particular to investment banks.[29]

Table 2 also presents the coefficients of the autoregressive term, which are estimated to be close to 1.[30] Note that although VaR measures are known to move wildly during crisis periods, the autoregressive structure is actually stronger during this time.[31]

Comparing the correlations reported in Table 1 to the results based on the SDSVaR model reported in Table 2, we find two striking differences. First, while the correlations do tend to increase in the crisis, the increase is much smaller than the increases in spillover coefficients estimated using SDSVaR. Relying on correlations may substantially underestimate the externality of one set of financial institutions on another set during times of financial distress. Second, the SDSVaR results suggest a much more prominent role for hedge funds as institutions that tend to generate significant spillover effects for other financial institutions. The differences are due to the fact that the SDSVaR model eliminates correlations that arise due to all financial institutions being hit by the same common shock and isolates the spillover effects. The spillover effects can be interpreted as evidence in the spirit of endogenous risk as recently proposed by Danielsson and Shin (2003) and Danielsson, Shin, and Zigrand (2009) and represent an amplification of the initial shock to the system.[32]

[29]Much of hedge fund distress was caused by investors' mass redemptions during the crisis period. We also estimated a version of Table 2 that includes as an exogenous variable the in- and outflows of funds to the aggregate hedge fund industry. This variable was only available in monthly frequency, so that our results are hardly definitive. Based on these estimates, however, the flows variable was economically and statistically insignificant. The results are available from the authors.

[30]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 little or no autocorrelation, with values generally below 0.15.

[31]Some coefficients are estimated to be slightly above 1. 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 1 are followed by positive shocks with coefficients below 1. 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.

[32]We also tested the spillover effects of different hedge fund strategies (see the Internet Appendix for details). Our results suggest that the importance of hedge funds in generating spillover effects to other financial institutions is not necessarily due to the convergence of hedge fund styles during volatile times.

C. Time-Varying Coefficient Estimates and One-Step-Ahead Forecasts

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, the SDSVaR model with coefficient estimates that correspond to the lower tail of the left-hand side VaR 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.[33]

We obtain the SDSVaR as the fitted values from equations (5a)–(5d). For instance, the SDSVaR of institution i, $\widehat{SDSVaR}_{i|j,k,l}$ can be expressed as

$$\widehat{SDSVaR}_{\{i|j,k,l\},t,\theta} = \hat{\alpha}_\theta + \hat{\beta}_{1,\theta}\widehat{VaR}_{j,t} + \hat{\beta}_{2,\theta}\widehat{VaR}_{k,t} + \hat{\beta}_{3,\theta}\widehat{VaR}_{l,t} + \hat{\beta}_{4,\theta}\widehat{VaR}_{i,t-1}. \tag{6}$$

Graph 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 Feb. 28, 2005–Dec. 31, 2010 (1,525 observations).[34] For comparison, the graph also shows the performance of the CoVaR model. While 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.[35] In this respect, the SDSVaR is also quite similar to established flexible VaR measures, such as the GARCH-type 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 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?"[36]

Graph 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 graph 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

[33]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 lose efficiency. The forecast performance will also depend on the stability of the current economic condition.

[34]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 Apr. 2, 2003 as before, but 500 days later.

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

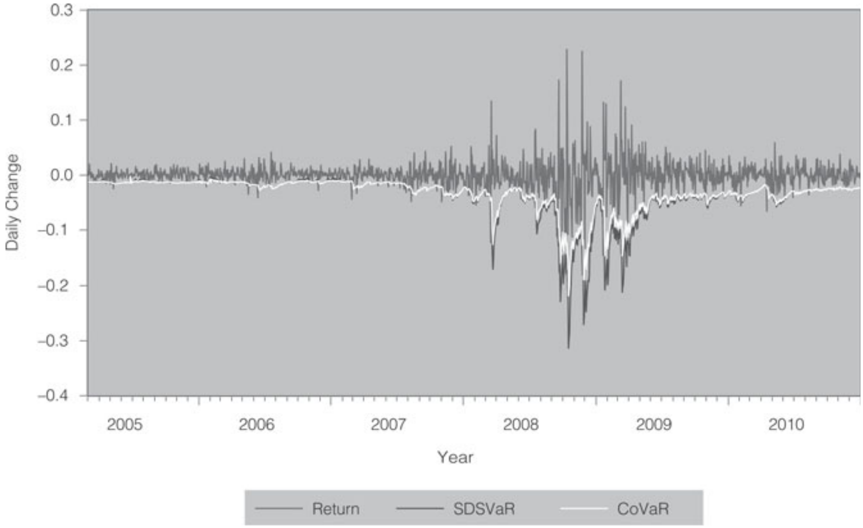
[36]We will answer these kinds of questions in Section IV.D when we model the dynamic effects of a one-time shock using IRFs.

FIGURE 2

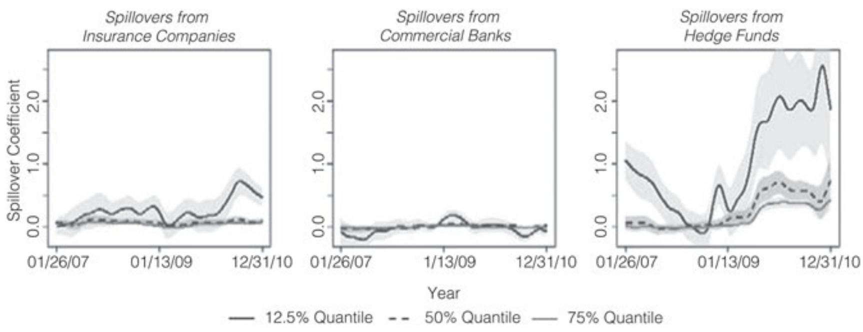
Dynamic SDSVaR Model for Investment Banks

Figure 2 shows the behavior and performance of the dynamic SDSVaR model for the period Mar. 1, 2005–Dec. 31, 2010 (1,524 obs.). Graph A shows the series of rolling window one-step-ahead forecasts of the SDSVaR that measures the spillover effects from insurance companies, commercial banks, and hedge funds to investment banks. Graph 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%-, 50%-, and 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.

Graph A. Out-of-Sample Dynamic SDSVaR



Graph B. Time-Varying Coefficients and Error Bands



companies and commercial banks but react strongly to changes in the VaR of hedge funds. For these institutions, risk spillovers remain close to 0 during tranquil market periods and are generally below 0.7 for normal market phases. During crisis periods, however, the magnitude of risk spillovers increases markedly, with coefficients for the lower 12.5%-quantile often being more than twice the size of the spillovers during normal market phases. The 2-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 start to respond to the new circumstances as the crisis period becomes a significant part of the rolling window. Thus, the sharp rise in hedge fund spillovers during 2009 in fact reflects occurrences from the second half of 2008, when the investment banks were first hit by the financial crisis.

D. 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 period of time and ii) to observe feedback effects among these institutions. In this section, we address this issue by employing IRFs that show the dynamic behavior of a system of SDSVaRs in the presence of a one-time shock to one financial institution.

The IRFs are computed similarly to classical vector autoregressions estimated from OLS. The only difference is that we do not have one coefficient matrix but three (one for each quantile) and hence three different responses. The IRFs are orthogonalized using the standard Cholesky decomposition. Since we have no theoretic guidance for a possible ordering of our variables, we choose the most conservative approach of ordering the shock-transmitting variable last. This means that we restrict the responses such that the shocked variable only affects itself at time t but generates no contemporaneous spillovers (the first spillovers start at time $t + 1$). While this approach means that our IRFs are potentially downward biased, they can be regarded as the smallest estimated response given a shock to one financial institution. More importantly, we mitigate the problem of an ad hoc ordering by treating all variables equally.

Figure 3 shows the IRFs 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 VaR distribution over the period Apr. 2, 2003–Dec. 31, 2010 (2,023 observations), respectively. We shock each financial institution in turn (the order from left to right being insurance companies, commercial banks, investment banks, and hedge funds) and observe the response from the other three institutions. The size of the immediate response depends on the size of the spillover estimates in Table 2, $\mathbf{B}'_{\boldsymbol{\theta}} = \left(\hat{\beta}_{1,\theta}, \hat{\beta}_{2,\theta}, \ldots, \hat{\beta}_{16,\theta}\right)$, whereas the persistence of the response depends on both, the spillover size $\mathbf{B}_\theta$ as well as the size of the own lag (e.g., $\hat{\beta}_{4,\theta}$ in equation (5a)). The VaRs of the financial institutions therefore show larger responses for low quantile states during which the distress coefficients are used to compute the response.

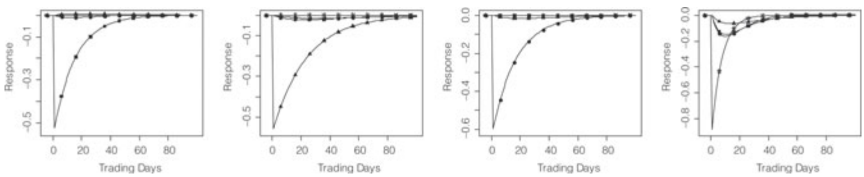
Each series is shocked once in the order of 1 standard deviation. During calm market periods, none of the shocks to the VaR measures of any of the four financial institutions leads to significant spillovers to the VaRs of other institutions. This supports our hypothesis that risk spillovers only take 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

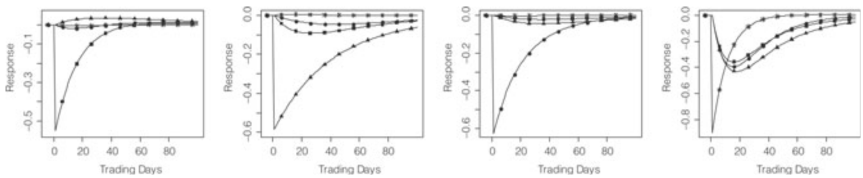
IRFs for Tranquil, Normal, and Volatile Market Conditions

Figure 3 shows how financial institutions respond to shocks originating from other institutions. The size of the shock of each series is 1 standard deviation. In addition to the size of the response, the IRFs also show how quickly institutions respond, as well as how persistent the response is. The estimates are obtained from a seven-equation system (four financial institutions and three control variables) using two-stage quantile regression. The Cholesky ordering is such that the shocked series comes last. This way, the IRFs show the most conservative spillover dynamics: The shocked series is assumed to have no spillover effects on the other three institutions in period *t* (i.e., spillovers start with a lag of 1 day). Ordering the series this way means our spillover estimates are likely to be downward biased. On the other hand, we avoid the problem of an ad hoc ordering by treating all series equally. The observation period ranges from Apr. 2, 2003–Dec. 31, 2010 (2,023 obs.). During volatile market conditions, the crisis coefficients are used only at the time of the shock in t_0. In the following days, the model returns to the normal market times' coefficients. Graph C shows the 0.125-quantile response together with the 0.15-quantile response (upper border of the bands) and the 0.1-quantile response (lower border of the bands).

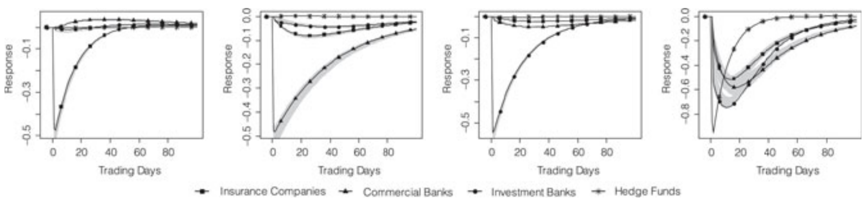
Graph A. Tranquil Market Conditions: 0.75-Quantile Response



Graph B. Normal Market Conditions: 0.5-Quantile Response



Graph C. Volatile Market Conditions: 0.125-Quantile Response



As we proceed toward 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 increase the absolute value of VaR for 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 around three-quarters 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 were 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 also containing positive returns. This also has implications for commercial banks' shock response over time. During normal market times, commercial banks have the largest lag coefficient (0.979). In addition, in normal times risk spillovers from hedge funds are estimated to be the largest for commercial banks. As a consequence, shocks in the banking sector are more persistent, with only about 50% of the initial shock being adjusted after three months. Note also 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 very 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 et al. (2012) 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 return spillover effects that occur *between* months. The majority of the risk spillover effects in our model, however, are effective *within* 1 month. These intramonth effects remain unobservable to empirical studies based on a monthly frequency.

V. Conclusion

In this paper, we propose a state-dependent sensitivity value-at-risk (SDSVaR) model that measures spillover effects in a system of simultaneous equations 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, and volatile), we find the size and duration of risk spillovers among financial institutions to change substantially depending on the state of the market. 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 1-percentage-point increase in the VaR of hedge funds is estimated to increase the VaR of investment banks by 0.09 percentage points. The same shock, however, increases the VaR of the investment bank industry by 0.71 percentage points during times of financial distress.

Our empirical results further show that, again during market distress, a 1% increase in the VaR of the hedge fund industry leads to a 0.34% increase in the VaR of insurance companies and a 0.28% increase in the VaR of commercial banks. Using a set of IRFs, we trace the responses of the same shocks over time and find that they reach their peak after 10–15 days.

The SDSVaR approach developed in this paper permits a delineation of common shocks affecting all institutions simultaneously from "pure" spillover effects in a quantile regression setting. Comparing the results to simple time-varying correlations, we show that correlations may overstate spillovers in normal times and understate spillovers in volatile times. In addition, we find that hedge funds may play an even more prominent role as transmission channels and amplifiers of systemic risk than previously thought.

Although the SDSVaR model is useful for measuring and quantifying spillover effects, it does not *explain* the mechanisms underlying the estimated spillovers. In order to trace spillover effects back to economic relationships, rather than statistical ones, one would need much more detailed information on the exposures among different financial institutions, their asset holdings, and their liability structure. In particular, for hedge funds, most of this information is currently unavailable. Hence, the findings support initiatives as in Lo (2008), who in his testimony for the U.S. House of Representatives emphasizes that hedge funds should be required to provide more information on a confidential basis to regulators, for example, leverage, liquidity, counterparties, and holdings, in order to enable supervisors to more accurately assess the risks in the financial sector.

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