Systemic Risk in the Financial Sector: What Can We Learn from Option Markets?

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Abstract

We propose a novel approach on how to estimate systemic risk and identify its key determinants. For US financial companies with publicly traded equity options, we extract option-implied value-at-risks and measure the spillover effects between individual company value-at-risks and the option-implied value-at-risk of a financial index. First, we study the spillover effect of increasing company risks on the financial sector. Second, we analyze which companies are mostly affected if the tail risk of the financial sector increases. Key metrics such as size, leverage, market-to-book ratio and earnings have a significant influence on the systemic risk profiles of financial institutions.

Key words: Systemic risk; Value-at-risk; Equity options; Implied volatility; Panel vector autoregression.

JEL Classification: G01, G28, G32

1 Introduction

In recent years, we have witnessed the enormous destructive power of a financial crisis. While researchers and policy makers still try to address the exact causes and consequences of the recent crisis, there is now a widespread consensus that regulation before the crisis has focused too heavily on the individual risks of financial companies and failed to address the interconnectedness in the financial sector. The focus of current regulation is on the default risks of individual companies and to a lesser extent on systemic risk, which is understood as the risk that the financial sector as a whole becomes distressed. Individual risks however have very different implications depending on the overall state in which they occur. During normal markets times, individual institutions can be taken over or unwound by the financial sector itself and do not threaten the real economy on a large scale. Only during times of severe financial distress of a multitude of financial institutions, the financial sector is unable to absorb failed institutions, credit becomes constraint and exhibits large negative externalities to the real economy. In addition, when the whole financial sector is in distress and does not have the capacity to stabilize itself, even governments as lenders of last resort might not be able to support the whole financial system anymore, as witnessed by the recent financial crisis. From a supervisory point of view it is thus essential to gain an understanding of how institutions behave in adverse market environments in order to properly regulate them ex ante or, where necessary, to support them ex post.

Along the lines of the existing research on systemic risk, we explore the interaction between tail risk measures for individual companies and the broader financial sector itself, which in our case is a value-at-risk (VaR). In contrast to the existing literature however, we do not estimate the VaR from past historical equity data but directly observe the VaR implied from equity option quotes. This direct observability of the VaRs simplifies not only its computation, but allows also for different econometric tools in the analysis of the interaction between the tail risks of individual companies and the whole financial sector. We implement our approach in order to estimate the systemic relevance of a broad range of financial institutions with publicly traded options on US stock exchanges. Based on accounting items and market valuation characteristics, we run several rounds of parametric and non-parametric panel regressions and panel vector autoregressions (PVARs) in order to estimate the spillover in the whole financial sector. In particular, we estimate a panel conditionally homogeneous vectorautoregressive (PCHVAR) model in order to analyze the influence of varying firm characteristics on the impulse-response functions of individual companies or the financial index. In line with earlier research findings by Adrian and Brunnermeier (2011) or Acharya et al. (2010), we find that larger financial institutions with higher leverage, lower market-to-book valuation, lower return on equity and a riskier balance sheet composition have a higher systemic risk profile. While size appears to be the dominant factors for a company's influence on the financial sector, we also find that negative shocks to the financial sector have larger effects on small and leveraged firms with low market-to-book valuations and low earnings. Furthermore, a riskier balance sheet composition as measured by a high maturity mismatch and high shares of level-3 assets tends to increase the systemic risk profile of a company even though the causality direction is more difficult to establish.

Our paper thus directly contributes to the growing literature on the measurement of systemic risk. This literature emphasizes the importance of a financial institution's interaction with systemic risk as a critical factor for its regulation. Of utmost importance is thereby the identification of institutions and sectors which have the largest impact on the overall financial stability as well as institutions which are most affected in the event of a marketwide financial collapse. While most existing papers have only analyzed one of these issues, in this paper, we study both aspects of an institution's contribution to systemic risk in a joint panel VAR approach. Thus we are not only able to estimate marginal VaR contributions and dependencies in a static framework along the lines of Adrian and Brunnermeier (2011), but also analyze the dynamics of spillover effects between the individual companies and the whole financial sector in a panel vector autoregression (PVAR) framework. The measurement of dynamic tail risk spillover effects has so far only been addressed by Adams et al. (2012) or White et al. (2010). Yet, in particular the latter include a much complexer setup which is more difficult to estimate, since they apply a numerically challenging VAR approach to their VaR framework. Adrian and Brunnermeier (2011) use historical US equity data and quantile regressions in order to estimate the marginal contribution of individual companies to the overall financial sector risk. Their focus is on the systemic risk measure ΔCoVaR_i which reflects the change in the financial sector VaR, conditional on institution i being in distress. The authors show that this measure can be directly related to institution i's size, leverage and maturity mismatch. Hautsch et al. (2012) extend the work of Adrian and Brunnermeier (2011) by explicitly allowing for cross-linkages in the tail risks of individual companies that are identified by penalized quantile regressions using statistical shrinkage techniques.

In contrast, Acharya et al. (2010) focus on the feedback from the sector on the individual company and base their analysis on a firm's Systemic Expected Shortfall (SES). In a stylized theoretical model, they find that financial institutions should be optimally taxed based on their expected default losses and their SES. A firm's SES is further shown to be directly related to its leverage and its Marginal Expected Shortfall (MES), which is the firm's own expected shortfall when the whole sector is in distress. The MES is empirically measured as an institution's mean return, conditional on the broader index having a return in its lower 5% quantile. Brownlees and Engle (2012) refine the measurement of the MES by introducing a joint dynamic model for sector and firm returns with time varying volatilities and correlations and estimate a short- and long-run MES using TARCH and DCC methods. Our panel VAR approach is closest related to the analysis by White et al. (2010) and Adams et al. (2012) with respect to the general research approach, but differs significantly in the econometric implementation since our option-implied VaRs are directly observable.

Option-implied information has been used in the past in order to estimate forward-looking VaRs or its key determinant, the future realized variance. Over the last two decades, a broad literature has evolved which compares the performance of the volatility and VaR estimates from option-implied and alternative models. While an early study by Canina and Figlewski (1993) concludes that the implied volatility from S&P 100 index options has almost no forecasting power for future realized variance, subsequent research finds that implied volatility is a strong predictor of future variance. Day and Lewis (1992) incorporate implied volatilities as an exogenous factor in a family of GARCH models, while Lamoureux and Lastrapes (1993) regress realized variance on option- and GARCH-implied information. Christensen and Prabhala (1998) find that the information content of implied volatilities has improved after the stock crash in October 1987 and provide evidence that implied volatilities capture all information from past volatilities. This is also documented by Blair et al. (2001) using implied volatilities from VIX options and high frequency index returns. More recent papers provide further evidence that implied volatilities better forecast future variance than historical return variances. Jian and Tian (2005) additionally find that Black-Scholes implied volatilities are outperformed by a measure of model-free implied volatility derived from a broad set of options with differing strike prices. Giot and Laurent (2007) run regressions of implied volatilities on realized intraday variances for the S&P 100 and 500 index and in general cannot reject the null hypothesis of a unit coefficient, while additional jump components contribute only marginally to explaining future variance. Busch et al. (2008) analyze the information content of implied volatilities in stock, bond and foreign exchange markets. Using high-frequency data, they find that implied volatilities are unbiased estimators of future variances in the stock and foreign exchange market and even capture all relevant information of past realized variances in the later.

In addition, there are a few studies which directly compare the performance of the VaR estimates from different model classes. Chong (2004) compares the estimates of exchange rate VaRs derived from different historical methods, univariate and multivariate GARCH models as well as option-implied counterparts. He finds that option-implied VaRs have comparable exceedance rates as the VaRs from other models, although option implied estimates are somewhat higher during normal market times. Christoffersen et al. (2001) use S&P 500 returns in order to analyze the VaR estimates from different models and test for statistical performance differences. They find that at conventional coverage values, Black-Scholes based option-implied VaR levels perform statistically indifferent to other GARCH or stochastic volatility based models.

In summary, option-implied volatilities are generally found to be among the best predictors of future realized variance, which provides strong evidence for the validity of option-implied VaR estimates. At the same time, daily option-implied VaRs can be directly calculated for the complete cross-section of option prices and do not rely on any parameter estimates from past or future observations. Hence, option-implied VaRs might provide a useful framework for analyzing the spillover effects in the financial system.

The remainder of the paper is structured as follows: Section 2 explains how to extract the VaR^{OI} from equity option data and introduces the model analyzing systemic risk links in a static and dynamic framework. Section 3 gives an overview of the data used in our analysis. Section 4 presents the main results of our paper and discusses the key determinants of systemic risk. Section 5 summarizes the results of robustness checks. Finally, Section 6 concludes.

2 Model

2.1 Measuring Option-implied value-at-risk

Our paper focuses on analyzing the tail risk dependencies between individual companies and the whole financial sector. One of the most common tail risk measures is the value-at-risk VaR_p, the expected loss that is only exceeded in $p\%$ of the cases and usually defined under the real-world probability measure. Following Adrian and Brunnermeier (2011), the VaR_p can be computed for individual companies and for an index itself and the relation between the two can then be explored. The main difficulty of this approach is that the physical VaR_p is not directly observable but must be estimated using non-trivial quantile regressions, uni- or multivariate GARCH processes or extreme value theory. We thus depart from the route of estimating the physical VaR_p and instead look at equity options and extract from their quotes the option-implied value-at-risk VaR_p^{OI}. For robustness reasons, we apply two different approaches to extract the VaR_p^{OI} from option quotes.

Given a financial company with stock price S_t and put price $P(S_t, K, T)$ where K and T are the strike price and the maturity of the option, the annualized implied Black-Scholes volatility $\widehat{\sigma}_K$ can be computed. Breeden and Litzenberger (1978) show that the option-implied probability of a put option ending up in the money is equal to the compounded first derivative of the put price with respect to the strike price, i.e. $\text{Prob}^{OI}(S_T \leq K) = \exp(rT)\frac{\partial P(S_t,K,T)}{\partial K}$. Hence, we can write the VaR_p^{OI} over the next time period T as

$$-VaR_{p,T}^{OI} = \frac{\overline{K} - S_t}{S_t} \tag{1}$$

with $\overline{K}$ such that $p = \text{Prob}^{OI}(S_T \leq \overline{K}) = \exp(rT)\frac{\partial P(S_t,\overline{K},T)}{\partial \overline{K}} = \exp(rT) \cdot \Delta_K$. Given a sufficient number of options with differing strike prices, it is thus possible to extract the $\text{VaR}_{p,T}^{OI}$ for the desired p-th quantile at any point in time. Furthermore, the put delta is equal to

$$\Delta_S = \frac{\partial P}{\partial S_t} = \Phi(-d_1) = \Phi\Big(- \frac{\ln(S_t/K) + (r + \widehat{\sigma}_K^2/2)T}{\widehat{\sigma}_K\sqrt{T}}\Big) \tag{2}$$

with $\Phi(x)$ being a standard normal cumulative distribution function. Furthermore, the dual delta, i.e. the first derivative of the option with respect to the strike price, can be written as

$$\begin{aligned}\Delta_K = \frac{\partial P}{\partial K} &= \exp(-rT)\Phi(-d_2) = \exp(-rT)\Phi\Big(- \frac{\ln(S_t/K) + (r - \widehat{\sigma}_K^2/2)T}{\widehat{\sigma}_K\sqrt{T}}\Big) \\ &= \exp(-rT)\Phi(-d_1 + \widehat{\sigma}_K\sqrt{T})\end{aligned} \tag{3}$$

For a given strike price $\overline{K}$, its according implied volatility $\widehat{\sigma}_{t,\overline{K}}$ and put delta Δ_S, the dual delta can hence be computed as:

$$\Delta_K = \exp(-rT)\Phi(\Phi^{-1}(\Delta_S) + \widehat{\sigma}_K\sqrt{T})) \quad (4)$$

with $\Phi^{-1}(x)$ being the inverse of a standard normal cumulative distribution function. We use the VaR estimated from (4) as our primary VaR measure as it incorporates all information from the implied return distribution function. For extreme p-quantiles, however, the corresponding options are not traded and we have to use the implied volatility of the option that is most OTM. Alternatively, under the simplifying assumption that logarithmic returns are conditionally normal distributed, the implied at-the-money (ATM) volatility $\widehat{\sigma}_{ATM}$ fully determines the option-implied $\text{VaR}_{p,T}^{OI}$ via

$$-VaR_{p,T}^{OI} = \exp(-\alpha_p\sqrt{T}\widehat{\sigma}_{ATM}) - 1 \quad (5)$$

with α_p being the value of the p-th quintile of a standard normal density function. As a robustness check, we thus repeat our analysis using the VaR estimates from (5) which only rely on information from more liquid ATM options (see Section 5).

After calculating the option-implied value-at-risk of individual stocks and an appropriate financial index from observable market data, we analyze their tail risk dependencies using a static and a dynamic framework. Unless stated otherwise, every value-at-risk refers to its option-implied counterpart and, for simplicity, we henceforth drop the superscript 'OI'.

2.2 Static Analysis

The first part of the econometric analysis is inspired by the underlying idea of Adrian and Brunnermeier (2011) who estimate both the financial index value-at-risk VaR_p^{Index} conditional on the individual firm value-at-risk VaR_p^i ($CoVaR$) and the individual firm value-at-risk VaR_p^i conditional on the financial index value-at-risk VaR_p^{Index} (*exposure* $CoVaR$). We call this approach static because it only measures the contemporaneous impact of the conditioning variable, while in the dynamic analysis we also estimate dynamic feedback effects over time.

We are thus interested in estimating the following underlying functional relations:

$$VaR_t^{Index} = c_{1,i} + \beta_{1,i} VaR_t^i + \gamma_x X + \epsilon_t \tag{6}$$

$$VaR_t^i = c_{2,i} + \beta_{2,i} VaR_t^{Index} + \gamma_y Y_i + \epsilon_t \tag{7}$$

where X and Y_i are sector and firm-specific control variables. Adrian and Brunnermeier (2011) compute their time-varying "forward-$\Delta CoVaRs$" based on those regressions and in a second step relate them to key characteristics of the firm. Even though our goal of identifying systemically relevant institutions based on observable firm characteristics is similar, we do not apply such a two-stage approach. Instead, we directly interact the right-hand side VaR-term with the key characteristics Z of interest:

$$VaR_t^{Index} = c_1 + \beta_1 \cdot VaR_t^i + \sum_{j=1}^{n} \beta_{1,j} \cdot VaR_t^i \cdot Z_{j,i,t} + \gamma_x X + \epsilon_t \tag{8}$$

$$VaR_t^i = c_2 + \beta_2 \cdot VaR_t^{Index} + \sum_{j=1}^{n} \beta_{2,j} \cdot VaR_t^{Index} \cdot Z_{j,i,t} + \gamma_y Y_i + \epsilon_t \tag{9}$$

where $Z_{j,i,t}$ is the value of characteristic j of company i at time t. Using panel regressions and fixed effects, we jointly estimate the beta parameters of all n firm characteristics of interest. Since we expect the ϵ_t's to be serially and cross-sectionally correlated, we use Driscoll and Kraay (1998) adjusted standard errors. While the β_1 and β_2 resemble the "average" feedback affects from and towards the individual companies, the $\beta_{1,j}$ and $\beta_{2,j}$ parameters indicate how much stronger the effect is for varying levels of e.g. size, leverage or earnings. Hence, the estimated beta-parameters can directly be interpreted to determine the key characteristics of systemically important institutions.

Other differences to the setup of Adrian and Brunnermeier (2011) are the following: First, they analyze the value-at-risk of total assets, while we study equity value-at-risk. Furthermore, due to the direct observability of the option-implied VaR_p^{OI}, we do not have to rely on quantile regressions, but can estimate the equations of interest by OLS. Note, however, that in the static approach similar to Adrian and Brunnermeier (2011) we cannot distinguish "whether the contribution is causal or simply driven by a common factor". Such an interpretation is only possible in the dynamic approach where causal relations are identified using VAR identification schemes.

We specifically test for structural differences stemming from various accounting items and other market observables: First, we are interested in the magnitude of a potential firm size effect as size is usually considered to be of first order importance for systemic risk. In our baseline regression, we measure size by total assets (AT).[1] Second, leverage might influence a firm's systemic risk profile as shown in the theoretical model by Acharya et al. (2010). We measure leverage (BLEV) as the ratio of total assets and book value of equity. Third, the riskiness of the balance sheet composition might also influence the systemic risk impact. In order to proxy for the asset liability mix of a company, we compute the ratio of level-3 assets[2] (LEV3A) to total assets. In addition, we approximate a company's maturity mismatch (MM) as the ratio of short-term debt over total assets. Fourth, we are interested in the potential role of earnings. We analyze the impact of earnings by the return on equity (ROE), as defined by total earnings excluding extraordinary items over the last four quarters divided by book value of equity. Finally, we look at the market-to-book valuation (MTB), which we measure as the market capitalization divided by its book value.

As conditioning variables X for the financial sector VaR_p^{Index} we use standard variables from interest rate and equity markets. In particular, we control for the effect of the short

[1]As a robustness check, we have also analyzed the impact of a firm's book equity value (CEQ) or its market capitalization (MCAP) as opposed to its total asset holdings. It turns out that the results are almost identical and we therefore do not report those results here.

[2]Level-3 assets are assets whose price cannot be observed directly in the market and which are mainly marked-to-model.

term interest rate, as measured by the 3-month treasury bill rate, and the slope of the term structure, as measured by the difference between the 10y- treasury yield and the 3-month treasury bill rate. Furthermore, we include corporate bond spreads, as defined by the average yield difference between Moody's seasoned Baa- and Aaa-rated corporate bonds, and a liquidity spread, which we compute as the yield difference between one-month financial and non-financial commercial papers. From the equity universe, we calculate the return of the S&P 500 over the last quarter. For the individual company's VaR_p^i, we use all above mentioned valuation items and the firm's quarterly stock return as the vector of conditioning variables Y_i.

2.3 Dynamic Analysis

With the exceptions of White et al. (2010) and Adams et al. (2012), most of the existing literature focuses on the contemporaneous interaction between individual and index tail risks. White et al. (2010) estimate a series of bivariate vector autoregressions (VARs) for the individual and sector VaRs. While their underlying idea of measuring the dynamic spillover effects between individual companies and the index using impulse response functions (IRF) is the same, we do not have to rely on their involved QML-estimation technique as our option-implied value-at-risk is directly observable. Instead we can use more standard panel VAR estimation techniques. Adams et al. (2012) examine the feedback effects between the average GARCH-implied VaRs of four different financial subindustries. By contrast, we make use of all individual option-implied VaRs in our panel and estimate the feedback effects between the individual company and the index conditional on the firm characteristics. This is possible, since we apply a new panel vector autoregression (PVAR) estimator derived by Georgiadis (2012). The underlying idea is to estimate a PVAR model that is only conditionally homogeneous, but delivers different PVAR and IRF estimates for various levels of one or more conditioning variables $Z_{i,t}$:

$$Y_{i,t} = \Phi_1(Z_{i,t})Y_{i,t-1} + \Phi_2(Z_{i,t})Y_{i,t-2} + \ldots + \epsilon_{i,t} \tag{10}$$

with $Y_{i,t} = [\text{VaR}_t^{Index}, \text{VaR}_t^i]'$ and $\epsilon_t = [\epsilon_t^{Index}, \epsilon_t^i]'$.[3] The model itself can be estimated using standard least squares techniques and allows for company fixed effects. As conditioning variables $Z_{i,t}$ we use the same variables as in Section 2.2 employing Chebyshev polynomials of up to second order.

The advantage of this dynamic approach is that based on a standard VAR identification scheme with a particular ordering of the variables we are able to identify sector and firm specific shocks, u_t^{Index} and u_t^i, and thus identify causal spillover effects. Following the identification strategy of White et al. (2010), we allow only index tail risk shocks to affect the individual company risk contemporaneously, while company shocks can influence the index only with a lag. After this adjustment, we obtain four basic types of orthogonalized impulse response functions for the next n periods, i.e.

1. $\partial VaR_{t+n}^{Index}/\partial u_t^{Index}$, the effect of an index shock on the index itself
2. $\partial VaR_{t+n}^{i}/\partial u_t^{Index}$, the effect of an index shock on the firm
3. $\partial VaR_{t+n}^{Index}/\partial u_t^{i}$, the effect of a firm specific shock on the index
4. $\partial VaR_{t+n}^{i}/\partial u_t^{i}$, the effect of a firm shock on the firm itself

Of particular relevance are the index and firm specific cross effects, as they give a direct view on potential spillover effects between the sector and individual companies. The advantage of the estimator by Georgiadis (2012) is that the impulse response functions are again functions of the underlying firm characteristics and their influence can be estimated directly. While the PVAR implied by (10) allows for the interpretation of causal spillover effects, it might

[3] See Appendix A for a more detailed description of the PCHVAR model.

still suffer from a potential omitted variable problem inherent in several empirical systemic risk studies, where the paper by Hautsch et al. (2012) is a notable exception. This is because in each cross-sectional regression only the impact of each company individually is analyzed ignoring the possible impact of other institutions. In order to control for that problem, we further expand our analysis to a trivariate PVAR with $Y_{i,t} = [\text{VaR}_t^{Index}, \overline{\text{VaR}}_{i,t}, \text{VaR}_t^i]'$ and $\overline{\text{VaR}}_{i,t} = \frac{1}{n-1}\sum_{j=1,j\neq i}^{n} \text{VaR}_t^j$. Similar to the idea of a global vector autoregression (GVAR), the effects of all other companies are aggregated in the second term and allow for a consistent estimation of the individual spillover effects.

3 Data

We use the Ivy DB OptionMetrics database and include all financial institutions with equity options traded on US exchanges which can be matched to the combined quarterly and annual Compustat database for the period January 2002 to December 2010. Financial institutions are identified based on their SIC codes and grouped into one of the following industry categories: depositories (SIC 6000-6099), broker-dealer (SIC 6200-6299), insurance (SIC 6300-6499) and other (SIC 6100-6199 and 6500-6699). Following Kelly et al. (2011), as a proxy for the whole financial sector we use the broadly diversified iShares financial sector ETF, which has the additional advantage that options on that ETF are traded on the CBOE (ticker IYF). For liquidity reasons, we restrict our analysis to short-term put options with a remaining maturity of one month. We then compute the VaR_p^{OI} based on ATM (see equation (5)) or OTM options. In the later case, we estimate Δ_K for each point of the implied volatility curve according to equation (4) and search for the strike price $\overline{K}$ such that $\Delta_K(\overline{K}) = p$. For extrapolations beyond the most OTM put options ($\Delta_S = 0.8$), we thereby keep the implied volatility constant. Furthermore, we use individual and index stock market data from CRSP, interest rate data from the Federal Reserve Board's H.15 report and the VIX from the Philadelphia Stock Exchange. We include a company in the sample if it has at least 200 non-missing daily volatility surfaces in a single year. The final sample consists of 399 financial institutions. The values for maturity mismatch, returns on equity and individual 3-month stock returns are winsorized at the 1% and 99% percentiles. Table 1 reports the summary statistics of the accounting data for the total sample and the industry subsamples. Depository banks constitute the largest group in the sample and are on average the largest institutions with the smallest cash share. Broker-dealers have the highest cash share and the highest market-to-book valuation. Their high average maturity mismatch of 13% is only exceeded by non-depository banks (17%) which also have the highest average leverage of 13.76. In the robustness analysis, we assign each company to one of five quintile portfolios based on those accounting characteristics. The grouping is carried out for each year and each balance sheet item such that each quintile group has approximately the same number of observations per year.

Table 2 summarizes the relevant market data that consists of 440,166 individual quotes. On average, a company is about 4.5 years in the sample. For both the individual companies and the index, the first two lines give summary statistics for the extracted one-month VaR's, computed for threshold levels of 5%-and 20% using ATM options. The $\mathrm{VaR}_{0.2}^{ATM}$ is mainly computed for comparison reasons. As expected, the VaRs computed from ATM options are substantially lower than its counterparts computed from OTM options (rows 3,4,7 and 8), as OTM options contain information about the implied fat tail return distribution. The remaining control variables (volatility, equity and interest rates) show large variations as a result of the crisis.

To shed further light on the link between the two different option-implied VaR^{OI} extraction methods and their relation with the VaR^{P} under the physical probability measure, Figure 1 depicts the time series of the financial sector VaR_t^{Index} computed using the two different methods for the threshold levels of $p = 0.20$ and $p = 0.05$. It compares them to the VaR_t^{P} computed from a standard GARCH(2,2) model. As can be seen from Figure 1, VaRs under the objective and option-implied probability measure move very much in tandem. This is confirmed by an R^2 of 0.89 resulting from a regression of the explicit tail risk VaR^{OI} on the VaR^{P} from the GARCH estimation. The results are comparable to those found in the literature that is discussed in Section 1. To summarize, our results suggest that even for extreme quantiles, option-implied VaRs behave qualitatively similar to the ones calculated under the physical probability measure.

4 Results

The following results are based on VaRs calculated from OTM options according to equation (4) and a threshold level of $p = 0.2$. A robustness analysis using ATM option volatilities and other threshold levels can be found in Section 5.

4.1 Static Analysis

Tables 3 and 4 report the regression results from the static analysis based on equations (8) and (9). All interacted variables with the exception of the dummy variables (D_{IB} and D_{Dep}) are standardized with mean zero and unit standard deviation.

Table 3 reports the regression results for the feedback from the individual company on the index itself. Overall, a larger size (as measured by total assets), a higher market-to-book ratio, a more pronounced maturity mismatch and higher earnings increase the spillover effect, while interestingly the effect is negative for book leverage. Also the broker dummy D_{IB} indicates a substantially higher feedback effect for investment banks. The deposits share DP_S is insignificant in all regressions. The regression in the third column also includes the share of level-3 assets, a balance sheet item only available from 2008 onwards for particular companies. The effect of these assets is negative. The signs of the control variables are in line with economic intuition: Higher credit and liquidity spreads or lower interest rates and equity index returns over the last quarter indicate times of heightened market stress and increase financial sector tail risk.

Table 3 summarizes the evidence from the static approach for a company's exposure to the sector risk. As expected, the average effect of an index shock is close to one but firm characteristics matter significantly. Higher market-to-book valuations and earnings reduce a companies exposure to sector risk, while it increases with book leverage and size. Once maturity mismatch and deposits share (for depository banks only) are included, the broker and depository dummies become positive, although the effect is strongly reduced by a larger deposits share. Regressions (2) and (3) also document that companies with a larger maturity mismatch and higher level-3 assets share are significantly more exposed to market wide risks. Again, the control variables are mostly in line with economic intuition as more leveraged firms with lower last quarter earnings and quarterly cumulative equity returns are more risky and feature higher tail risks.

Both the return on equity and the market-to-book ratio are indicators of a firm's financial healthiness. By contrast, maturity mismatch and level-3 asset share are measures for the riskiness of the left- and right-hand side of the balance sheet. Results from the static analysis thus provide evidence that in particular the tail risk of large and healthy financial institution has a high impact on the whole financial sector risk. Furthermore, the results suggest that large and highly leveraged companies with a risky asset liability mix are particularly exposed to sector-wide downturns. The effect is even more pronounced for less healthy firms with below average earnings and low market valuations.

4.2 Dynamic Analysis

As discussed in Section 2.2, one of the drawbacks of the static approach is the difficulty to establish causality of the effects. Here, the PVAR approach offers an insightful alternative, since the orthogonalized VAR error terms allow for a causal interpretation of the results.

At the same time, the estimation approach by Georgiadis (2012) enables us to determine the impact of the conditioning firm variables on the impulse response functions. We use the same identification strategy as White et al. (2010) and orthogonalize the error terms by assuming that only the index can affect individual firms contemporaneously but not vice versa. Finally, we compare the resulting impulse response functions, in this case with a forecast horizon of up to $t = 22$ business days. Overall, we find that a firm's exposure to sector-wide shocks increases in its leverage and level-3 asset holdings and decreases in its size, market-to-book ratio, return on equity and maturity mismatch. On the other hand, a company's impact on the overall sector increases in its size and maturity mismatch.

Before looking at the impulse response functions, Table 5 reports that all items have a statistically significant influence on the VaR coefficient matrix Γ. All regressions include the level of the VIX and the quarterly stock returns as additional conditioning variables. Yet, even though all variables in the Γ-matrix are statistically significant at the 10% confidence level, the economic significance of the effect on the estimated impulse response function varies. Each of the four graphs in (a) and (c) of Figures 2 to 5 depict the estimated impulse response functions as a function of time and the standardized conditioning variable. The two-dimensional graphs (b) and (d) depict the same information but focus on the response functions after $t = 22$ business days and additionally include the estimated 95%-confidence bands.

For each conditioning variable, the lower left-hand graphs of (a) and (c) in Figures 2 to 5 depict the point estimate of the response function of the index tail risk after an (orthogonalized) unit shock to a company. Similar as in the static approach, a firm's impact on the index strongly increases in its size. In addition, the index response function increases in a firm's maturity mismatch. These effects are also statistically significant, as shown by the confidence bands in the bottom left-hand graphs of Figures 2 (b) and 4 (b). By contrast, the positive (negative) effects of the market-to-book ratio (leverage) are not statistically significant (see Figures 2 (b) and Figures 3 (b)). On the other hand, the effect of a tail risk shock of the financial sector on individual companies can be seen in the upper right corner of the graphs labeled by (a) and (c). A high leverage, maturity mismatch and level-3 asset share as well as a low market-to-book ratio or return on equity are characteristics of companies with strong dependence on the index tail risk. Interestingly, independent of the choice of the size variable (total assets, equity book value or market capitalization), we find evidence for a negative relation between size and a firm's dependence on the sector tail risk, i.e. an increase in sector risks affects smaller companies more than larger ones. Again, the displayed confidence bands in (b) and (d) of Figures 2 to 4 show that these effects are also statistically strongly significant. Finally, the results for the VIX control variables (Figure 5) suggest that there are increased spill-over effects during higher volatility regimes and times of more market distress.

One potential issue of the bivariate PVAR approach might be that we estimate the influence of one company on the index independent of the influence of all other companies. As outlined in Section 2.3, in order to overcome that potential problem we include $\overline{\text{VaR}}$, the average of all other company VaRs, as an additional variable in the VAR. While both the VaR_{Index} and the $\overline{\text{VaR}}$ can now be interpreted as sector shocks, the cross-sectional results displayed in Figures 6 to 9 are qualitatively similar to the bivariate case. Conditioning on each firm characteristic, the top row graphs in plots (a) and (b) of Figures 6 to 8 depict the point estimates of the company VaR^i response after an unit shock to the overall sector VaR^{Index} or the average firm $\overline{\text{VaR}}$. On the other hand, the bottom rows of (a) and (c) display the response functions of the sector VaR^{Index} or the average firm $\overline{\text{VaR}}$ after a company VaR^i shock. Focusing on the confidence intervals after 22 business days (plots (b) and (d)), the shape of the response function in the cross-sectional dimension is very similar for the top or bottom rows. Looking at the response functions in the bottom row of plots (a) and (c) of Figures 6 to 8, a firm's impact on the sector still increases in its size and maturity mismatch and declines in its market-to-book-ratio and return on equity, just as in the bivariate setup. Yet, the effects remain significant only for the maturity mismatch (see plots (b) and (d)).

The level-3 assets and leverage effect however are broadly flat now. By contrast, a firm's exposure to sector wide risk shocks can be seen in the top rows of Figures 6 to 8. In line with earlier results, more leveraged small firms with low market-to-book ratio/returns on equity and high level-3 asset holdings are most exposed to sector wide risk changes. The significant negative relation between size and a firm's dependence on the sector tail risk remains also in the trivariate case (Figure 6 (b)).

In addition, the size of the response functions after a company or sector VaR shock can be compared for the bivariate and trivariate PVARs. The average VaR^i response 22 business days after a sector shock VaR^{Index} remains in the range between 0.2 and 0.4 in both setups. Yet, in the trivariate PVAR the estimated sector VaR^{Index} response after a company VaR shock and 22 business days drops to about $0 - 0.05$(down from about $0.05 - 0.15$). Estimating individual systemic risk contributions without conditioning on other companies might therefore overestimate individual effects by a factor of three.

In summary, both PVAR estimation setups qualitatively agree on the key characteristics of systemically relevant institutions. Nevertheless, precise inference about individual systemic risk contributions seems to be difficult in the trivariate case. The contribution of individual risk characteristics to the index risk are rather small and often not significant. One potential reason might be the structure of the identification strategy. In the trivariate setting it is assumed that individual company shocks affect the index only with a lag of two business days. By contrast, the measurement of the systemic risk dependence is not affected by the choice of the estimation setup. If one is mainly interested in the identification of those characteristics and a causal interpretation is of less interest, ignoring the impact of other companies does not seem to be a major problem. The same, however, does not hold true if the goal is to quantify systemic risk contributions and for instance to tax financial institutions based on their systemic risk profile. In that case, using information on all other companies is essential, since otherwise individual risk contributions might be significantly overestimated.

Comparing the results from the static and dynamic approach, we find similar effects for most of the variables in question. However, individual differences in the direction of the size, market-to-book ratio and earnings effects highlight the importance of the identification scheme. While both approaches identify the same systemically relevant firm characteristics, an appropriate causal interpretation is only possible in the dynamic approach. Generally speaking, the results show the importance of an appropriate identification scheme to distinguish between a company's systemic risk dependence and its own risk contribution. By contrast, the mere inclusion of company and sector specific control variables does not seem to be sufficient to identify the direction of the effects in any kind of non-causal static framework.

5 Robustness Analysis

5.1 Pre- vs Post-Crisis Analysis

The total dataset covers the complete time span from 2002 to 2010 so that the second half of the sample is dominated by the recent financial crisis. In order to analyze the impact of these different regimes, we split the sample into a pre- and post-crisis period and conduct the static and dynamic analysis for each subsample individually.[4] In the static analysis, prior to July 2007 only size appears to significantly increase systemic risk contributions, while size and leverage increase the dependence on sector risk. Besides, the estimated sign for the market-to-book ratio is positive and significant. All other effects, including the sign switch for the market-to-book ratio, occur in the data only afterwards. Interestingly, the company size effect on the index is much stronger before the crisis. Finally, depositary and broker dummies indicate that the systemic risk related to banks was largely underestimated, since its coefficients are negative before the crisis and only catch up during the crisis. The results

[4] The results are not reported in this paper, but are available upon request.

suggest that market participants focused on market valuations before the crisis and underestimated systemic bank risks. Only with the onset of the crisis they payed full attention to the systemic downside risks stemming from a company's balance sheet composition and its business model. These findings are supported by the dynamic analysis if we split the sample as well. Again, the effects are weaker or insignificant before the crisis, resulting in much flatter impulse response functions. Only from July 2007 onwards one can observe the patterns as shown in Section 4.2.

5.2 Non-parametric Estimation Approach

The static and dynamic approaches in Section 4 are based on a parametric specification of the link between firm characteristics and feedback effects. In order to exclude any effects from a potential misspecification, we also apply a non-parametric approach. Instead of interacting the VaRs with the conditioning variables, we now sort each company into one of five quintiles based on characteristics such as size, leverage, market-to-book ratio, maturity mismatch, level-3 asset share and return on equity. In a second step, we analyze the impacts of the various quintile groups by running the following panel estimations:

$$VaR_t^{Index} = c_1 + \beta_1 \cdot VaR_t^i + \sum_{j=2}^{5} \beta_{1,K,j} \cdot VaR_t^i \cdot D_{K,j} + \gamma_x X + \epsilon_t \quad (11)$$

$$VaR_t^i = c_2 + \beta_2 \cdot VaR_t^{Index} + \sum_{j=2}^{5} \beta_{2,K,j} \cdot VaR_t^{Index} \cdot D_{K,j} + \gamma_y Y_i + \epsilon_t \quad (12)$$

where $D_{K,j}$ is a dummy that is one if company i belongs to quintile group j for accounting item K and zero otherwise. The sorting into the quintile groups is then repeated for the various accounting items and we can check for monotone patterns in the estimated β coefficients. If for instance we expect a higher leverage to have a positive influence on a company's systemic risk contribution, we would expect monotonically increasing β's going from group five to one. Tables 6 and 7 report the regression results from the non-parametric static analysis with univariate sorting. Table 6 summarizes the evidence on key characteristics of firms with a large impact on the whole financial sector. Going from group 5 to 1, there are clear monotonic increasing patterns for both size variables (total assets (AT) and book equity value (CEQ)) as well as for the market-to-book-ratio (MTB) and return on equity (ROE). The empirical results are less conclusive for leverage (BLEV), the maturity mismatch (MM) or the level-3 asset share (LEV3A) which show no clear evidence of monotonicity. With respect to the feedback from the sector on the individual companies, Table 7 reports clear monotonically increasing pattern for both size measures, leverage as well as the maturity mismatch and level-3 asset share. On the other hand, the pattern is decreasing for the market-to-book ratio and the return on equity.

We use a similar approach for the PVAR estimation. Again, we sort each company into one of the five quintile groups and estimate the unconditional average impulse response functions for each group separately. Table 8 reports the 95% confidence bands of the estimated spillover effects after 22 business days. Overall, the patterns appear to be more distinct for the spillover effects from the index on the individual companies (left-hand side of Table 8). Larger companies with higher leverage and more level-3 assets are more exposed to sector-wide shocks, even if the response functions for the last quantiles are not perfectly monotone. Similarly, a small market-to-book ratio and a small return on equity are characteristics of companies whose tail risks depend heavily on the state of the whole financial sector. Regarding the maturity mismatch, the impulse response functions are rather similar for all but the last quintile group, which is substantially lower. With respect to the feedback from individual shocks on the index (right-hand side of Table 8), size seems to be one of the dominant factors. Interestingly, however, a monotone pattern can only be observed for the quantiles 2-4 with respect to total assets, while the first quantile is significantly lower than the second. In addition, there are positive patterns for the quintile groups of the market-to-book ratio and return on equity. By contrast, there are no distinctive patterns with respect to leverage, maturity mismatch and level-3 assets.

As a further robustness check, we also estimate the conditional PVAR employing second-order Chebyshev polynomials. The inclusion of higher order polynomials however does not change the main results. We only find minor differences for the market-to-book and total assets items. Here, the response curve is slightly u-shaped after a VaR^{i} shock and the positive size effects flattens out for large companies. Additionally, we repeat all estimations using a VaR threshold level of $p = 0.05$ or VaRs calculated from ATM options according to equation (5). The only difference is that the firm leverage effect on the average sector VaR is positive, while it is negative but almost flat for VaR^{Index} . Otherwise the results are qualitatively and quantitatively similar to the ones from Section 4. Overall, the results in the non-parametric approach are broadly comparable and show only minor deviations from the parametric baseline approach.

6 Conclusion

In this paper, we propose a novel approach on how to estimate systemic tail risk dependencies in the financial sector. Value-at-risks are extracted from equity options. Tail risk dependencies between individual companies and the sector are estimated using panel and panel VAR estimation techniques. We find that key accounting and market valuation metrics such as size, leverage, market-to-book ratio, earnings as well as the riskiness of the balance sheet have a significant influence on an institution's contribution to systemic risk. Our panel VAR approach allows for a structural decomposition of a firm's impact on the financial sector and a firm's vulnerability to financial sector risks. In contrast to earlier studies that quantify only contemporaneous contagion, our panel VAR approach measures dynamic spillover effects using impulse response functions and allows for a causal interpretation of the effects. The results of all test setups suggest that firm size is of first-order importance for a company's contribution to systemic risk. Furthermore, a company with a high maturity mismatch, low earnings and a low market-to-book ratio has a higher systemic risk impact. On the other hand, highly leveraged small institutions with a low market-to-book ratio and low earnings are most sensitive to changes in overall financial sector risk. Additionally, the results point towards a higher systemic risk profile for companies with a riskier asset liability mix. A higher level-3 asset share further increases an institution's dependence on the sector tail risk.

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A The PCHVAR Model

Georgiadis (2012) assumes the following time-varying VAR model:

$$y_t = \Phi_1(z_{i,t})y_{i,t-1} + \Phi_2(z_{i,t})y_{t-2} + \ldots + \Phi_p(z_{i,t})y_{i,t-p} + \epsilon_t \tag{13}$$

such that the effective VAR parameter can be time-varying and depend on the conditioning variable z_t in an unknown functional form. It is therefore assumed that the individual scalar coefficients $\phi_{j,rc}(z_{it})$ can be approximated by a linear function of τ-th order Chebyshev polynomials such that

$$\phi_{j,rc}(z_{i,t}) = \pi(z_{it}) \cdot \gamma_{j,rc} \tag{14}$$

with $\pi(z_{it})$ a $1 \times \tau$ vector of Chebyshev polynomials and $\gamma_{j,rc}$ the $\tau \times 1$ vector of linear coefficients. Hence,

$$\begin{aligned}\Phi_j(z_{i,t}) &= \begin{bmatrix} \pi(z_{i,t}) \cdot \gamma_{j,11} & \ldots & \pi(z_{i,t}) \cdot \gamma_{j,1K} \\ \vdots & \ddots & \vdots \\ \pi(z_{i,t}) \cdot \gamma_{j,K1} & \ldots & \pi(z_{i,t}) \cdot \gamma_{j,KK} \end{bmatrix} \\ &= \begin{bmatrix} \gamma'_{j,11} & \cdots & \gamma'_{j,1K} \\ \vdots & \ddots & \vdots \\ \gamma'_{j,K1} & \cdots & \gamma'_{j,KK} \end{bmatrix} \cdot \Big[I_K \otimes \pi'(z_{i,t}) \Big] \\ &= \Gamma \cdot \Big[I_K \otimes \pi'(z_{i,t}) \Big] \end{aligned} \tag{15}$$

and equation (13) can thus be re-written as

$$\begin{aligned} y_t &= \sum_{j=1}^{p} \Gamma_j \Big[I_K \otimes \pi'(z_{i,t}) \Big] y_{i,t-j} + \epsilon_{i,t} \\ &\equiv \sum_{j=1}^{p} \Gamma_j x_{i,t-j} + \epsilon_{i,t} \end{aligned} \tag{16}$$

Industry	No of firms	No of quarterly firm items	Variable	Mean	Median	Std	Min	Max
Total	399	7,128	AT	143,163	14,264	364,758	37	2,950,316
		7,128	CEQ	9,228	2,303	19,900	35	210,000
		6,848	CASH	0.06	0.03	0.10	-	0.84
		7,084	MM	0.07	0.02	0.12	-	0.70
		7,128	BLEV	10.03	8.59	9.08	1.00	76.82
		7,128	MTB	1.99	1.52	1.97	0.12	36.61
		2,044	LEV3A	0.03	0.01	0.06	-	0.86
		7,116	ROE	0.10	0.12	0.18	- 1.33	0.61
Agents	12	246	AT	137,425	3,400	239,964	66	1,330,066
		246	CEQ	8,398	1,097	12,027	55	48,624
		246	CASH	0.11	0.06	0.16	-	0.77
		246	MM	0.02	0.01	0.02	-	0.10
		246	BLEV	7.94	4.11	7.56	1.09	31.03
		246	MTB	2.44	2.23	1.41	0.15	5.83
		35	LEV3A	0.03	0.04	0.02	-	0.05
		246	ROE	0.13	0.15	0.22	- 1.33	0.61
Broker	66	1,146	AT	92,384	4,105	271,287	37	2,528,580
		1,146	CEQ	5,001	1,065	9,237	35	85,318
		1,102	CASH	0.13	0.08	0.13	-	0.84
		1,142	MM	0.13	0.02	0.19	-	0.70
		1,146	BLEV	8.58	2.99	10.84	1.00	58.57
		1,146	MTB	3.23	2.04	3.28	0.46	28.94
		263	LEV3A	0.03	0.02	0.04	-	0.17
		1,142	ROE	0.12	0.13	0.24	- 1.33	0.61
Depository	164	2,653	AT	234,040	23,508	502,084	293	2,950,316
		2,653	CEQ	14,126	2,275	28,999	122	210,000
		2,581	CASH	0.03	0.02	0.04	-	0.37
		2,613	MM	0.10	0.08	0.07	-	0.54
		2,653	BLEV	13.11	11.28	6.85	1.49	64.53
		2,653	MTB	1.86	1.61	1.77	0.20	36.61
		756	LEV3A	0.02	0.01	0.02	-	0.11
		2,653	ROE	0.09	0.13	0.16	- 1.33	0.61
Insurance	112	2,392	AT	80,279	15,095	217,434	593	1,916,658
		2,392	CEQ	7,046	3,505	11,393	141	160,000
		2,248	CASH	0.06	0.02	0.09	-	0.76
		2,392	MM	0.01	-	0.03	-	0.45
		2,392	BLEV	7.09	4.29	7.58	1.13	76.82
		2,392	MTB	1.51	1.25	1.03	0.12	8.95
		818	LEV3A	0.02	0.01	0.03	-	0.23
		2,388	ROE	0.10	0.12	0.15	- 1.33	0.61
Non-Depository	29	543	AT	124,079	14,275	238,584	259	1,020,934
		543	CEQ	6,434	2,122	8,453	43	32,398
		523	CASH	0.05	0.03	0.07	-	0.35
		543	MM	0.17	0.09	0.18	-	0.70
		543	BLEV	13.76	7.81	14.27	1.15	65.21
		543	MTB	2.02	1.53	1.60	0.19	7.70
		140	LEV3A	0.11	0.03	0.19	-	0.86
		539	ROE	0.14	0.16	0.24	- 1.33	0.61
Real-Estate	16	148	AT	3,251	1,472	4,347	108	20,420
		148	CEQ	1,036	895	1,264	92	7,883
		148	CASH	0.12	0.05	0.18	-	0.72
		148	MM	0.03	0.01	0.05	-	0.22
		148	BLEV	3.27	2.25	4.21	1.09	25.19
		148	MTB	1.76	1.53	1.04	0.26	5.51
		32	LEV3A	0.01	0.01	0.01	-	0.02
		148	ROE	0.06	0.08	0.11	- 0.21	0.25

Table 1: **Summary statistics of the accounting information, split by industry.** This table reports the (arithmetic) mean, median, standard deviation, absolute minimum and maximum of the following conditioning accounting variables: total assets (AT), equity book value (CEQ), leverage as measured by total asset to equity book value (BLEV), market-to-book ratio (MTB), cash (CASH), maturity mismatch (MM) and level-3 assets (LEV3A) as a share of total assets, earnings-per-share (EPS) and return on equity (ROE) as defined by total earnings divided by equity market value. The numbers are provided for the total sample and for each industry subsector. The second and third row report the number of firms included in the total sample and for each subsector as well as the number of quarterly and annually reported firm items.

Category	Variable	Obs	Mean	Median	Std. Dev.	Min	Max
VaR^i	$p = .20,\ ATM$	440,166	9%	8%	5%	1%	53%
	$p = .05,\ ATM$	440,166	17%	14%	9%	2%	78%
	$p = .20,\ OTM$	440,166	12%	10%	8%	2%	77%
	$p = .05,\ OTM$	440,166	21%	18%	11%	4%	89%
VaR^{Index}	$p = .20,\ ATM$	2,265	7%	5%	4%	2%	26%
	$p = .05,\ ATM$	2,265	12%	10%	7%	4%	45%
	$p = .20,\ OTM$	2,265	8%	7%	6%	3%	38%
	$p = .05,\ OTM$	2,265	15%	13%	9%	5%	55%
Volatility	VIX	2,267	21.6	19.3	10.3	9.9	80.9
Equity	3M S&P500 c. return	2,267	1%	2%	9%	-41%	38%
	3M c. stock return	439,733	2%	2%	22%	-94%	1068%
Rates	3M TB yield	2,250	2.03	1.64	1.70	0.00	5.19
	Slope	2,250	2.05	2.48	1.32	-0.64	3.85
	Liquidity Spread	2,198	0.07	0.03	0.18	-0.10	2.36
	Credit Spread	2,251	1.19	1.04	0.55	0.57	3.50

Table 2: **Summary statistics of the VaRs and other market data.** This table reports the (arithmetic) mean, median, standard deviation, absolute minimum and maximum for the individual and index VaR, the VIX volatility index, daily S&P500 and individual stock returns and the interest rate. The individual VaRs (row 1-4) and index VaRs (row 5-8) are estimated using ATM options according to equation (5) (row 1,2,5,6) or using OTM options according to equation (4) (row 3,4,7,8) for the 20% percentile (row 1,3,5,7) or the 5% percentile (row 2,4,6,8).

	Dependent variable: VaR^{Index}, $p = 0.2$, OTM (1)		(2)		(3)	
VaR^i	0.121	***	0.124	***	0.139	***
$\text{VaR}^i \cdot AT_S$	0.007	***	0.005	**	0.000	
$\text{VaR}^i \cdot BLEV_S$	-0.006	***	-0.006	***	-0.006	**
$\text{VaR}^i \cdot MTB_S$	0.007	**	0.007	**	0.027	***
$\text{VaR}^i \cdot ROE_S$	0.004	**	0.004	*	-0.002	
$\text{VaR}^i \cdot D_{IB}$	0.027	***	0.026	***	0.019	***
$\text{VaR}^i \cdot D_{Dep}$	0.01	***	0.014	**	-0.002	
$\text{VaR}^i \cdot MM1_S$			0.005	***	0.006	***
$\text{VaR}^i \cdot DP_S$			-0.007		0.017	
$\text{VaR}^i \cdot LEV3A_S$					-0.005	***
Constant	0.038	***	0.036	***	0.005	
3-month TB yield	-0.011	***	-0.011	***	-0.002	
Baa spread	0.055	***	0.055	***	0.057	***
Slope	-0.009	***	-0.008	***	0.000	
Liquidity spread	0.035	***	0.035	***	0.030	***
3-month S&P500 c. return	-0.093	***	-0.092	***	-0.081	***
Observations	428,957		377,817		109,884	
Number of groups	398		371		200	
R^2	0.62		0.62		0.65	

Table 3: **Panel regression results I for static analysis.** This table reports the estimation results according to equation (9) using VaRs computed from OTM options according to equation (4) and $p = 0.2$. The dependent variable VaR^{Index} is regressed on VaR^i, interacted with a set of standardized firm characteristics (AT, BLEV, MTB, ROE, MM, DP, LEV3A) and broker (D_{IB}) and depository (D_{Dep}) dummy variables as well as a set of control variables. The dummy variables are one if the firm is a broker or a depository bank and zero otherwise. The share of deposits is constrained to be zero if the bank is a not depository bank. Asterisks correspond to the following p-values: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The confidence levels are Driscoll and Kraay (1998) adjusted for serially and cross-sectionally correlated error terms.

	Dependent variable: VaR^i, $p = 0.2$, OTM					
	(1)		(2)		(3)	
VaR^{Index}	0.911	***	0.9	***	0.969	***
$\text{VaR}^{Index} \cdot AT_S$	0.022	**	0.020	**	0.080	***
$\text{VaR}^{Index} \cdot BLEV_S$	0.079	***	0.058	***	0.073	***
$\text{VaR}^{Index} \cdot MTB_S$	-0.057	***	-0.050	***	-0.053	***
$\text{VaR}^{Index} \cdot ROE_S$	-0.049	***	-0.044	***	-0.045	***
$\text{VaR}^{Index} \cdot D_{DEP}$	-0.013		0.057	***	0.063	
$\text{VaR}^{Index} \cdot D_{IB}$	-0.019		0.007		0.013	
$\text{VaR}^{Index} \cdot MM_S$			0.033	***	0.01	
$\text{VaR}^{Index} \cdot DP_S$			-0.044	***	-0.096	***
$\text{VaR}^{Index} \cdot LEV3A_S$					0.149	***
log(AT)	-0.007	***	-0.005	***	-0.006	
BLEV	0.001	***	0.001	***	-0.001	***
MTB	-0.001	***	-0.002	***	-0.007	***
MM			-0.045	***	-0.059	***
3M c. stock return	-0.028	***	-0.029	***	-0.015	***
ROE	-0.034	***	-0.029	***	0.023	***
LEV3A					-0.352	***
Constant	0.113	***	0.097	***	0.135	***
Observations	439,088		386,800		112,706	
Number of groups	398		371		200	
R^2	0.88		0.88		0.89	

Table 4: **Panel regression results II for static analysis.** This table reports the estimation results according to equation (8) using VaRs computed from OTM options according to equation (4) and $p = 0.2$. The dependent variable VaR^i is regressed on the VaR^{Index}, interacted with a set of standardized firm characteristics (AT, BLEV, MTB, ROE, MM, DP, LEV3A) and broker (D_{IB}) and depository dummy variables D_{Dep} as well as a set of control variables. The dummy variables are one if the firm is a broker or a depository bank and zero otherwise. The share of deposits is constrained to be zero if the bank is a not depository bank. Asterisks correspond to the following p-values: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The confidence levels are Driscoll and Kraay (1998) adjusted for serially and cross-sectionally correlated error terms.

		$\Phi(1,1)$		$\Phi(1,2)$		$\Phi(2,1)$		$\Phi(2,2)$	
Full Sample	Constant	**0.925**	***	**0.137**	***	**0.024**	***	**0.826**	***
	AT	**-0.008**	***	**-0.022**	***	**0.006**	***	**0.018**	***
	BLEV	**0.002**	***	**0.012**	***	**-0.001**	***	**0.003**	***
	MTB	**-0.005**	***	**-0.007**	***	**0.002**	***	**-0.004**	***
	MM	**-0.008**	***	**-0.008**	***	**0.004**	***	**0.007**	***
	ROE	**-0.005**	***	**-0.002**	*	**0.003**	***	**-0.007**	***
	VIX	**0.013**	***	**-0.003**	***	**-0.003**	***	**0.007**	***
	3M c. stock return	**0.006**	***	**0.014**	***	**-0.002**	***	**-0.012**	***
incl. LEV3A	Constant	**0.961**	***	**0.208**	***	**0.012**	***	**0.748**	***
	AT	**-0.022**	***	**-0.032**	***	**0.011**	***	**0.036**	***
	BLEV	**0.002**	**	**-0.015**	***	**-0.001**	*	**0.018**	***
	MTB	**-0.003**	***	**0.015**	***	**0.005**	***	**-0.036**	***
	MM	**-0.006**	***	**0.029**	***	**0.004**	***	**-0.025**	***
	ROE	**-0.002**	***	**0.013**	***	**0.002**	***	**-0.013**	***
	LEV3A	**-0.003**	***	**-0.014**	***	**0.001**	**	**0.018**	***
	VIX	**0.001**	**	**-0.022**	***	**0.001**	***	**0.025**	***
	3M c. stock return	**0.005**	***	**0.011**	***	**-0.002**	***	**-0.009**	***

Table 5: **Estimated parameters of the Γ matrix using OTM options and p=0.20**. This table reports the estimated parameters of the matrix Γ in equation (16) which determine the VaR coefficient matrix Φ. The individual entries of the matrix Φ are estimated as linear functions of the standardized values of total assets (AT), leverage (BLEV), market-to-book-ratio (MTB), maturity mismatch (MM), return-on-equity (ROE), level-3 assets (LEV3A), the VIX and the 3-month cumululative past stock return. Leverage is measured as total assets over equity book value and MTB as the ratio of market to book value of equity. Maturity mismatch and level-3 asset share are calculated as the ratio of short-term debt less cash and level-3 assets to total assets. Return on equity is measured as total earnings over equity book value. Asterisks correspond to the following p-values: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Dependent variable: VaR^{Index}, $p = 0.2$, OTM													
	AT		CEQ		MLEV		MTB		MM		LEV3A		ROE	
VaR^i	**0.088**	***	**0.093**	***	**0.078**	***	**0.102**	***	**0.081**	***	**0.057**	***	**0.100**	***
$\text{VaR}^i \cdot D_{AT2}$	**0.000**													
$\text{VaR}^i \cdot D_{AT3}$	**-0.006**	***												
$\text{VaR}^i \cdot D_{AT4}$	**-0.006**	**												
$\text{VaR}^i \cdot D_{AT5}$	**-0.010**	***												
$\text{VaR}^i \cdot D_{CEQ2}$			**0.000**											
$\text{VaR}^i \cdot D_{CEQ3}$			**-0.005**	**										
$\text{VaR}^i \cdot D_{CEQ4}$			**-0.006**	**										
$\text{VaR}^i \cdot D_{CEQ5}$			**-0.021**	***										
$\text{VaR}^i \cdot D_{BLEV2}$					**0.011**	***								
$\text{VaR}^i \cdot D_{BLEV3}$					**0.027**	***								
$\text{VaR}^i \cdot D_{BLEV4}$					**0.019**	***								
$\text{VaR}^i \cdot D_{BLEV5}$					**0.019**	***								
$\text{VaR}^i \cdot D_{MTB2}$							**0.000**							
$\text{VaR}^i \cdot D_{MTB3}$							**-0.005**	***						
$\text{VaR}^i \cdot D_{MTB4}$							**-0.012**	***						
$\text{VaR}^i \cdot D_{MTB5}$							**-0.025**	***						
$\text{VaR}^i \cdot D_{MM2}$									**0.004**	***				
$\text{VaR}^i \cdot D_{MM3}$									**0.004**	***				
$\text{VaR}^i \cdot D_{MM4}$									**0.009**	***				
$\text{VaR}^i \cdot D_{MM5}$									**-0.018**	***				
$\text{VaR}^i \cdot D_{LEV3A2}$											**0.008**	***		
$\text{VaR}^i \cdot D_{LEV3A3}$											**0.017**	***		
$\text{VaR}^i \cdot D_{LEV3A4}$											**0.009**	***		
$\text{VaR}^i \cdot D_{LEV3A5}$											**0.010**	***		
$\text{VaR}^i \cdot D_{ROE2}$													**0.005**	***
$\text{VaR}^i \cdot D_{ROE3}$													**0.003**	**
$\text{VaR}^i \cdot D_{ROE4}$													**-0.012**	***
$\text{VaR}^i \cdot D_{ROE5}$													**-0.025**	***
Constant	0.044	***	0.044	***	0.043	***	0.043	***	0.043	***	0.007		0.043	***
3-month TB yield	-0.012	***	-0.012	***	-0.012	***	-0.012	***	-0.012	***	-0.003		-0.012	***
Baa spread	0.058	***	0.058	***	0.058	***	0.058	***	0.058	***	0.063	***	0.058	***
Slope	-0.010	***	-0.010	***	-0.010	***	-0.010	***	-0.010	***	0.001		-0.010	***
Liquidity spread	0.039	***	0.038	***	0.039	***	0.038	***	0.039	***	0.032	***	0.038	***
3-month S&P500 c. return	-0.093	***	-0.093	***	-0.093	***	-0.093	***	-0.095	***	-0.081	***	-0.093	***
Observations	429,666		429,666		429,666		429,666		426,992		122,854		428,957	
Number of groups	399		399		399		399		399		223		398	
R-squared	0.89		0.89		0.89		0.89		0.89		0.89		0.89	

Table 6: **Panel regression results I from static analysis with univariate sorting.** This table reports the estimation results according to equation (11) using VaRs computed from OTM options according to equation (4) and $p = 0.2$. The dependent variable VaR^{Index} is regressed on the VaR^i, interacted with a dummy variable $D_{k,l}$ and a set of control variables. The dummy variable $D_{j,i}$ is one if the company i belongs to the quantile group l with respect to the conditioning variable k and zero otherwise. Asterisks correspond to the following p-values: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The confidence levels are Driscoll and Kraay (1998) adjusted for serially and cross-sectionally correlated error terms.

	Dependent variable: VaR^i, $p = 0.2$, OTM						
	AT	CEQ	MLEV	MTB	MM	LEV3A	ROE
VaR^{Index}	**1.120** ***	**1.058** ***	**1.233** ***	**0.768** ***	**0.964**	**1.189** ***	**0.846** ***
$\text{VaR}^{Index} \cdot D_{AT2}$	**-0.213** ***						
$\text{VaR}^{Index} \cdot D_{AT3}$	**-0.280** ***						
$\text{VaR}^{Index} \cdot D_{AT4}$	**-0.393** ***						
$\text{VaR}^{Index} \cdot D_{AT5}$	**-0.407** ***						
$\text{VaR}^{Index} \cdot D_{CEQ2}$		**-0.161** ***					
$\text{VaR}^{Index} \cdot D_{CEQ3}$		**-0.200** ***					
$\text{VaR}^{Index} \cdot D_{CEQ4}$		**-0.331** ***					
$\text{VaR}^{Index} \cdot D_{CEQ5}$		**-0.284** ***					
$\text{VaR}^{Index} \cdot D_{BLEV2}$			**-0.218** ***				
$\text{VaR}^{Index} \cdot D_{BLEV3}$			**-0.384** ***				
$\text{VaR}^{Index} \cdot D_{BLEV4}$			**-0.504** ***				
$\text{VaR}^{Index} \cdot D_{BLEV5}$			**-0.545** ***				
$\text{VaR}^{Index} \cdot D_{MTB2}$				**0.073** ***			
$\text{VaR}^{Index} \cdot D_{MTB3}$				**0.088** ***			
$\text{VaR}^{Index} \cdot D_{MTB4}$				**0.144** ***			
$\text{VaR}^{Index} \cdot D_{MTB5}$				**0.346** ***			
$\text{VaR}^{Index} \cdot D_{MM2}$					**-0.077** ***		
$\text{VaR}^{Index} \cdot D_{MM3}$					**-0.093** ***		
$\text{VaR}^{Index} \cdot D_{MM4}$					**-0.109** ***		
$\text{VaR}^{Index} \cdot D_{MM5}$					**-0.127** ***		
$\text{VaR}^{Index} \cdot D_{LEV3A2}$						**-0.102** ***	
$\text{VaR}^{Index} \cdot D_{LEV3A3}$						**-0.250** ***	
$\text{VaR}^{Index} \cdot D_{LEV3A4}$						**-0.366** ***	
$\text{VaR}^{Index} \cdot D_{LEV3A5}$						**-0.383** ***	
$\text{VaR}^{Index} \cdot D_{ROE2}$							**-0.042** ***
$\text{VaR}^{Index} \cdot D_{ROE3}$							**-0.002** ***
$\text{VaR}^{Index} \cdot D_{ROE4}$							**0.103** ***
$\text{VaR}^{Index} \cdot D_{ROE5}$							**0.225** ***
Constant	0.206 ***	0.187 ***	0.159 ***	0.129 ***	0.147 ***	0.053 *	0.110 ***
log(AT)	-0.017 ***	-0.015 ***	-0.012 ***	-0.009 ***	-0.011 ***	0.000	-0.008 ***
BLEV	0.002 ***	0.002 ***	0.001 ***	0.002 ***	0.002 ***	0.001 **	0.002 ***
MTB	-0.001 ***	-0.001 **	-0.001 ***	0.001 **	0.000	-0.008 ***	0.000 ***
MM	-0.006	-0.007	-0.016 ***	-0.016 ***	-0.037 ***	0.056 ***	-0.013 ***
3-month c. stock return	-0.024 ***	-0.024 ***	-0.020 ***	-0.021 ***	-0.025 ***	-0.018 ***	-0.024 ***
ROE	-0.050 ***	-0.051 ***	-0.043 ***	-0.050 ***	-0.051 ***	-0.010 ***	-0.027 ***
Observations	436,359	436,359	436,359	436,359	436,359	126,022	436,359
Number of groups	398	398	398	398	398	223	398

Table 7: **Panel regression results II from static analysis with univariate sorting.** This table reports the estimation results according to equation (12) using VaRs computed from OTM options according to equation (4) and $p = 0.2$. The dependent variable VaR^i is regressed on the VaR^{Index}, interacted with a dummy variable $D_{k,l}$ and a set of control variables. The dummy variable $D_{j,i}$ is one if the company i belongs to the quantile group l with respect to the conditioning variable k and zero otherwise. Asterisks correspond to the following p-values: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The confidence levels are Driscoll and Kraay (1998) adjusted for serially and cross-sectionally correlated error terms.

		$\frac{\partial VaR^i}{\partial VaR^{Index}}$		$\frac{\partial VaR^{Index}}{\partial VaR^i}$	
		lower bound	upper bound	lower bound	upper bound
AT	quantile 1	0.64	0.69	0.21	0.24
	quantile 2	0.35	0.43	0.36	0.42
	quantile 3	0.25	0.31	0.10	0.14
	quantile 4	0.39	0.48	0.04	0.06
	quantile 5	0.33	0.41	0.05	0.08
CEQ	quantile 1	0.63	0.67	0.21	0.24
	quantile 2	0.49	0.55	0.25	0.28
	quantile 3	0.51	0.61	0.09	0.12
	quantile 4	0.43	0.51	0.03	0.05
	quantile 5	0.46	0.58	0.02	0.04
BLEV	quantile 1	0.58	0.64	0.17	0.21
	quantile 2	0.53	0.61	0.09	0.12
	quantile 3	0.28	0.36	0.22	0.27
	quantile 4	0.33	0.39	0.18	0.25
	quantile 5	0.42	0.47	0.15	0.20
MTB	quantile 1	0.42	0.47	0.17	0.22
	quantile 2	0.44	0.50	0.13	0.17
	quantile 3	0.42	0.48	0.16	0.20
	quantile 4	0.47	0.53	0.10	0.13
	quantile 5	0.74	0.85	0.07	0.10
MM	quantile 1	0.54	0.60	0.16	0.19
	quantile 2	0.57	0.66	0.08	0.11
	quantile 3	0.61	0.67	0.10	0.14
	quantile 4	0.56	0.64	0.08	0.12
	quantile 5	0.36	0.42	0.12	0.16
LEV3A	quantile 1	0.73	0.92	0.07	0.14
	quantile 2	0.58	0.71	0.12	0.18
	quantile 3	0.51	0.65	0.04	0.09
	quantile 4	0.40	0.55	0.08	0.13
	quantile 5	0.45	0.65	0.02	0.10
ROE	quantile 1	0.46	0.51	0.13	0.16
	quantile 2	0.42	0.48	0.11	0.15
	quantile 3	0.39	0.45	0.10	0.13
	quantile 4	0.53	0.61	0.08	0.11
	quantile 5	0.63	0.72	0.08	0.11

Table 8: **Estimated confidence intervals for impulse response functions after 22 business days using OTM options and p=0.2.** This table reports lower and upper limits to the 95% confidence intervals for the estimated impulse response function of the VaR^i (VaR^{Index}) following an index (individual) VaR shock after 22 days. The VaRs are calculated from OTM options according to equation (4) and for $p = 0.2$. The impulse response functions are estimated individually for each quantile of the conditioning variables total assets (AT), book equity value (CEQ), book leverage (BLEV), market-to-book-ratio (MTB), maturity mismatch (MM), level-3 asset share (LEV3A) and return-on-equity (ROE). Leverage is measured as total assets over book equity value and MTB as the ratio of market to book value of equity. Maturity mismatch, cash share and level-3 asset share are calculated as the ratio of short-term debt less cash holdings and level-3 assets to total assets. Return on equity is measured as total earnings over book equity value.

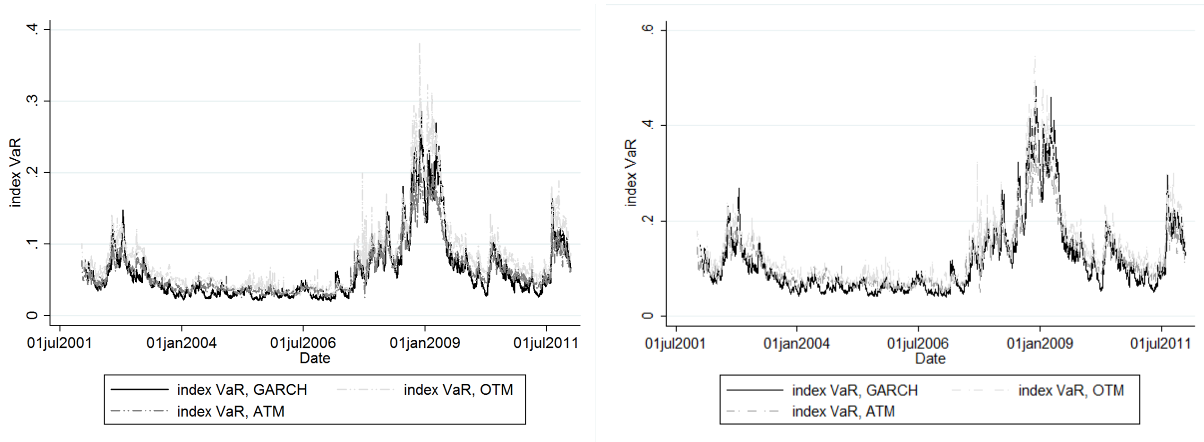


Figure 1: **Comparison of GARCH- and option-implied index VaRs.** These figures depict the estimated time-series evolution of the index VaR, computed for the 20% (left) and 5% (right) percentile. The dark grey line depicts the option-implied VaR^{OI}, calculated as in equation (5) using ATM option volatilites, while the light grey line depicts the option-implied VaR^{OI} calculated according to equation (4) using OTM option volatilites. The black line depicts the VaR estimated by a GARCH(2,2) model using the daily close of business share prices of the underlying financial sector index ETF (ticker: IYF) from 2002 to 2012.

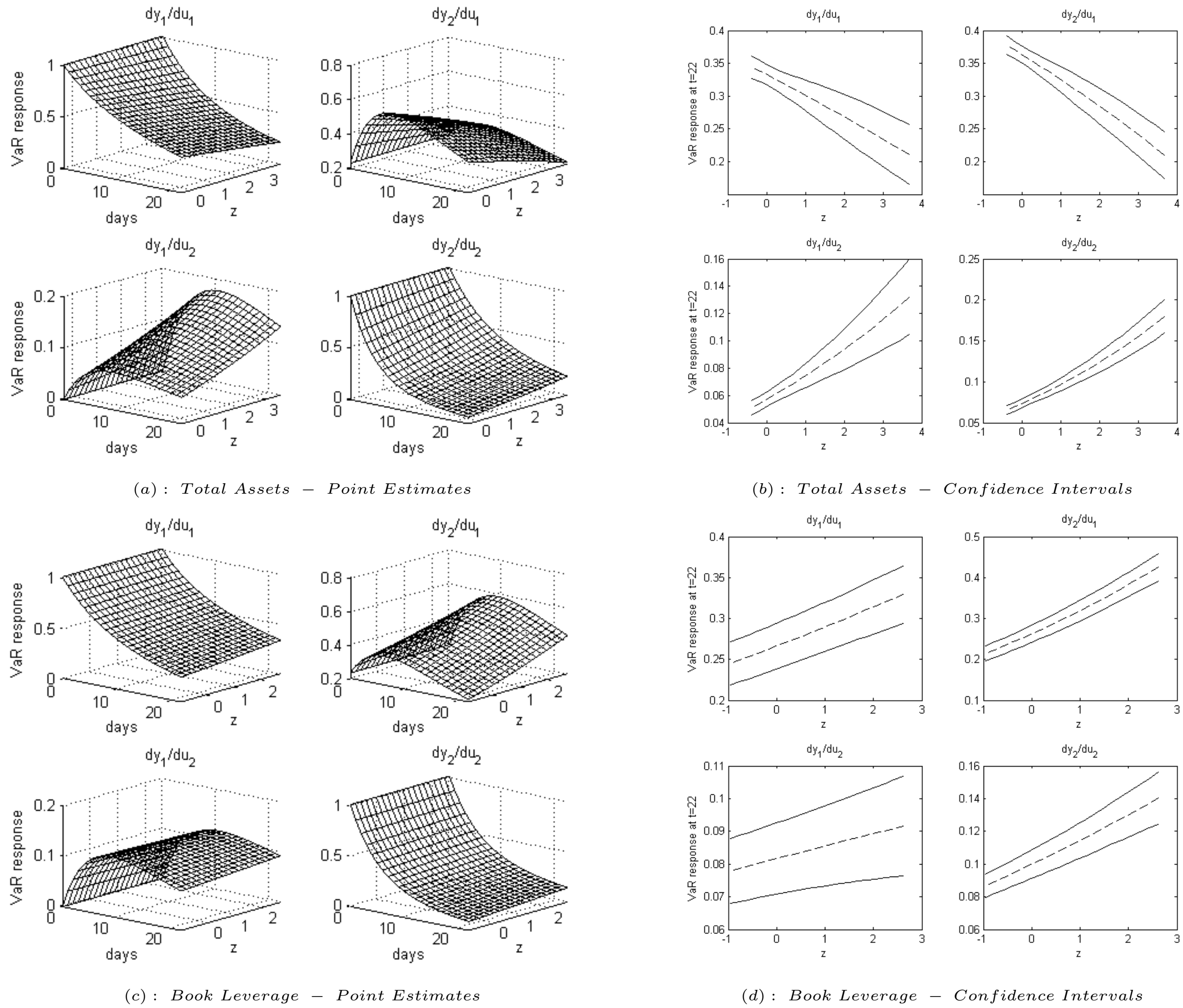
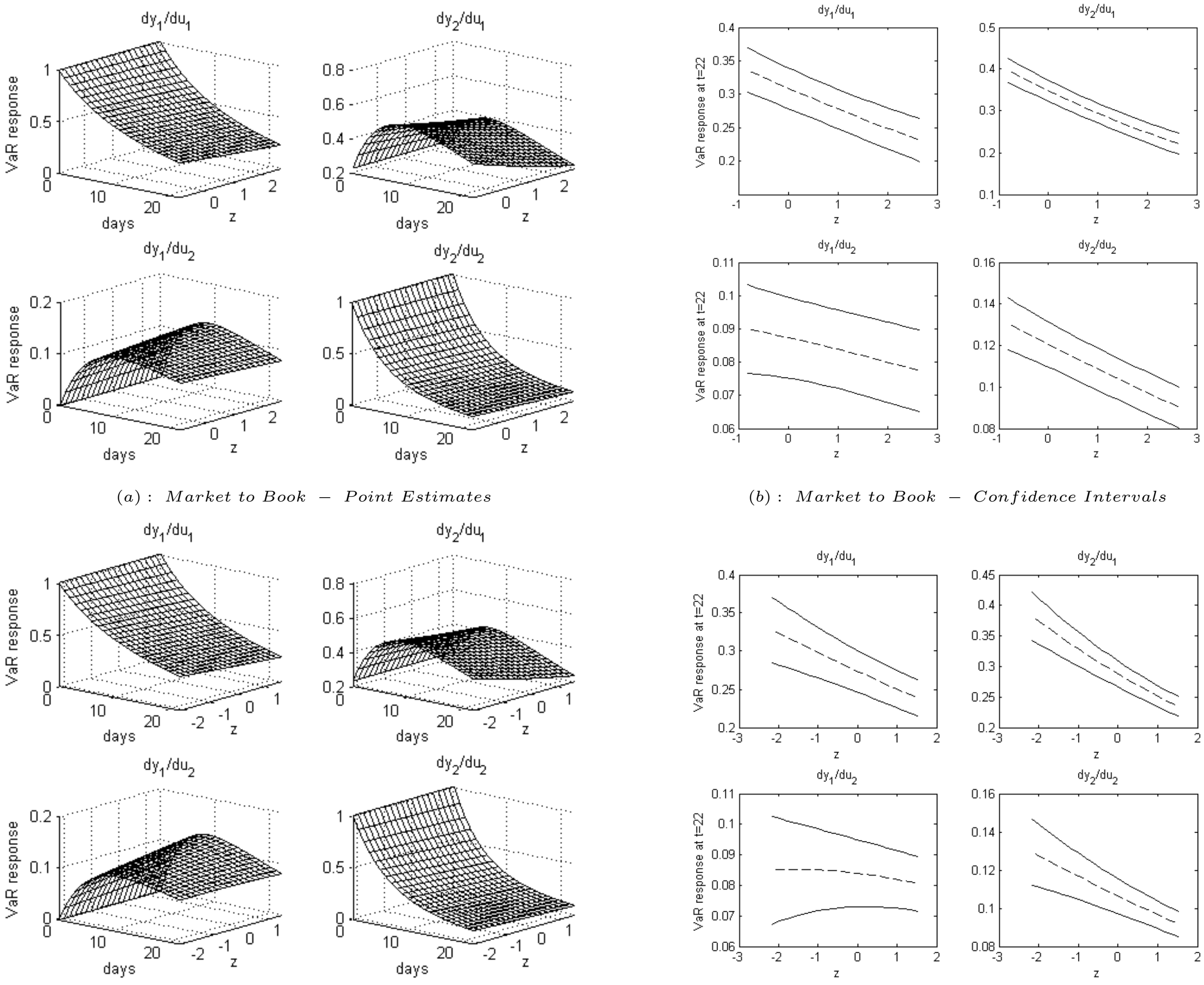


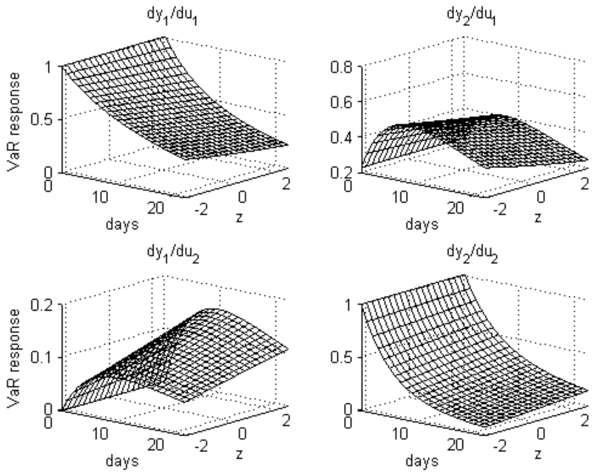
Figure 2: **Impulse response functions conditional on total asset size and book leverage.** These figures depict the impulse response functions estimated conditional on selected accounting or market valuation items, the VIX and the 3-month cumulative stock return by the PCHVAR model of Georgiadis (2012). For each conditioning variable, the impulse responses represent the response functions of the index VaR (left top and bottom) or the individual company VaR (right top and bottom) after an orthogonalized unit shock to the sector VaR^{Index} (top left and right) or to the individual company VaR^{i} (bottom left and right). The impulse responses are functions of time (left axis, in days) and the conditioning variable (right axis, standardized values). Point estimates in (a) and (c) are displayed for the first 22 days. 95%-confidence intervals (solid lines) in (b) and (d) are estimated after 22 days.



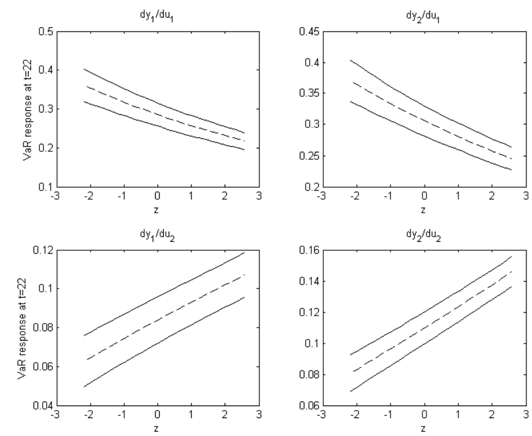
(c) : *Return on Equity − Point Estimates*

(d) : *Return on Equity − Confidence Intervals*

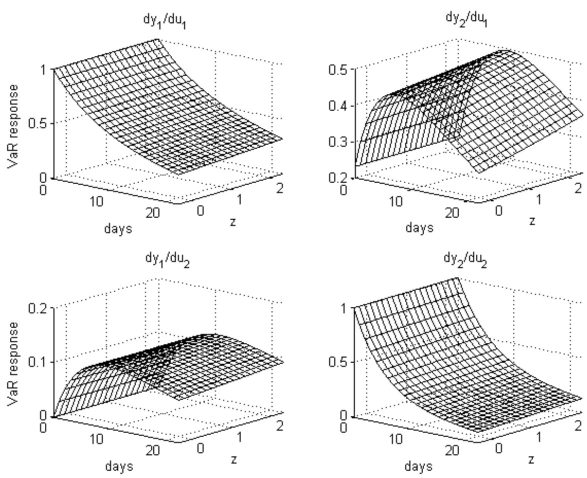
Figure 3: **Impulse response functions conditional on market to book and return on equity.** These figures depict the impulse response functions estimated conditional on selected accounting or market valuation items, the VIX and the 3-month cumulative stock return by the PCHVAR model of Georgiadis (2012). For each conditioning variable, the impulse responses represent the response functions of the index VaR (left top and bottom) or the individual company VaR (right top and bottom) after an orthogonalized unit shock to the sector VaR^{Index} (top left and right) or to the individual company VaR^{i} (bottom left and right). The impulse responses are functions of time (left axis, in days) and the conditioning variable (right axis, standardized values). Point estimates in (a) and (c) are displayed for the first 22 days. 95%-confidence intervals (solid lines) in (b) and (d) are estimated after 22 days.



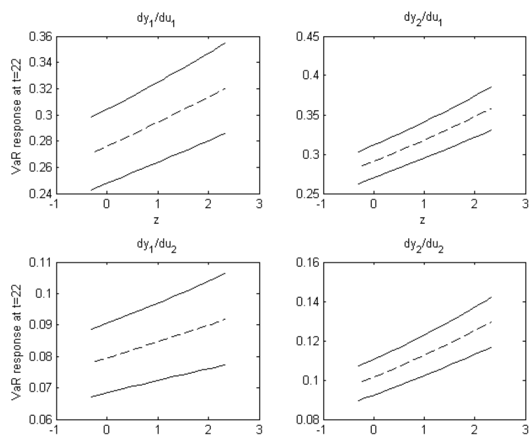
(a) : *Maturity Mismatch − Point Estimates*



(b) : *Maturity Mismatch − Confidence Intervals*

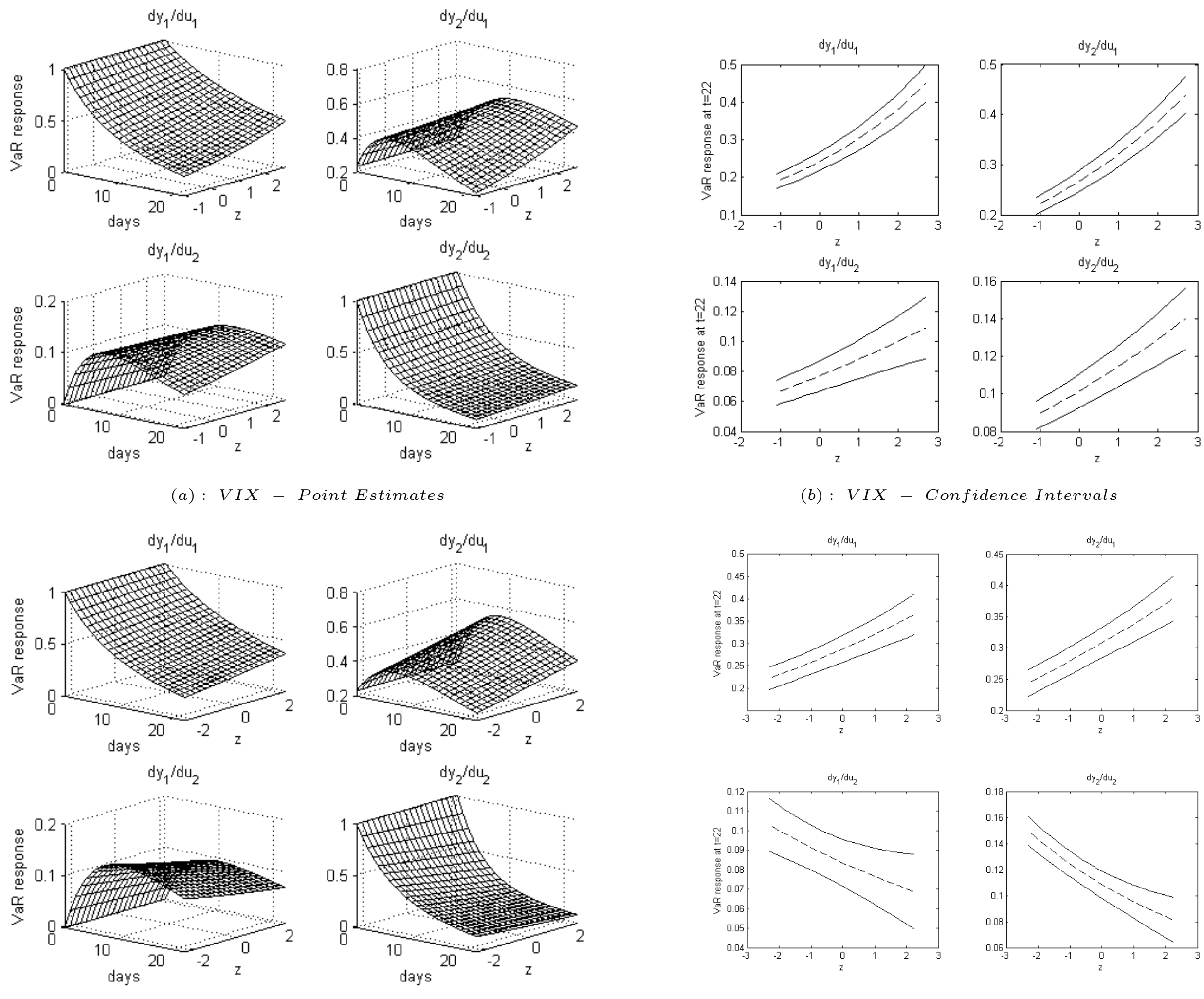


(c) : *Level − 3 Assets − Point Estimates*



(d) : *Level − 3 Assets − Confidence Intervals*

Figure 4: **Impulse response functions conditional on maturity mismatch and the share of level-3 assets.** These figures depict the impulse response functions estimated conditional on selected accounting or market valuation items, the VIX and the 3-month cumulative stock return by the PCHVAR model of Georgiadis (2012). For each conditioning variable, the impulse responses represent the response functions of the index VaR (left top and bottom) or the individual company VaR (right top and bottom) after an orthogonalized unit shock to the sector VaR^{Index} (top left and right) or to the individual company VaR^{i} (bottom left and right). The impulse responses are functions of time (left axis, in days) and the conditioning variable (right axis, standardized values). Point estimates in (a) and (c) are displayed for the first 22 days. 95%-confidence intervals (solid lines) in (b) and (d) are estimated after 22 days.



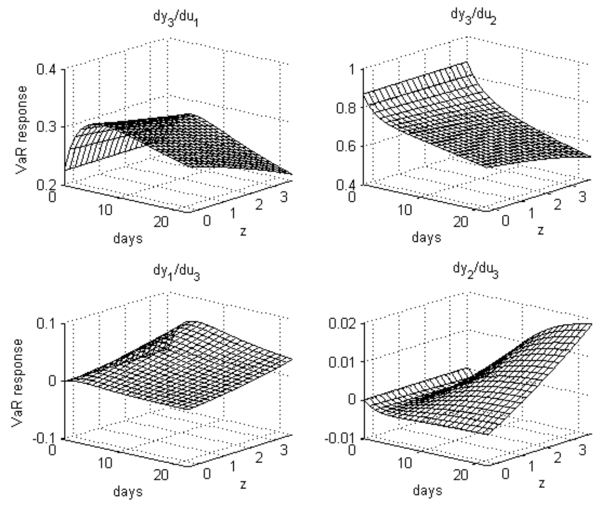
(a) : VIX − Point Estimates

(b) : VIX − Confidence Intervals

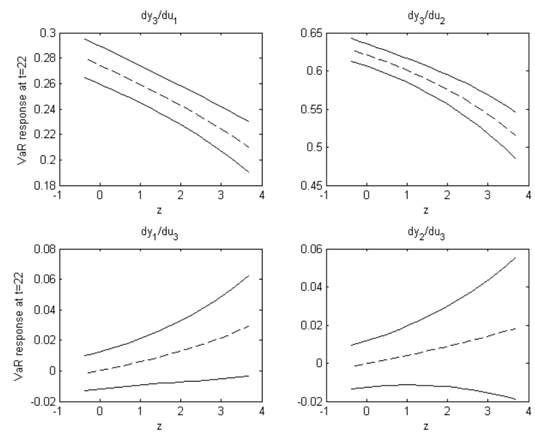
(c) : 3 − month c. stock return − Point Estimates

(d) : 3 − month c. stock return − Confidence Intervals

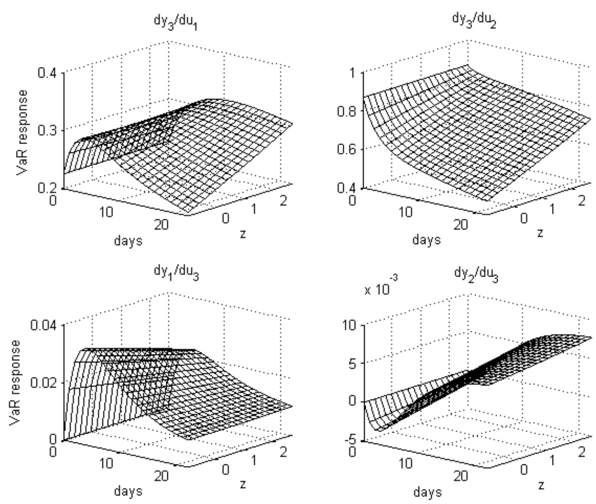
Figure 5: **Impulse response functions conditional on the VIX and the 3-month cumulative stock return.** These figures depict the impulse response functions estimated conditional on selected accounting or market valuation items, the VIX and the 3-month cumulative stock return by the PCHVAR model of Georgiadis (2012). For each conditioning variable, the impulse responses represent the response functions of the index VaR (left top and bottom) or the individual company VaR (right top and bottom) after an orthogonalized unit shock to the sector VaR^{Index} (top left and right) or to the individual company VaR^{i} (bottom left and right). The impulse responses are functions of time (left axis, in days) and the conditioning variable (right axis, standardized values). Point estimates in (a) and (c) are displayed for the first 22 days. 95%-confidence intervals (solid lines) in (b) and (d) are estimated after 22 days.



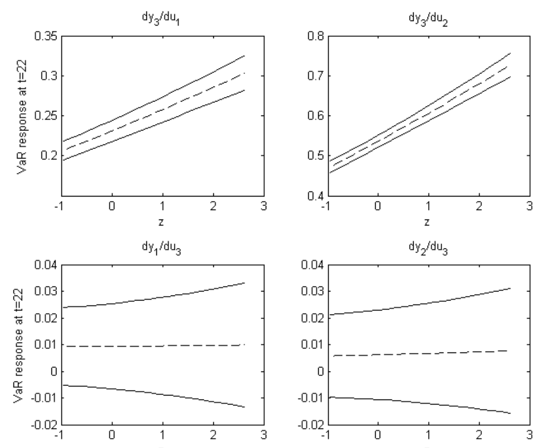
$(a): \ Total\ Assets\ -\ Point\ Estimates$



$(b): \ Total\ Assets\ -\ Confidence\ Intervals$

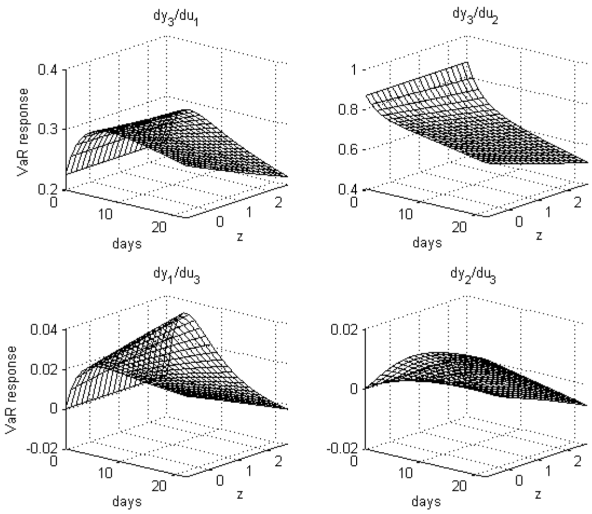


$(c): \ Book\ Leverage\ -\ Point\ Estimates$

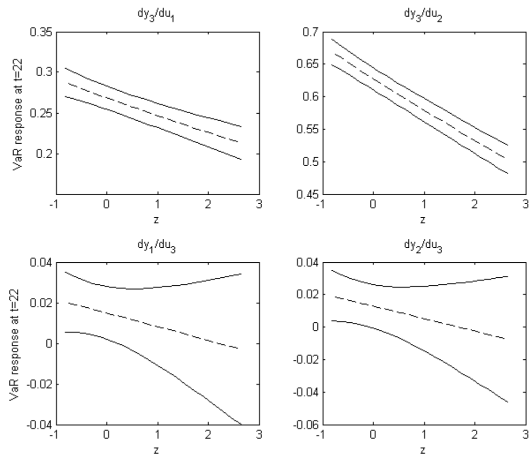


$(d): \ Book\ Leverage\ -\ Confidence\ Intervals$

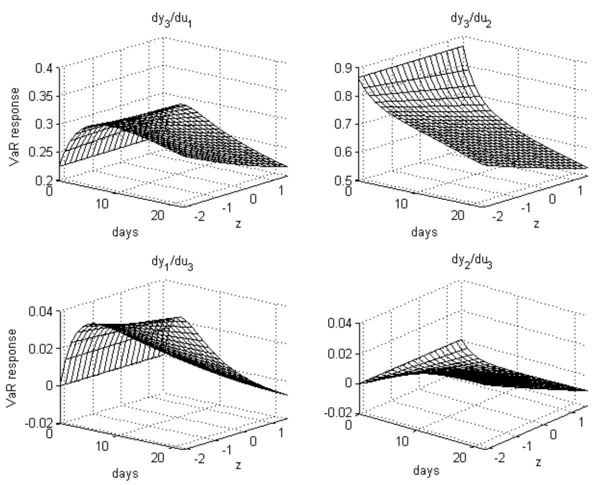
Figure 6: **Impulse response functions from trivariate VAR conditional on Total Asset size and Book Leverage.** Above pictures depict the impulse response functions, estimated conditional on selected accounting or market valuation items, the VIX and the 3-month cumulative stock return by the PCHVAR model of Georgiadis (2012). For each conditioning variable, the impulse responses represent the response functions of the index VaR (bottom left), average company VaR (bottom right) or the individual company VaR (top right and left) after an orthogonalized unit shock to the sector VaR^{Index} (top left), average company VaR (top right) or to the individual company VaR^{i} (bottom left and right). The impulse responses are functions of time (left axis, in days) and the conditioning variable (right axis, standardized values). The impulse responses are functions of time (left axis, in days) and the conditioning variable (right axis, standardized values). Point estimates in (a) and (c) are displayed for the first 22 days. 95%-confidence intervals (solid lines) in (b) and (d) are estimated after 22 days.



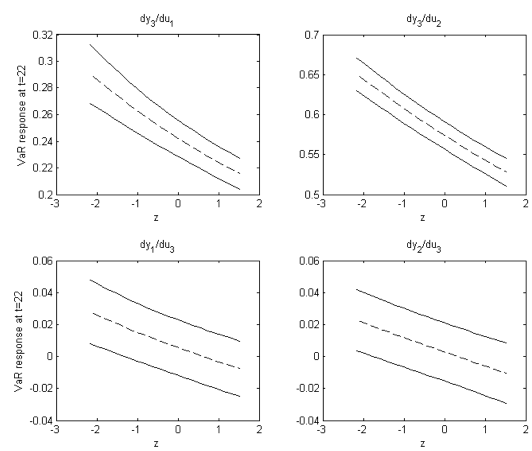
$(a): \ Market\ to\ Book\ -\ Point\ Estimates$



$(b): \ Market\ to\ Book\ -\ Confidence\ Intervals$

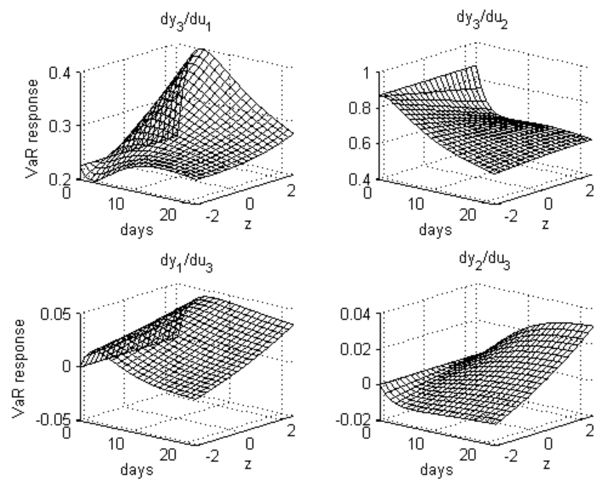


$(c): \ Return\ on\ Equity\ -\ Point\ Estimates$

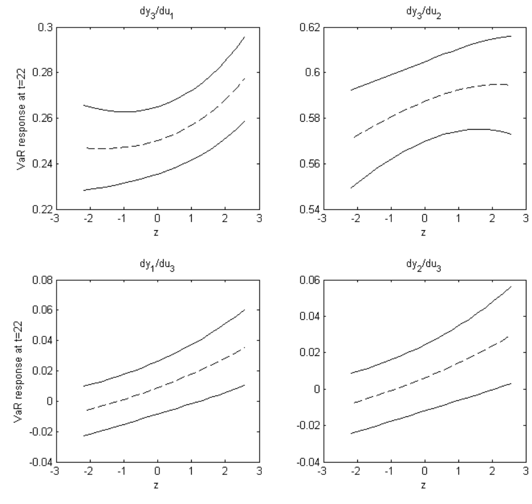


$(d): \ Return\ on\ Equity\ -\ Confidence\ Intervals$

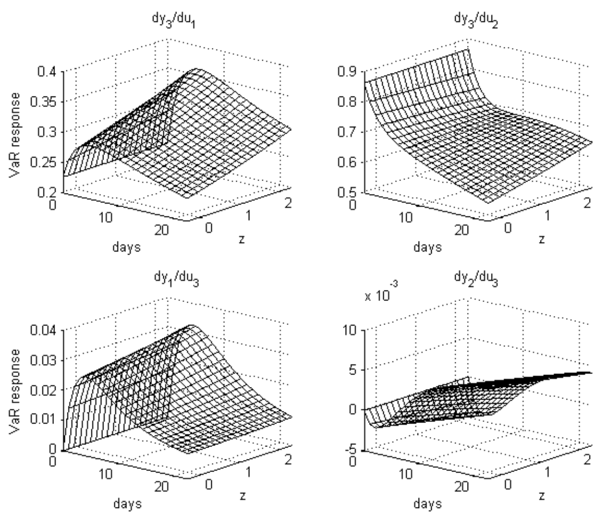
Figure 7: **Impulse response functions from trivariate VAR conditional on market to book and return on equity.** These figures depict the impulse response functions estimated conditional on selected accounting or market valuation items, the VIX and the 3-month cumulative stock return by the PCHVAR model of Georgiadis (2012). For each conditioning variable, the impulse responses represent the response functions of the index VaR (bottom left), average company VaR (bottom right) or the individual company VaR (top right and left) after an orthogonalized unit shock to the sector VaR^{Index} (top left), average company VaR (top right) or to the individual company VaR^{i} (bottom left and right). The impulse responses are functions of time (left axis, in days) and the conditioning variable (right axis, standardized values). The impulse responses are functions of time (left axis, in days) and the conditioning variable (right axis, standardized values). Point estimates in (a) and (c) are displayed for the first 22 days. 95%-confidence intervals (solid lines) in (b) and (d) are estimated after 22 days.



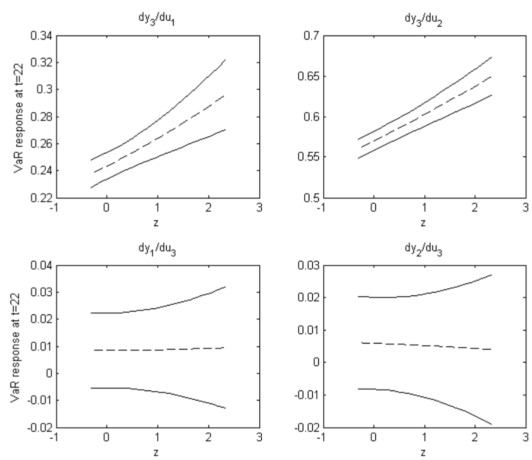
(a) : *Maturity Mismatch − Point Estimates*



(b) : *Maturity Mismatch − Confidence Intervals*

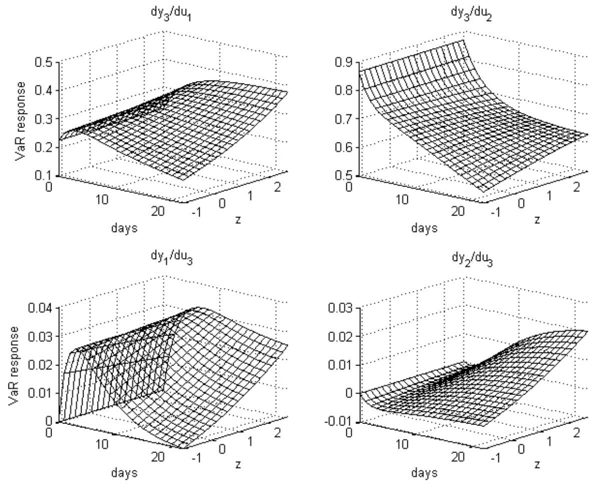


(c) : *Level − 3 Assets − Point Estimates*

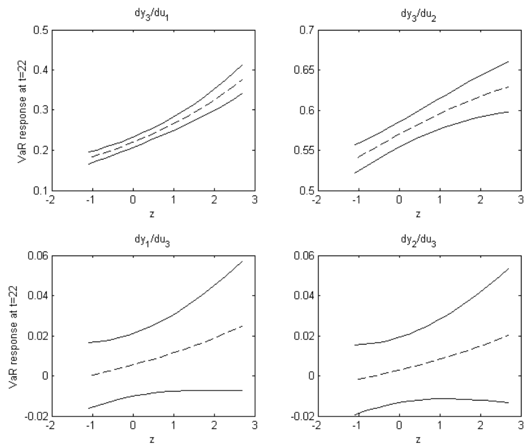


(d) : *Level − 3 Assets − Confidence Intervals*

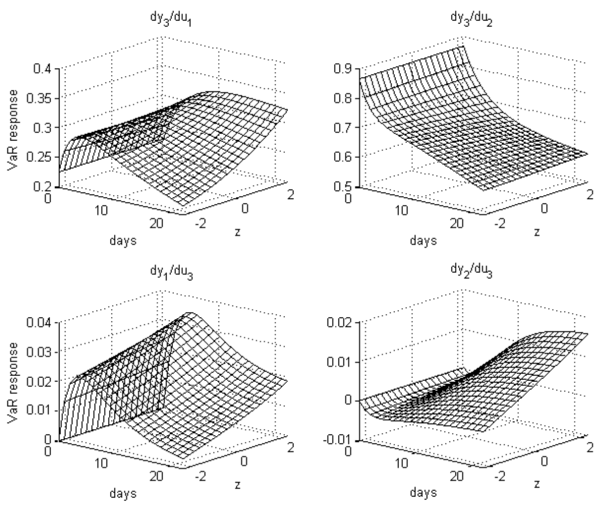
Figure 8: **Impulse response functions from trivariate VAR conditional on maturity mismatch and the share of level-3 assets.** These figures depict the impulse response functions estimated conditional on selected accounting or market valuation items, the VIX and the 3-month cumulative stock return by the PCHVAR model of Georgiadis (2012). For each conditioning variable, the impulse responses represent the response functions of the index VaR (bottom left), average company VaR (bottom right) or the individual company VaR (top right and left) after an orthogonalized unit shock to the sector VaR^{Index} (top left), average company VaR (top right) or to the individual company VaR^{i} (bottom left and right). The impulse responses are functions of time (left axis, in days) and the conditioning variable (right axis, standardized values). The impulse responses are functions of time (left axis, in days) and the conditioning variable (right axis, standardized values). Point estimates in (a) and (c) are displayed for the first 22 days. 95%-confidence intervals (solid lines) in (b) and (d) are estimated after 22 days.



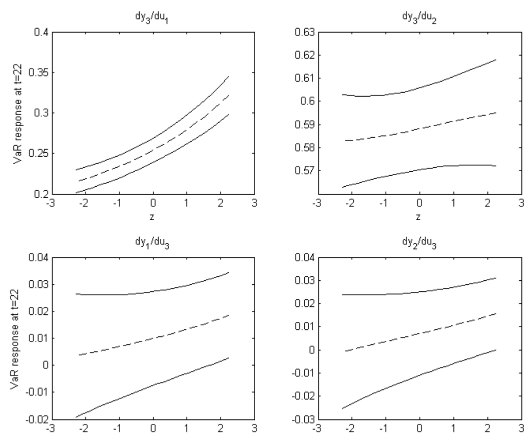
$(a):\ VIX\ -\ Point\ Estimates$



$(b):\ VIX\ -\ Confidence\ Intervals$



$(c):\ 3-month\ c.\ stock\ return\ -\ Point\ Estimates$



$(d):\ 3-month\ c.\ stock\ return\ -\ Confidence\ Intervals$

Figure 9: **Impulse response functions from trivariate VAR conditional on the VIX and the 3-month cumulative stock return.** These figures depict the impulse response functions estimated conditional on selected accounting or market valuation items, the VIX and the 3-month cumulative stock return by the PCHVAR model of Georgiadis (2012). For each conditioning variable, the impulse responses represent the response functions of the index VaR (bottom left), average company VaR (bottom right) or the individual company VaR (top right and left) after an orthogonalized unit shock to the sector VaR^{Index} (top left), average company VaR (top right) or to the individual company VaR^{i} (bottom left and right). The impulse responses are functions of time (left axis, in days) and the conditioning variable (right axis, standardized values). The impulse responses are functions of time (left axis, in days) and the conditioning variable (right axis, standardized values). Point estimates in (a) and (c) are displayed for the first 22 days. 95%-confidence intervals (solid lines) in (b) and (d) are estimated after 22 days.