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Risk-Neutral Systemic Risk Indicators

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Abstract

This paper describes a set of indicators of systemic risk computed from current market prices of equity and equity index options. It displays results from a prototype version, computed daily from January 2006 to January 2013. The indicators represent a systemic risk event as the realization of an extreme loss on a portfolio of large-intermediary equities. The technique for computing them combines risk-neutral return distributions with implied return correlations drawn from option prices, tying together the single-firm return distributions via a copula to simulate the joint distribution and thus the financial-sector portfolio return distribution. The indicators can be computed daily using only current market prices; no historical data are involved. They are therefore forward-looking and can exploit all the information impounded in current prices. However, the indicators blend both market expectations and the market's desire to protect itself against volatility and tail risk, so they cannot be readily decomposed into these two elements. The paper presents evidence that the indicators have some predictive power for systemic risk events and that they can serve as a meaningful market-adjusted point of comparison for fundamentals-based systemic risk indicators.

Key words: systemic risk, option pricing, copula methods, risk-neutral distributions, implied correlation

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Contents

1 Introduction

This paper describes a set of indicators of systemic risk based on market prices of equity and equity index options. We display results from a prototype version, computed daily from January 2006 to January 2013.

The indicators described here are related to the "market-based" metrics described in recent papers applying financial risk management tools to the measurement of systemic risk: Segoviano and Goodhart (2009), Acharya, Pedersen, Philippon and Richardson (2010), Adrian and Brunnermeier (2011), Huang, Zhou and Zhu (2011), Brownlees and Engle (2011), Gray and Jobst (2011), and Hovakimian, Kane and Laeven (2012).[1]

The approaches in these papers have in common the definition of systemic risk as an extreme loss on a portfolio of assets related to financial intermediaries' balance sheets. This definition of systemic risk focuses on the financial health of intermediaries, rather than on monetary and credit conditions, as the proximate determinant of the likelihood of a severe crisis.

The systemic risk measures in these papers differ in several key dimensions:

Metric of loss: The metric of loss in this literature is typically a balance-sheet quantity, that is, the firms' debt securities, as in Huang et al. (2011), the firms' equity market value, as in Acharya et al. (2010) and Brownlees and Engle (2011), or the firms' asset value, as in Adrian and Brunnermeier (2011). The systemic risk indicators presented here define a systemic risk event as a large loss in the equity market capitalization of a portfolio of financial firms.

The metric can also be framed as an insurance premium. Huang et al. (2011) and Hovakimian et al. (2012) compute the premium cost of insurance against losses on the aggregate debt of individual intermediaries and of the banking or financial sector.

Distributional characteristic: The risk of an extreme loss over a specified time horizon can be measured by the probability of occurrence of a loss of given size, as a quantile of the loss distribution corresponding to a given low probability (Value-at-Risk, or VaR), or as the expected value of a loss if a given quantile is exceeded (expected shortfall). VaR and expected shortfall can be expressed in dollars or as a return. The time horizon, the threshold loss size, and threshold

[1] See Bisias, Flood, Lo and Valavanis (2012) for a comprehensive survey of the current state of research on systemic risk measurement. In Bisias et al.'s (2012) main taxonomy of systemic risk measures, some of the indicators described in this paper would be denoted "forward-looking" or "cross-sectional."

probability can be varied. The option-based approach described in this paper can generate all these risk metrics.

Entity and conditioning: The probability, magnitude, or expected value of an extreme loss can be measured for an individual financial intermediary or for a portfolio of firms, representing the financial system. The metrics can be unconditional, or conditional on the occurrence an of an extreme loss of an individual firm. Conversely, the probability, magnitude, or expected value of a firm's extreme loss can be unconditional, or conditional on the occurrence an of an extreme loss of the system or portfolio. The approach described in this paper can generate conditional and unconditional risk metrics at both the firm and portfolio levels.

Type of data: Systemic risk measures can be computed using historical data on market prices and fundamentals, as in Adrian and Brunnermeier (2011), using historical market prices of equity and debt securities issued by the firms, as in Acharya et al. (2010) and Brownlees and Engle (2011), or using both historical and current market prices of the firms' debt and equity issues, or credit default swaps (CDS), as in Huang et al. (2011). Most historical data on fundamentals is available at monthly or quarterly frequency.

The approach described here relies only on market data that is available daily. They can be computed daily using only current market prices of options, equities, and in a variant of the indicators, CDS; no historical data are involved.

To distinguish this new set of indicators while retaining its association with those presented in the previous literature, we will denote them as Option-Based Systemic Expected Shortfall Statistics (OBSESS). In contrast to the papers just cited, OBSESS are entirely market-based. They are therefore forward-looking, and can exploit all the information impounded in current prices.

However, they are therefore also risk-neutral and it is worth reiterating the well-known fact that they are thereby not the same as real-world probabilities, correlations and quantiles. Rather, they are influenced, perhaps heavily, by risk preferences. Change in OBSESS can be due to changes in real-world probabilities and correlations, or risk preferences, or both. OBSESS blend both market expectations and the market's desire to protect itself against tail risk, and can't be easily decomposed into these two elements. They can therefore best be thought of as benchmarks that translate current market prices into risk measures, rather than forecasts.

2 Construction of the risk-neutral indicators

Our estimation procedure relies on the copula approach, in which a set of simulations from a multivariate distribution chosen by the modeler is combined with estimates of the marginal return distributions of the portfolio constituents to arrive at an estimate of the portfolio return distribution. Copulas are widely used in valuation and risk modeling of credit portfolios and structured credit products, and are used in several of the papers just cited. The copula in our application is computed from two estimated components, the risk-neutral probability distributions of the individual financial firms' equity returns, and the risk-neutral implied equity return correlation.

There thus three key components in our approach: estimates of individual firms' equity return distributions, an estimate of the return correlation, and an estimate of the copula that ties them together. In the implementation described here, we use a normal copula with a constant pairwise correlation parameter. The marginal return distributions are estimated as the equity option-based risk-neutral distributions of the constituents, incorporating additional information in the credit default swap spreads of the constituents. The normal copula correlation is estimated as the risk-neutral implied correlation.

2.1 Included firms and data

The portfolio of shares of financial intermediaries includes the 8 U.S. banks listed as global systemically important banks (G-SIBs) as updated in Financial Stability Board (2012). This table lists the included firms, their market capitalization in millions of dollars, and their shares (percent) in the total market cap of the portfolio as of Jan. 14, 2013:

Ticker	Name	Market cap	Share of total	Cum. share
WFC	Wells Fargo & Co	183,039	23.9	23.9
JPM	JPMorgan Chase & Co	174,408	22.8	46.7
C	Citigroup Inc	123,811	16.2	62.9
BAC	Bank of America Corp	123,625	16.2	79.0
GS	Goldman Sachs Group Inc	65,970	8.6	87.6
MS	Morgan Stanley	39,625	5.2	92.8
BK	Bank of New York Mellon Corp	31,225	4.1	96.9
STT	State Street Corp	23,710	3.1	100.0

Time series data on the option implied volatility surface are available from Bloomberg for these firms and for the equity indexes we discuss in the paper. The implied vol surfaces are calculated daily by Bloomberg from exchange-traded option data. In this paper, we use as inputs the Bloomberg volatility smile for options with three months' remaining maturity. It includes implied vols for exercise prices equal to 80, 90, 95, 97.5, 100, 102.5, 105, 110, and 120 percent of the cash market underlying price, that is, nine strikes in total. I also rely on Bloomberg for cash market prices, trailing dividend yields and 3-month U.S. T-bill rates.[2]

The techniques described in this paper can be carried out for other portfolios chosen to represent the financial system, provided option data are available, for example, a portfolio including large non-U.S. banks. In Section 5, for example, we consider the results for a larger portfolio of U.S. intermediaries that includes the larger regional banks and some non-banks.

2.2 Risk-neutral probability distributions

The risk-neutral probability distributions of the future market value of each firm or index can be computed from their equity option prices, together with the current 3-month T-bill rate and each firm's dividend yield. The fact that a distribution of future underlying prices is implied by the current market prices of options with the same tenor and a range of exercise prices was originally stated by Breeden and Litzenberger (1978) and Banz and Miller (1978). It can be expressed in terms of puts or calls; the future value of the rate of change of the put price as the exercise price increases is equal to the cumulative probability distribution function of the future underlying price. Letting $p(t, \tau, X)$ denote the time-t price of a τ-year put struck at X, r the time-t τ-year financing rate, and $\tilde{\Pi}(S_{t+\tau})$ the risk-neutral distribution function of the future asset price $S_{t+\tau}$,

$$\tilde{\Pi}(S_{t+\tau}) = e^{r\tau} \frac{\partial}{\partial X} p(t, \tau, X).$$

Figlewski (2010) provides some nice intuition for this statement. Consider the increasing value of a put option, for a given current market price of the underlying, as the exercise price varies from low to high. At very low exercise prices this function has a slope of zero and at very high ones a slope equal to $e^{r\tau}$. As we increase the exercise price from X to a nearby point $X + \Delta$, the risk-neutral expected future value of the payoff of the option increases by Δ times the risk-neutral probability $\tilde{\Pi}(X + \Delta)$ that the option expires in-the-money.

The computation sequence is fairly standard, and is described in greater detail in Malz (2013). The pros and cons of the choices involved are reviewed in Bliss and

[2]The option data are retrieved as fields pertaining to the stock or index tickers. The raw data on which the Bloomberg data is based are displayed, for each firm or index, with the OMON function. Future work may explore alternative data sources such as OptionMetrics LLC's Ivy DB.

Panigirtzoglou (2002), Jackwerth (2004), and Mandler (2003). In the first step, as I've implemented it for this paper, the Bloomberg implied volatilities are used to estimate a smooth interpolating function, specifically, a cubic spline with endpoints clamped so that the slope of the interpolating function is zero beyond the lowest- and highest-strike options, i.e. those with exercise prices 20 percent above and below the cash price. The extrapolated volatilities outside the range of observed volatilities are thus equal to those at the edges of the range.

This approach to interpolation and extrapolation has the virtues that it passes through all the implied volatilities in the Bloomberg data set, that it is quite smooth, and that it avoids letting the extreme tail volatilities get very high or low. Extreme volatilities are not in themselves a problem, but an extremely steep slope of the volatility smile can violate no-arbitrage restrictions on option prices.[3] The interpolation approach taken here arbitrarily flattens the volatility smile outside the ± 20 percent moneyness range.

In the next step, the interpolated volatility function is substituted into the Black-Scholes European call option value formula, providing us with the estimated market value of an option with any stipulated exercise price. The risk-neutral distribution and density functions, finally, can then be computed by taking differences of option prices. The differencing interval is set to be large enough to avoid negative densities.

The systemic risk indicators presented here do not crucially depend on this particular approach to estimating risk-neutral distributions, though the specific numerical results, of course, do. It would be useful in future work to compare the results when computed via one of the many alternative approaches to risk-neutral density estimation. Figure 1 displays the resulting risk-neutral distributions for February 11, 2011. The points in each panel correspond to the moneyness of the option data. All the distributions on that date are heavily skewed to the left; this is a persistent feature for all 8 firms and over the entire period covered by the data set.

Figure 2 displays, for each firm, time series of the risk-neutral probability of a loss of 25 percent or more of equity value over the subsequent three months. These probabilities peaked for all firms, unsurprisingly, at the end of 2008 or the first quarter of 2009. Sharp increases also took place following the initial Greek bailout request in April 2010, and particular following the debt-ceiling agreement and resurgence of euro area stress in July and August 2011. Tail risk has declined for all firms since then, and by early 2013 had fallen nearly, but not quite, to pre-crisis levels.

Expected shortfall at a given confidence level can also be computed for each firm at each date from the simulated returns. At a 5 percent confidence level, with 10,000 simulations, it is equal to the average of the 500 worst simulated returns. It can be

[3]See Hodges (1996) and Malz (2013).

expressed as a proportional return, or in dollars. We don't display these results in the paper. But for all the included firms, measured over the crisis, expected shortfall expressed in dollars falls rapidly from its peak as large market-value losses were realized, and rises again from the end of the first quarter of 2009, when values began to recover. Once a large part of the market cap has been obliterated, less remains to be obliterated going forward. Expected shortfall expressed in percent, in contrast, remains at its peak from late 2008 through the first quarter of 2009 for the included firms.

2.3 Implied correlations

A risk-neutral implied return correlation between financial stocks can be estimated from the implied volatilities of individual stocks in the KBW Bank Sector Index (managed by Keefe, Bruyette & Woods, Bloomberg ticker BKX), and the implied volatility of options on the BKX index itself. We obtain an estimate of the constant pairwise correlation among the constituent stocks that is consistent with the option data.

The constituents of the BKX index are 24 money-center and large regional banks, weighted by their market capitalization. The BKX constituents overlap with but are not identical to the list of firms used in estimating OBSESS[4]. There are no other indexes of U.S. financial firms for which option-price data are readily available, so we don't have the luxury of choosing one that coincides exactly with the set of firms included in the OBSESS.[5] Rather, we use the BKX constituents to obtain a single, reprsentative implied correlation of financial firms.

The index volatility is

$$r_{\text{index},t} = \sum_{k}^{K} \omega_{kt} r_{kt},$$

where $r_{\text{index},t}$ represents the time-t index return, and ω_{kt} and r_{kt} the time-t weights and returns on the $k = 1, \ldots, K$ constituent stocks (with $K = 24$). Assuming that the pairwise correlation $\rho_{jk,t} = \rho_t, \forall j, k$ is the same for all the constituents, the index return volatility $\sigma_{\text{index},t}$ is related to the K volatilities σ_{kt}^2 of individual stock returns by

$$\sigma_{\text{index},t}^2 = \sum_k \omega_{kt}^2 \sigma_{kt}^2 + 2\rho_t \sum_k \sum_{j<k} \omega_{jt}\omega_{jt}\sigma_{kt}\sigma_{kt}.$$

We know the weights in the index. If we also know the volatilities, we can estimate a risk-neutral ρ_t as

$$\rho_t = \frac{\sigma_{\text{index},t}^2 - \sum_k \omega_{kt}^2 \sigma_{kt}^2}{2\sum_k \sum_{j<k} \omega_{jt}\omega_{jt}\sigma_{kt}\sigma_{kt}}$$

[4] GS and MS are not in BKX.

[5] One could, however, compute a version of the OBSESS using the constituents of the BKX index.

by substituting the observed at-the-money implied volatilities for the population return standard deviations. Risk-neutral correlation is high when the index vol is high relative to the "typical" single-stock vol.

Skintzi and Refenes (2005) describe the empirical characteristics of implied equity correlation and its efficacy as a forecast of future realized correlation.[6] Driessen, Maenhout and Vilkovn (2009) provide evidence that correlation risk commands a negative risk premium. That is, financial products such as index options, which have better payoffs when return correlation increases, are too dear relative to single-stock options to be fully explained by expected realized volatilities and pairwise correlations. Buyers of index options are thus paying an insurance or risk premium to sellers.

The correlation risk premium is related to market pricing of idiosyncratic relative to systematic risk. In a period of stress, the magnitude of this risk premium tends to increase, as market participants are eager to quickly hedge all long exposures, rather than specific positions. They therefore seize on index volatilities, which are more liquid and require fewer trades to get the portfolio covered, leading to an increase in implied correlation.

Figure 3 displays the time series of bank-sector implied correlation.[7] The correlation has generally been higher, but also more variable, since the onset of the crisis. Like firms' tail risk measures, it has recently been declining, but not all the way back to pre-crisis levels.

However, as noted by Kelly, Lustig and Van Nieuwerburgh (2011), prices of options on financial firms also reflect implicit public-sector guarantees such as the too-big-to-fail policy. The perception of such guarantees may have the opposite effect to portfolio hedging, by increasing the idiosyncratic risk that shareholders of some individual financial firms will take large losses or be wiped out, even if most firms and the financial sector as a whole are supported. One could think of this as "Lehman risk."

The public-sector subsidy or guarantee thus increases the value of options on at least some individual firms relative to index options, lowering the implied equity correlation. As seen in Figure 3, bank-sector implied correlation was highest in the early phases of the financial crisis, but reached a low in the second quarter of 2009, after the full range of government and Federal Reserve emergency lending programs had been rolled out.

Other firm-specific and market-based measures of systemic risk use historical rather than current market data to compute return correlations among firms. For example,

[6] Earlier studies of option-implied correlation, for example Campa and Chang (1998) and Lopez and Walter (2000), focused on correlations among U.S. dollar exchange rate pairs implied by prices of cross-currency options.

[7] A few vol data points are missing for some firms (44 in total). The implied correlation is computed using all the vols available on a given day.

Huang et al. (2011) and Brownlees and Engle (2011) apply Dynamic Conditional Correlation.[8] Adrian and Brunnermeier's (2011) $CoVaR$ does not compute firms' pairwise return correlations explicitly. Rather, the interaction between firms is captured through the estimated relationships or "betas" (a) between firms' or the portfolio's outlier returns and outliers in the factors driving risk and (b) between firms' and the portfolio's outlier returns. By using historical data, these approaches are able to distinguish the different dependence relations of different pairs of firms, while our approach is constrained to a single correlation for all pairs of firms.

2.4 Computing the indicators via a copula

The indicators presented in this paper endeavor to capture the interaction between individual firms and the financial sector, and are computed using a copula. Copula techniques are useful when we don't know the joint distribution of a set of random variables, but believe we possess at least some information about their correlations, and good information about the marginal distributions. The copula lets us simulate the joint distribution of the individual firms' returns given their marginal probability distributions and an estimate of their return correlation.

Copula techniques were introduced into finance as an approach to modeling of portfolio credit returns, for which the same problem arises as in our context: good information on marginal distributions, but limited information on the joint distribution of returns. An early application was Li (2000).

We use a multivariate normal (Gaussian) copula. This isn't tantamount to assuming the equity returns themselves are jointly normally distributed. Rather, the date-t returns are posited to consistent with

$$\Phi[\Phi^{-1}(u_{t1}), \ldots, \Phi^{-1}(u_{tN}); \mathbf{R}_t],$$

where $\Phi(x)$ represents the univariate standard normal cumulative distribution function and $\Phi(\mathbf{x}; \mathbf{R})$ the distribution function of a multivariate standard normal with a correlation matrix $\mathbf{R}$. The u_{tn} are the probabilities we obtain from the date-t risk-neutral distributions. The date-t correlation matrix $\mathbf{R}_t$ has dimension equal to N, the number of firms in the portfolio (with $N = 8$ here). All its off-diagonal elements are set equal to the risk-neutral implied correlation for that date, as described in the previous subsection. The $\Phi^{-1}(u_{tn})$ are the "shadow" or latent normal variates that "would have delivered" the marginal probabilities u_{tn}, and it is these that are assumed to be jointly normal, not the returns themselves.

For each date, the simulation follows these steps:

[8] See Engle(2002, 2009).

- Generate $I = 10,000$ simulated values z_{tin} from an N-dimensional multivariate standard normal with correlation matrix $\mathbf{R}_t$.
- The marginal probability $u_{tin} = \Phi(z_{tin})$ of each of the $I \times N$ simulated values is computed as the value of the univariate cumulative probability function of a standard normal random variable, taking the simulated value as its argument.
- Each marginal probability u_{tin} is then mapped to a corresponding return or equity value using the risk-neutral distributions. The corresponding return is that with a risk-neutral probability equal to the simulated $u_{tin} = \Phi(z_{tin})$.[9]

The result for each date is an $I \times N$ table of I simulated proportional returns on each of the N stocks. They can be used together with market capitalizations to compute dollar returns for the firms, which in turn can be added across firms to compute the I simulations of the portfolio dollar return on each date. A high correlation will fatten both tails of the portfolio return distribution, since extreme outcomes for individual firms will have a greater propensity to coincide in each simulation. The OBSESS are then computed from the quantiles and order statistics of the simulation results of individual firms and of the portfolio.

The copula approach is consistent with what we think we know, given each day's option data, about the marginal distributions and the correlations, but adds to it enough modeling apparatus to enable us to simulate the joint distribution. The data don't prescribe any particular copula. We could, for example, readily substitute a multivariate Student's t copula for the multivariate normal to generate the $I \times N$ table of simulated values in the first step of the procedure. In contrast to the normal, the univariate t distribution has heavy tails, and the multivariate t distribution has positive coefficients of lower and upper tail dependence.

Simulations using the t copula would therefore likely lead to greater clustering of extreme outcomes in the simulated returns, and there is empirical evidence that the t copula better captures the behavior of equity returns than the normal copula.[10] But

[9] An earlier version of this paper incorporated CDS data as follows: If, in a simulation, the marginal probability is less than or equal to the CDS-based three-month default probability, the equity loss for that firm in that simulation is 100 percent. The CDS are not essential to the computations. If they are included, and the default probabilities are high enough, they will fatten the left tails of the firm and portfolio return distributions by generating a material number of simulations in which there is a 100 percent loss.

[10] Demarta and McNeil (2005) compare the t copula and its tail dependence properties to others, including the normal. The multivariate t copula is recommended for portfolios with nonlinear risks such as options by Glasserman, Heidelberger and Shahabuddin (2002). Mashal, Naldi and Zeevi (2003) present evidence that the t copula is more accurate than the normal for forecasting extreme events. A (likely) less crucial issue is that the choice of copula is arbitrary. In future work, one could compare OBSESS computed using a multivariate t distribution with, say, four degrees of freedom, but the same correlation matrix.

the typically rather stout left tails of the individual banks' risk-neutral distributions, together with high implied correlations, themselves induce a good deal of clustering of left-tail outcomes in the simulations.[11] Moreover, as we will see below in our discussion of the results, comovement of variance and correlation premiums, together with the clustering of left-tail outcomes, make it more difficult to discriminate between results for different firms.

But the market data themselves do not provide guidance on which copula is appropriate, only on the risk-neutral marginal return distributions and return correlations. The t-copula is infrequently used in practice. Risk management sensitivities based on the normal copula are routinely computed for standard tranches of credit index default swaps such as the CDX and iTraxx, and serve a standardization function similar to that of the Black-Scholes formulas in option markets.

3 Indicators of systemic risk

The risk-neutral systemic risk indicators are computed from the simulated returns. As with any distribution-based risk measures, the "user" must choose thresholds—events and quantiles—that define "extremeness." We define a systemic risk event as a large loss of equity market value of the portfolio of included firms, specifically, a loss of x percent in the aggregate market capitalization of the 8 firms, with x set to a large number: 15, 20 or $33\frac{1}{3}$, over the subsequent 3 months. With the volatility of the S&P 500 index roughly equal to about 16 percent per annum, this corresponds roughly to 2, 3, and 4 standard deviations below a standard normal mean, a reasonable range of extreme, yet still conceivable, losses. We choose 95 percent, that is, the 5-th percentile of the return distribution, as the confidence level for expected shortfall measures.[12]

The OBSESS are expressed in terms of the market value of equity rather than of assets. They therefore don't explicitly take leverage into account, in contrast to some other market-based approaches. However, by incorporating data on the book values of debt and equity, one could change the loss metric to assets, as in Adrian and Brunnermeier's (2011) $CoVaR$, though there is still no daily revaluation of assets and liabilities, only of equity. It would also be possible to derive the probability or quantile of a capital shortfall vis-à-vis a regulatory minimum.[13]

[11] Using CDS to simulate defaults and wiping out the equity in those outcomes, as described in footnote 9, increases the induced lower tail dependence even more.

[12] This could be increased to 99 percent, but for OBSESS at very high confidence levels to be meaningful likely requires more simulations than 10,000, and option data extending deeper into the tails than ± 20 percent.

[13] An example of such a measure in $SRISK\%$, a firm's share of the financial sector's shortfall below a

3.1 Portfolio systemic risk indicators

The probability of a systemic event is estimated using the risk-neutral distribution of returns on the portfolio consisting of the firms' aggregate equity. It is equal to the fraction of simulations in which a loss of x percent occurs in the portfolio. Figure 4 displays the time series of systemic event probabilities for different loss levels.

For comparison and reality checking, we compare these probabilities to the risk-neutral probabilities of an equal loss in positions in the S&P 500 (ticker SPX) and KBW Bank Sector indexes. The latter measures are computed the same way as the firm-specific risk-neutral tail risk metrics displayed in Figure 2, using Bloomberg's fitted three-month volatility smile data for those index tickers. The index tail risk metrics for the S&P and KBW indexes are plotted in Figure 4 in blue and red.

Focusing on the center panel, which displays the risk-neutral probabilities of a 25 percent loss over the next three months, we see that during the low-volatility period preceding the crisis, the option portfolio-based probability was lower and less volatile than the BKX and SPX probabilities. Since the crisis began, the option portfolio-based probability has generally taken on values between the two index-based probabilities.[14] Overall, the three have roughly the same order of magnitude and display the same behavior over time, giving us some confidence that they are reasonable estimates. But it also illustrates the propensity of equity implied correlation and option skew to rise and fall in tandem for most stocks.

Figure 5 displays time series of the 3-month risk-neutral system expected shortfall at a 95 percent confidence level. With 10,000 simulations, system expected shortfall is equal to the average of the 500 worst simulated portfolio returns. It appears to track the probability of a systemic risk event in Figure 4 closely.

Other risk measures can be developed in this framework, for example, a portfolio Value-at-Risk (VaR), computed as a quantile of the system return distribution. With $I = 10,000$, the VaR at a 95 percent confidence level is the magnitude of the 500-th worst simulated portfolio return, or the average of a few simulations neighboring the 500-th worst. The system VaR is smaller than the system expected shortfall for any confidence level.

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given capital adequacy threshold in the event of a crisis, as described in Acharya, Engle and Richardson (2012).

[14] The difference between the occasionally much-higher estimate based on BKX options and that based on the portfolio is likely due to spikes in the BKX vol. Although the spikes increase the implied correlation, the increase in left-tail clustering may be dampened if spikes in the individual firms' tail risk don't coincide perfectly. The differences between the portfolio and BKX tail-risk measures may also be due to the differences in composition between the BKX and the portfolio. The issue is worth exploring further.

3.2 Probability of systemic risk event conditional on individual firm distress

We have two types of conditional risk measure to consider, depending on the direction of conditioning: from the system to individual firms or vice versa. Terminology here is a bit hard to disambiguate. We'll refer to the conditional probability of a systemic risk event, given that an individual large-bank loss occurs, as a "conditional systemic event probability." It is computed as the ratio of the number of simulations in which both events occur to the number of simulations in which the individual bank loss occurs. The conditional systemic event probability depends on the size of the systemic and the firm loss assumed.

Figure 6 displays time series of the conditional systemic event probability for each firm. Each plot shows the probability of the portfolio of banks sustaining a 25 percent or greater loss over the next three months, conditional on the specific firm sustaining a 25 percent loss or worse. Several patterns and characteristics are worth noting:

- For all firms, the conditional systemic event probability was low prior to the crisis, and rose in sharp spikes as the crisis deepened. For most of the firms, it is currently well below its crisis peaks, but still higher than before the crisis, and even somewhat higher than in the second quarter of 2011.
- The firms' conditional systemic event probabilities are very roughly equal, and somewhat more so than the individual risk-neutral probabilities of an extreme loss displayed in Figure 2. This result indicates the extent of tail dependence, or clustering of different firms' extreme losses within scenarios, despite using a normal rather than t copula. It is due to the generally high implied correlation among the firms, and to the fact that the firms' risk-neutral probabilities tend to spike together.
- For many of the firms, conditional systemic event probabilities are very high, reaching nearly 100 percent, at times of high stress.

"System conditional expected shortfall" is another way of seeing how badly the financial system fares if a particular firm endures a stress event. It is related to a quantile of the portfolio and firm loss distributions rather than to the probability of a given loss. It is computed by ordering scenarios by the loss of a given firm. For each firm, system conditional expected shortfall is the average loss on the entire portfolio, in dollars or percent of market capitalization, in the worst 5 percent of simulations for the individual firm. System conditional expected shortfall is analogous to $CoVaR$ (Adrian and Brunnermeier (2011)), but differs from $CoVaR$ in focusing on equity market rather than asset value.

Figure 7 displays box plots of the system conditional expected shortfall (I've omitted the time series plots for this indicator). The results underscore the risk-neutral "flatness" of the firms; in any scenario in which one of the firms has a large loss, it is likely that quite a few others, and the financial-sector portfolio, will do so, too.

Other risk measures in which conditioning runs from individual firms to a systemic risk event can be computed in this framework:

- Confidence levels can be varied: a conditional 99-percent VaR for the system can be computed as the system loss conditional on the firm realizing its 1 percent quantile return
- Loss sizes can be varied, and can be expressed in dollars or in percent. For example, the probability of a system loss of 15 percent conditional on a firm loss of 25 percent can be computed.
- The time horizon of the forecast can be varied if prices of options with the corresponding maturity are available

3.3 Probability of firm distress conditional on systemic risk event

We can also use the simulations to compute indicators of the risk that the realization of a systemic risk event poses to each individual firm. In these indicators, conditioning is from the system/portfolio to the individual firm, and we order the scenarios by the portfolio losses.

"Conditional expected shortfall" is defined as a bank's expected shortfall, given an extreme loss on the portfolio. With $I = 10,000$, the conditional expected shortfall at the 95 percent confidence level is the average loss for an individual firm in the first 500 ordered scenarios for the system/portfolio.[15]

Time series of the risk-neutral three-month conditional expected shortfall are displayed in Figure 8, expressed as a (decimal) return. Like the conditional systemic event probability, these indicators rose sharply during the worst part of the crisis in late 2008. After a long and steady decline trough the first half of 2011, conditional expected shortfall rose sharply in the second half of 2011, following the U.S. debt-ceiling debate and the resurgence of concern about European public debt. For all firms, conditional expected shortfall remains higher than pre-crisis, and for most firms, as of early 2013, higher than in the second quarter of 2011.

[15]These measures are generally called "marginal" rather than "conditional" in risk management parlance.

Conditional expected shortfall is analogous to Acharya et al.'s (2010) SES and Huang et al.'s (2011) DIP, in that it states an individual firm's loss conditional on a systemic risk event. It differs from SES in that the conditioning event is a loss on the portfolio of financial stocks, rather than the broader stock market. It differs from DIP in that loss is measured in terms of equity market value rather than as an expected loss given default, and in that the conditioning event is a loss on the portfolio of the firms' stocks, rather than the portfolio of their liabilities.

To control for the influence of firm size, and help discriminate between the results for different firms, Figure 9 displays the time series of the ratio of each bank's conditional expected shortfall to the financial-sector/system expected shortfall.[16] It shows which firms are contributing out of proportion or less than proportionately, relative to their market capitalization, to aggregate risk. This metric discriminates more sharply those firms that are "punching above (or below) their weight" in contributing to system expected shortfall. For example, the late-2011 increase in conditional expected shortfall for BAC and MS can be clearly distinguished.

Figure 10 displays the "conditional expected shortfall elasticities," or shares of the 8 firms' conditional expected shortfall in the system expected shortfall. These elasticities are equal to each firm's conditional expected shortfall, weighted by its market capitalization and divided by the system expected shortfall.[17] A firm's elasticity is determined by its size and by how badly it fares in a stress scenario relative to other firms, in other words, the size of its left tail in the risk-neutral distribution. One can see, for example, that in late 2008 and early 2009, as Citi's equity value evaporated, its share of system expected losses in a stress scenario, and to a lesser extent BAC's, declined, while those of JPM, GS, BK, and STT increased.[18]

4 Discussion of the results

The OBSESS have all risen sharply and become more volatile since the beginning of the financial crisis in February 2007. Even in relatively quiet periods in markets, such as the second quarter of 2011 or early 2013, they have not fully returned to pre-crisis levels. This is consistent with the behavior of other financial risk indicators, such as the VIX or the S&P option-based tail probability (the blue plots in Figure 4). The

[16] The denominator, that is, is the data in Figure 5 times the market capitalization of the portfolio. The cap-weighted average of the data in Figure 9 equals unity, since the cap-weighted sum of the firm's conditional expected shortfalls is equal to the system expected shortfall

[17] They are therefore also equal to the conditional expected shortfall ratios in Figure 9, weighted by market capitalization, and sum to unity on each date.

[18] The decline in Citi's anmd BAC's elasticities is even more abrupt if weighted by book rather than market value.

VIX, for example, while at times reaching the low teens over the past five years, has not at time of writing returned to the single-digit lows of the turn of 2007.

The systemic event probabilities were low between 2006 and mid-2007, but rose sharply just before February 27, 2007. The latter is a good date for distinguishing more and less "prescient" crisis gauges, as it marked the first serious and widespread market tremor of the crisis.[19] Systemic event probabilities continued to rise through the second quarter of 2007, before spiking up in early August following the "quant event" and the Paribas redemption halt. New highs were reached in the runup to Bear Stearns' failure, and then following the Lehman bankruptcy. Late-2011 values were the highest since mid-2009, but have been falling most recently.Systemic event probabilities using a smaller "extreme loss" are more sensitive before the crisis, as seen in the lower panel of Figure 4, but not once the crisis begins in earnest.

The low levels of the OBSESS and of the individual firms' tail risk probabilities (Figure 2) before the crisis provide a good illustration of the "paradox of risk" or "volatility paradox." Systemic risk, as we now know *ex post*, was extremely high prior to the spring of 2007. Yet all the OBSESS exhibit their lowest levels during the winter of 2006-2007. It was those extremely low levels, rather than an uptick, that provided the best advance warning signal of the crisis. A similar exhibition of complacency or high risk appetite may have taken place in the second quarter of 2011, once markets calmed down from the impact of the Japanese tsunami disaster, or currently. In spite of mediocre macroeconomic data, tail risk declined to its lowest levels since before the crisis, only to skyrocket beginning in late July 2011.

While all these systemic risk indicators began very low and remain elevated, there is a potentially important contrast between the pre-crisis and crisis ordering of the portfolio-based and S&P- based overall tail risk measures. Prior to mid-2007, the probability of a 25 percent decline in the value of the large-bank portfolio was generally either at or close to zero. Since the end of July 2007, it has not fallen below 1 percent. Also, prior to the crisis, S&P tail risk, while also low, was generally higher than than the OBSESS systemic risk probability. Since the crisis, S&P tail risk has generally been lower. The exception is the first half of 2011, where both were again low (though still above pre-crisis levels), but OBSESS tail risk was lower. These patterns may reflect a market perception that the financial sector is more exposed to tail risk, that systemic risks are more likely to emanate from the financial sector, and an increased unwillingness of market participants to bear those risks.

We noted above that some of the risk-neutral indicators exhibit "flatness" or lack of discrimination across firms. Risk assessments communicated through option prices have a propensity to rise and fall in unison. Whether this is driven by reassessments

[19]But note the "false positive" in mid-2006, an even larger volatility event, and widely noted at the time.

of the the likelihood of tail events or by risk premiums is not clear. But it affects a wide variety of option prices, including the prices of options on different firms. One consequence is to dampen the market discrimination among firms, since risk-neutral distributions are driven in part by common changes in risk premiums. Flatness is also due partly to a constant pairwise correlation that doesn't capture potentially important differences among the pairwise correlations between different firms' returns.

This flatness in the results affects conditional systemic risk measures more than the unconditional metrics. Comparing, for example, the firms' conditional systemic event probabilities in Figure 6 with their risk-neutral tail risk (Figure 2), we observe greater variation in the latter, even after the crisis begins. Between the peak in tail risk of late 2007 and the first Greek bailout request in April 2010, both the conditional systemic event and risk-neutral tail risk fell rapidly. But the former fall in a less precipitous "concave" fashion, and remained high relative to pre-crisis levels, while the latter fell in "convex" fashion, and to levels closer to pre-crisis. "Conditional flatness" becomes even more evident when we view the results in a box-whisker plot, as in Figure 7. The lack of differentiation in the conditional measures might be reduced by taking a higher quantile than 95 percent for our measures, but , as noted above, would require a larger number of simulations and possibly also more extensive option data to be meaningful.

The persistent high level of risk after the crisis across all the risk-neutral indicators indicates that the market considers both the individual firms and the financial system to be more susceptible to extreme losses than before the crisis. Tail dependence, "conditional flatness," and the high level of risk reflected in the conditional measures are consistent with an "interconnectedness" interpretation of financial crises, in which a shock to one or a few firms is transmitted to others, increasing the likelihood of a systemic risk event. But these features are perhaps more consistent with a "common shock" or "common factor" interpretation. If a shock to a common factor is severe enough to cause a large loss even to a relatively strong firm, it is likely to be severe enough to cause a large loss to other firms and to the financial-sector portfolio.

5 Validation and comparison of the results

We approach "validation" of the OBSESS in three ways. First, I present a bit of evidence on their ability to predict future losses. Second, I compare the OBSESS to the results of the 2012 Federal Reserve review of major banks' capital plans. Third, I compare the OBSESS to another publicly available systemic risk measure. The latter two exercises don't constitute validation in the sense of testing against empirical data, but rather points of comparison. Each exercise is carried out via a cross-sectional regression.

5.1 Option-based indicators and crisis losses

An obvious (but not necessarily answerable) question regarding any risk measure is its ability to predict losses. For option-based risk measures, this question may be framed as a search for a negative volatility risk premium, that is, are options more expensive than their actuarial value in protecting against the return volatility of the underlying asset?, or for a positive underlying asset return risk premium, that is, does volatility cheapen assets relative to predictions based on the their future returns? Like all questions concerning the relationship between option prices and underlying returns, these questions are hard to answer mainly because of the difficulty identifying expected future underlying asset return behavior. But there is evidence to suggest that such a negative risk premium is a material determinant of option prices.[20]

For option-based tail risk measures such as those presented in this paper, answering the analogous questions empirically is even more difficult. Not only is the anticipated future return distribution hard to identify, but tail risk events are exceedingly rare, arguably even unique events, making it difficult to compare their frequency with the likelihood implied by option prices. For this reason, emphasis on validation in this sense may be misplaced.

Nonetheless, it is informative to compare the forecasts implied by option prices to events in the markets when those tail risk events actually occur, as in the financial crisis of 2007 to date. The option-based indicators appear to have had some, but limited, efficacy in predicting losses in the cross section of firms. As an example, consider a simple cross-sectional regression of option-based conditional expected shortfall on crisis returns. The independent variable is conditional expected shortfall for each of the 8 firms as of July 3, 2007, and the dependent variable is the set of equity market losses from that date to the end of 2008 (t-statistics are in parentheses):[21,22]

slope coeff.	std. error	t-statistic	p-value	adj. R^2
8.805	4.456	1.976	0.096	0.065

The null of predictive ability is not rejected, and significance and explanatory power are passable. The data and regression line are displayed in Figure 11. Conditional

[20]Zhou (2010) and Bakshi, Panayotov and Skoulakis (2011), for example, present evidence that higher implied volatilities are associated with higher equity returns, and Xing, Zhang and Zhao (2010) that future equity returns are lower for stocks exhibiting a larger "put skew."

[21]This exercise is analogous to that displayed on the first row of Table 4 of Acharya et al. (2010). Option data are missing for some firms on some dates early in the observation interval, and there is an unfortunate bad patch for MS in June 2007. The date July 3, 2007 is the closest to the end of June 2007 on which data for all firms is available.

[22]Note that the returns in the dependent variable are measured over a longer, interval than the forecast horizon of the risk-neutral distributions.

expected shortfall for the firms, as of July 3, 2007, falls in a narrow range of about 14 to 21 percent. That is, the market estimated that, if the portfolio of the 8 firms' equities were to breach its 95 percent 3-month VaR, each firm's mean loss would be 14-21 percent. Realized losses over the subsequent 18 months fell in a range of 17.4 to 87.1 percent, a range bracketed by WFC and C. The farthest outliers from the regression line are C, with its surprisingly high loss, and JPM, with a loss of 36.1 percent.

The market thus seems to have badly underestimated the typical size of the losses that would be realized in the crisis, but had some, albeit weak, ability to identify the relative size of different firms' losses. This result supports one reason often provided for the sharp increase in the term spread between overnight and longer-term interbank lending rates: While the markets had a strong sense that large intermediary losses were in the offing, it could not identify accurately in mid-2007 those that would incur the severest losses.

5.2 Option-based indicators and supervisory stress tests

The next point of comparison is between OBSESS and the results of the Federal Reserve's Comprehensive Capital Analysis and Review (CCAR) for 2012. The CCAR is an annual process by which the Federal Reserve ascertains the capital adequacy of large U.S. banks and is a critical element in supervisory approval of capital distributions such as dividends. The first CCAR took place in 2011, and was modeled after the 2009 Supervisory Capital Assessment Program (SCAP). In the CCAR process, banks are asked to estimate their trading, loan and other losses and net income in an extreme market and economic stress scenario. The reported results for CCAR 2012 included these loss and net income estimates.

The results of the CCAR, SCAP, and similar supervisory stress-testing programs outside the United States include forecasts of stress losses of important intermediaries and can therefore be thought of as systemic risk measures. We compare the CCAR 2012 loss estimates with a set of OBSESS computed for the portfolio of 18 publicly-traded banks included in the CCAR. The portfolio includes the following banks in addition to the FSB G-SIFIs:

Ticker	Name
AXP	American Express Co
USB	U.S. Bancorp
MET	MetLife Inc
PNC	PNC Financial Services Group
COF	Capital One Financial Corp
BBT	BB&T Corp
FITB	Fifth Third Bancorp
STI	SunTrust Banks Inc
KEY	KeyCorp
RF	Regions Financial Corp

Ally Bank, a successor of General Motors Acceptance Corporation (GMAC), is privately held and is excluded.

OBSESS are estimated for the 18 stress-test banks using the same techniques as for the 8 G-SIFIs. The results for the banks included in both portfolios are different in the two exercises because of the interaction with the other 10 banks.

The independent variable in the regression is the average of the daily conditional systemic expected shortfall during the month preceding the Federal Reserve's initial announcement of the stress test results on March 12, 2012. This was defined above (subsection 3.3) as the average loss in scenarios in which the portfolio experiences a systemic risk event (a loss of 25 percent), expressed as a loss (in percent of the firm's market capitalization). The dependent variable in the regression is calculated using data in Table 4 of Board of Governors of the Federal Reserve System (2012), as the ratio of Net Income before Taxes in the stress scenario to the firms average market capitalization during the month preceding March 12, 2012.[23]

A scatter plot of the data and the regression line are displayed in Figure 12. The results indicate that OBSESS would have provided a reasonably accurate indicator of losses in the supervisory stress scenario:

slope coeff.	std. error	t-statistic	p-value	adj. R^2
4.968	1.016	4.888	0.000	0.573

The markets appear to have agreed with the CCAR as to which institutions are likely to suffer severe losses in an adverse environment. We can also interpret the results

[23]There is a timing mismatch between the historical observation date of the market cap used in the denominator of our dependent variable and the time period underlying the supervisory stress scenario. The stress scenario is of erosion of capital over a long discrete interval (Q4 2011 to Q4 2013), while our market capitalization measure is essentially at a point in time.

as offering some validation of the supervisory stress scenario; the firms suffering the largest losses in that scenario tend to be those for which the market price of protection against extreme losses is highest. The results also suggest that the OBSESS may be a useful complement to the "fundamentals-based" CCAR process.

5.3 Option-based indicators and other systemic risk measures

We compare OBSESS, finally, with another systemic risk measure, marginal expected shortfall (MES). MES is defined as the loss a firm would suffer in the event of a 2 percent decline in the broader equity market.[24] We run the regression using results for the 18-firm SCAP/CCAR portfolio. The independent variable in the regression is, again, the conditional systemic expected shortfall, averaged for each firm over the daily results for April 2012. The data on MES, the dependent variable, are obtained by scraping the web page `http://vlab.stern.nyu.edu/analysis/RISK.USFIN-MR.MES` with the date set to end-Apr. 2012. As can be seen from the regression results, the agreement is close.[25]

slope coeff.	std. error	t-statistic	p-value	adj. R^2
24.893	3.190	7.803	0.000	0.779

6 Conclusions and issues

The innovation and chief advantage of option portfolio-based systemic risk indicators is that they are based entirely on contemporaneous market prices, and are computed using a "light" modeling structure. They can therefore be computed daily, and reflect up-to-date market perceptions. Historical market prices are not rich in observations on extreme tails. Measures of the likelihood of tail events based on historical and fundamentals data therefore may not quickly update when conditions or perceptions change.

The systemic risk measures developed here appear to be sensitive indicators of concern about the fragility of the financial system and of the contribution of individual firms to that fragility. The portfolio indicators of systemic risk show some ability to anticipate crises, but are also useful indicators of possible complacency in markets during quiet periods, as discussed in Section 4. There are episodes during which the bank-portfolio measures provide some additional information to that conveyed by more generic measures such as option-based S&P tail risk.

[24] See Acharya et al. (2010), Brownlees and Engle (2011), and Acharya et al. (2012).
[25] Similar results are obtained for the related measure $SRISK\%$, described in Acharya et al. (2012).

The firm-specific conditional metrics appear to provide useful information about the systemic risks presented by individual firms. The discrimination among firms conveyed by these measures is somewhat less sharp than that conveyed by stand-alone risk-neutral tail risk measures. The blurring of discrimination is greater for measures in which conditioning is from the individual firm to the portfolio/system than for conditioning from the system to the individual firm.

However, option-based probabilities also present two major challenges, both related to active research areas on option pricing. First, they are risk-neutral, commingling views on distributions with preferences over them. The second is determining the extent of predictive power of risk-neutral indicators. There is at least some weak evidence that option prices, because they are sensitive to market participants' assessments of tail risk, can provide early warning of problems in the financial system. But the bundling of these assessments with risk premiums, the paucity of data on extreme losses, and the many false alarms provided by option-based indicators make the predictive power hard to verify.[26] And when they signal market anxiety, option prices don't point to the specific grounds of that anxiety. Rather, they are only a piece of the puzzle.

The OBSESS, like other systemic risk indicators, may have value even if their predictive performance is underwhelming. They may help to identify imbalances, potential risk events, or sources of stress, and indicate that market expectations are not well anchored. Options on particular underlying assets mayu help policymakers understand what's worrying markets. These insights can inform policymakers' judgement even if they do not lead to improved forecasting of tail events. Because they can be updated frequently and are based entirely on current prices, they can serve as a benchmark for other measures of systemic risk.

Researchers and regulators have set great store by the potential contribution of firm-specific systemic risk indicators. It is hoped that they will provide accurate guidance to regulators in several areas, from predicting problems at specific firms with potential systemic implications to identifying systemically important firms that can be subjected to more rigorous regulatory scrutiny or to Pigovian taxes.

However, the basic motivation underpinning systemic risk indicators remains unclear. Do we look at the large banks because we believe their collective fragility is the primary cause of financial crises? Or because we believe, rather, that in the event of a crisis brought about by broader macroeconomic or monetary conditions they will behave like the canary in the coal mine, providing the earliest signal of the impending disaster? Thinking about how these measures are to be used may be a more daunting task than developing them.[27]

[26] See Malz(2000, 2001).

[27] Hansen (2012) discusses several additional questions concerning these measures, such as the absence of a relationship between these and macroeconomic measures, and their reliance on publicly-traded

Version 3.3

equity markets.

References

Acharya, V., Engle, R. and Richardson, M. (2012). Capital shortfall: A new approach to ranking and regulating systemic risks, *American Economic Review* **102**(3): 59–64.

Acharya, V., Pedersen, L. H., Philippon, T. and Richardson, M. (2010). Measuring systemic risk, *Technical report*, New York University, Stern School of Business. `http://vlab.stern.nyu.edu/public/static/SR-v3.pdf`.

Adrian, T. and Brunnermeier, M. K. (2011). CoVaR, *Staff Reports 348*, Federal Reserve Bank of New York.

Bakshi, G., Panayotov, G. and Skoulakis, G. (2011). Improving the predictability of real economic activity and asset returns with forward variances inferred from option portfolios, *Journal of Financial Economics* **100**(3): 475–495.

Banz, R. W. and Miller, M. H. (1978). Prices for state-contingent claims: some estimates and applications, *Journal of Business* **51**(4): 653–672.

Bisias, D., Flood, M., Lo, A. W. and Valavanis, S. (2012). A survey of systemic risk analytics, *Working Paper 1*, Office of Financial Research, U.S. Department of the Treasury. `http://www.treasury.gov/initiatives/wsr/ofr/Documents/OFRwp0001_BisiasFloodLoValavanis_ASurveyOfSystemicRiskAnalytics.pdf`.

Bliss, R. R. and Panigirtzoglou, N. (2002). Testing the stability of implied probability density functions, *Journal of Banking and Finance* **26**(2–3): 381–422.

Board of Governors of the Federal Reserve System (2012). Comprehensive capital analysis and review 2012: Methodology and results for stress scenario projections, *Report to the congress*. `http://www.federalreserve.gov/newsevents/press/bcreg/bcreg20120313a1.pdf`.

Breeden, D. T. and Litzenberger, R. H. (1978). Prices of state-contingent claims implicit in option prices, *Journal of Business* **51**(4): 621–651.

Brownlees, C. T. and Engle, R. F. (2011). Volatility, correlation and tails for systemic risk measurement, *Technical report*. `http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1611229`.

Campa, J. M. and Chang, P. K. (1998). The forecasting ability of correlations implied in foreign exchange options, *Journal of International Money and Finance* **17**(6): 855–880.

Demarta, S. and McNeil, A. J. (2005). The t copula and related copulas, *International Statistical Review* **73**(1): 111–129.

Driessen, J., Maenhout, P. J. and Vilkovn, G. (2009). The price of correlation risk: evidence from equity options, *Journal of Finance* **64**(3): 1377–1406.

Engle, R. F. (2002). Dynamic Conditional Correlation: A simple class of multivariate Generalized Autoregressive Conditional Heteroskedasticity models, *Journal of Business and Economic Statistics* **20**(3): 339–350.

Engle, R. F. (2009). *Anticipating correlations: A new paradigm for risk management*, Princeton University Press, Princeton, NJ.

Figlewski, S. (2010). Estimating the implied risk-neutral density for the U.S. market portfolio, *in* T. Bollerslev, J. Russell and M. Watson (eds), *Volatility and Time Series Econometrics: Essays in Honor of Robert F. Engle*, Oxford University Press, Oxford and New York, pp. 323–353.

Financial Stability Board (2012). Update of group of global systemically important banks (G-SIBs). `http://www.financialstabilityboard.org/publications/r_121031ac.pdf`.

Glasserman, P., Heidelberger, P. and Shahabuddin, P. (2002). Portfolio value-at-risk with heavy-tailed risk factors, *Mathematical Finance* **12**(3): 239–269.

Gray, D. F. and Jobst, A. A. (2011). Modelling systemic financial sector and sovereign risk, *Sveriges Riksbank Economic Review* (2): 1–39. `http://www.riksbank.se/Upload/Rapporter/2011/POV_2/er_2011_2_gray_jobst.pdf`.

Hansen, L. P. (2012). Challenges in identifying and measuring systemic risk, *NBER Working Paper 18505*, National Bureau of Economic Research. `http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2158946`.

Hodges, H. M. (1996). Arbitrage bounds on the implied volatility strike and term structures of European-style options, *Journal of Derivatives* **3**(4): 23–35.

Hovakimian, A., Kane, E. J. and Laeven, L. (2012). Variation in systemic risk at U.S. banks during 1974-2010, *NBER Working Paper 180432*, National Bureau of Economic Research.

Huang, X., Zhou, H. and Zhu, H. (2011). Systemic risk contributions, *Finance and Economics Discussion Series 2011-08*, Board of Governors of the Federal Reserve System.

Jackwerth, J. C. (2004). Option-implied risk-neutral distributions and risk aversion, *Monograph*, Research Foundation of CFA Institute. `http://www.cfapubs.org/doi/pdf/10.2470/rf.v2004.n1.3925`.

Kelly, B. T., Lustig, H. N. and Van Nieuwerburgh, S. (2011). Too-systemic-to-fail: What option markets imply about sector-wide government guarantees, *Research Paper 11-12*, Chicago Booth. `http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1762312`.

Li, D. X. (2000). On default correlation: a copula function approach, *Journal of Fixed Income* **9**(4): 43–54.

Lopez, J. A. and Walter, C. A. (2000). Is implied correlation worth calculating? evidence from foreign exchange options, *Journal of Derivatives* **7**(3): 65–82.

Malz, A. M. (2000). Do implied volatilities provide early warning of market stress?, *RiskMetrics Journal* **1**(1): 41–60.

Malz, A. M. (2001). Crises and volatility, *Risk* **14**(11): 105–108.

Malz, A. M. (2013). A simple and reliable way to compute option-based risk-neutral distributions, Federal Reserve Bank of New York.

Mandler, M. (2003). *Market expectations and option prices: techniques and applications*, Physica-Verlag, Heidelberg and New York.

Mashal, R., Naldi, M. and Zeevi, A. (2003). Extreme events and multi-name credit derivatives, *in* J. Gregory (ed.), *Credit derivatives: the definitive guide*, Risk Books, Amsterdam, pp. 1–25.

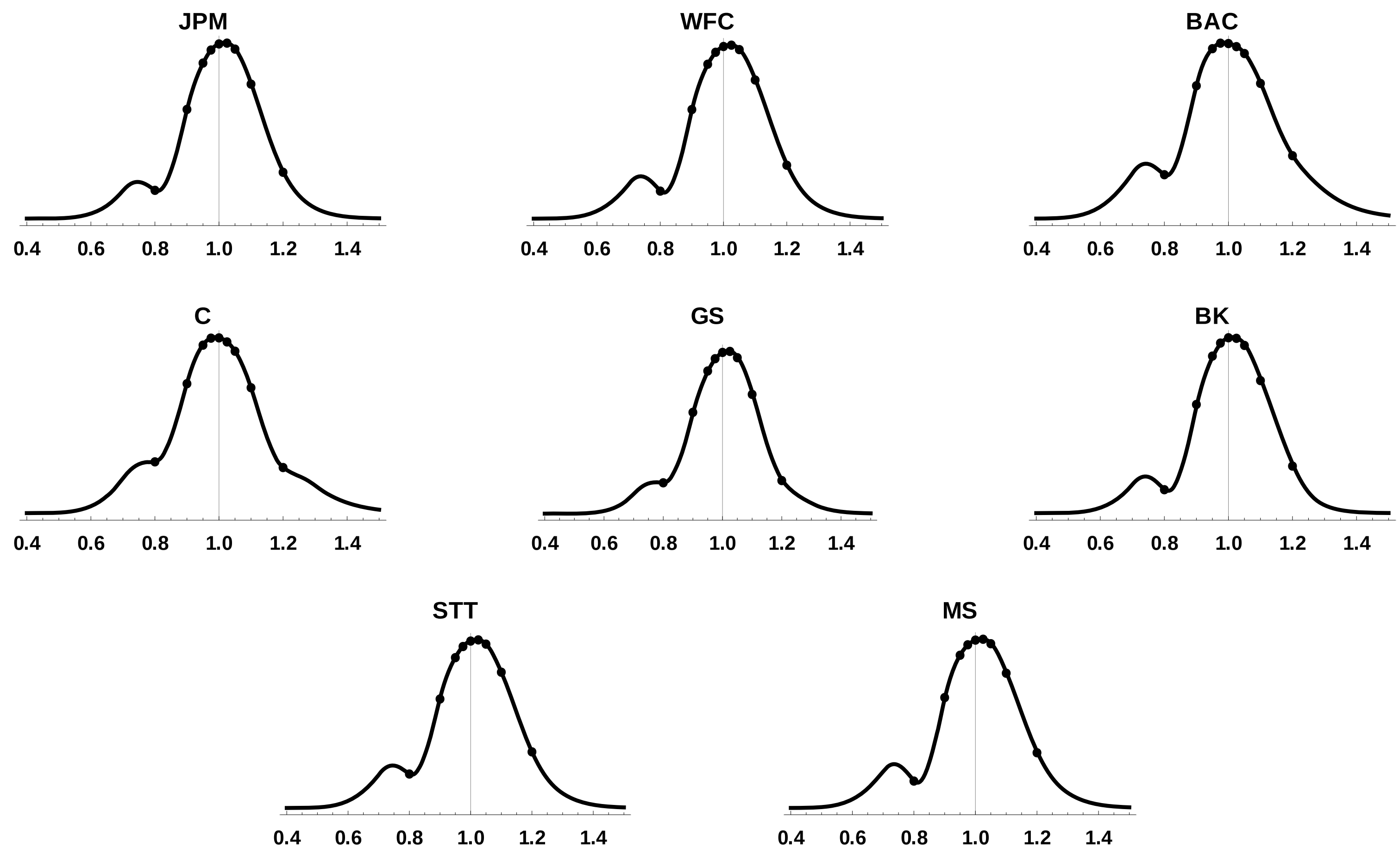
Segoviano, M. A. and Goodhart, C. (2009). Banking stability measures, *Working Paper 4*, International Monetary Fund.

Skintzi, V. D. and Refenes, A.-P. N. (2005). Implied correlation index: A new measure of diversification, *Journal of Futures Markets* **25**(2): 171–197.

Xing, Y., Zhang, X. and Zhao, R. (2010). What does the individual option volatility smirk tell us about future equity returns?, *Journal of Financial and Quantitative Analysis* **45**(3): 641–662.

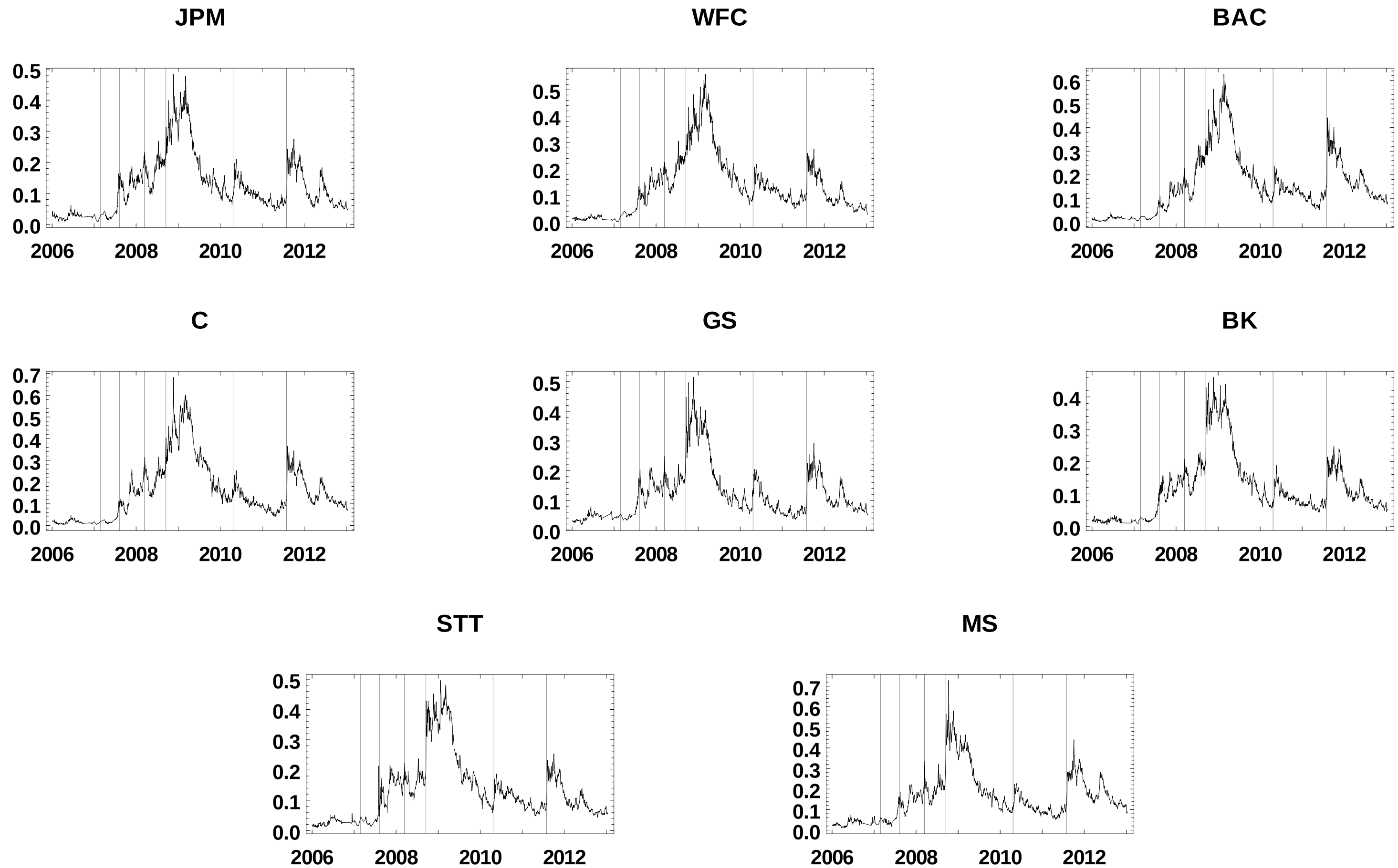
Zhou, H. (2010). Variance risk premia, asset predictability puzzles, and macroeconomic uncertainty, *Finance and Economics Discussion Series 2010-14*, Board of Governors of the Federal Reserve System.

Figure 1: Risk-neutral densities of major U.S. financial firms



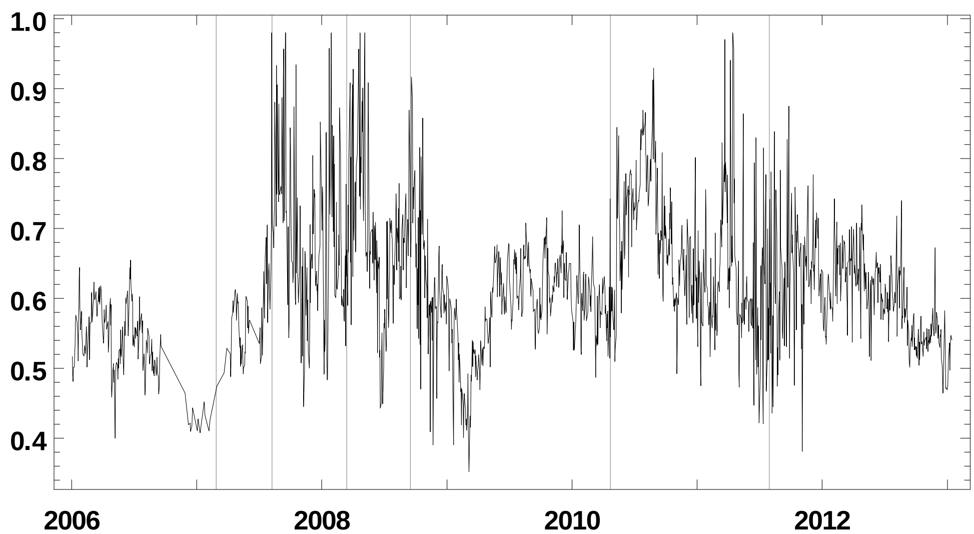
Density of the ratio of the stock price three months hence to the current outright forward price, Feb. 11, 2011. The forward price is computed using the 3-month T-bill yield and a trailing dividend yield. The points represent the exercise prices of the observed implied volatilities.

Figure 2: Risk-neutral probabilities of large loss of major U.S. financial firms 2006-2012



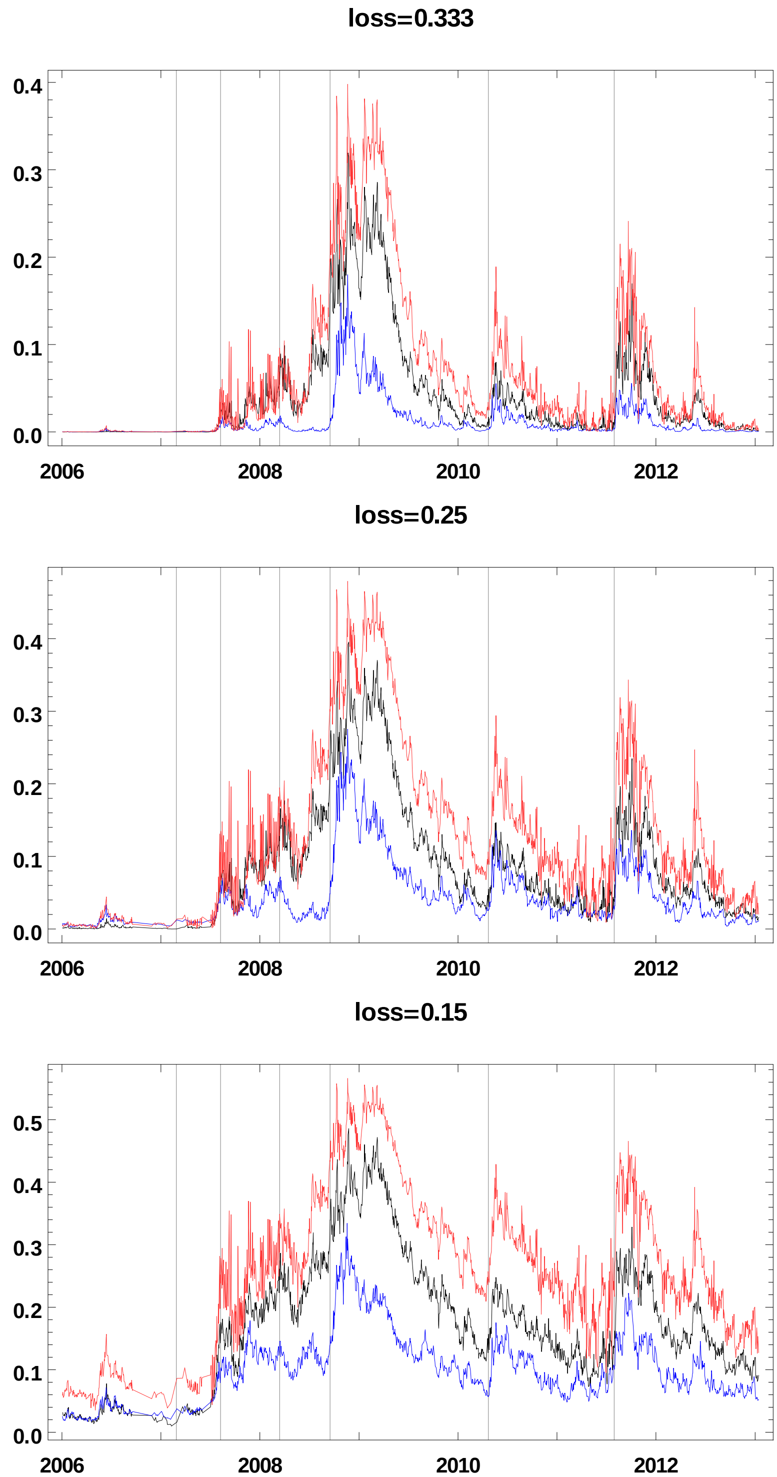
Risk-neutral cumulative probability of a decline in equity value in excess of 25 percent over the subsequent three months, daily, Jan. 4, 2006 to Jan. 14, 2013. The grid lines are set at the dates of the first volatility event of the crisis (27 Feb. 2007), the BNP Paribas redemption halt (09Aug07), the Bear Stearns run (14Mar08), the Lehman bankruptcy (16Sep08), the Greek bailout request (23Apr10), and the U.S. debt ceiling deal (31Jul2011).

Figure 3: Risk-neutral implied correlation for the BKX index 2006-2012



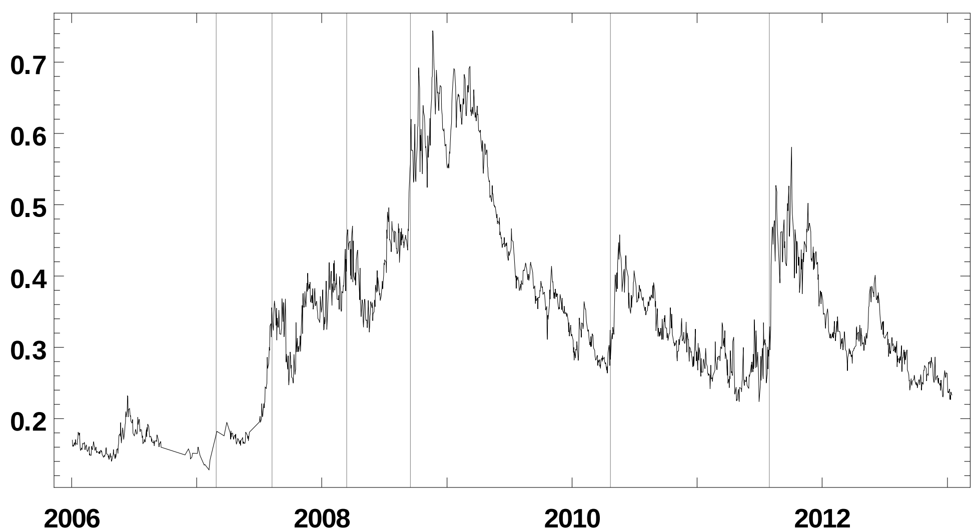
Daily, Jan. 4, 2006 to Jan. 14, 2013. Vertical grid lines as in Figure 2.

Figure 4: Risk-neutral probability of a systemic risk event 2006-2012



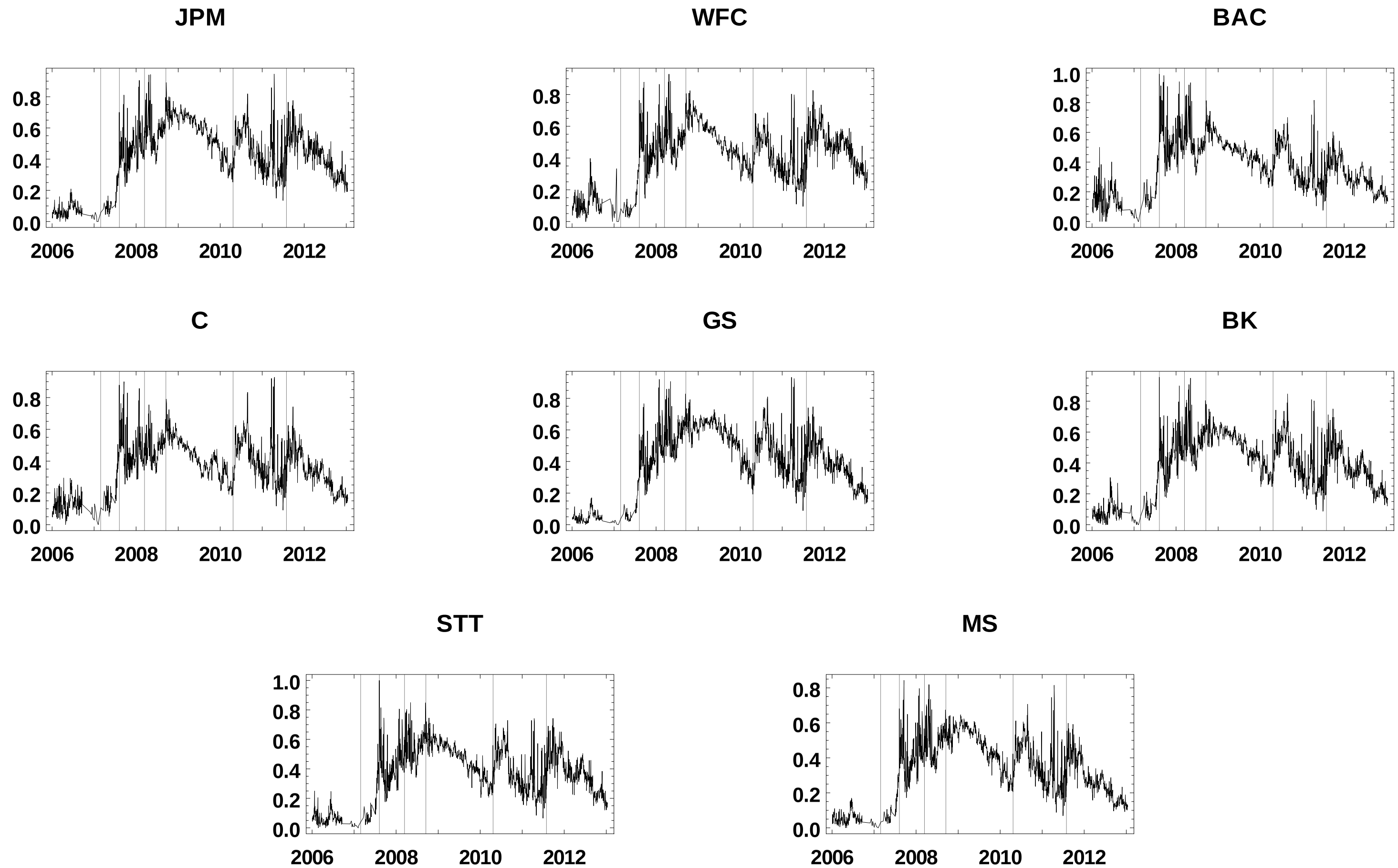
Daily, Jan. 4, 2006 to Jan. 14, 2013. Black plot: OBSESS portfolio-based systemic risk probability, blue plot: SPX index-based probability, red plot: BKX index-based probability. Vertical grid lines as in Figure 2.

Figure 5: Risk-neutral system expected shortfall 2006-2012



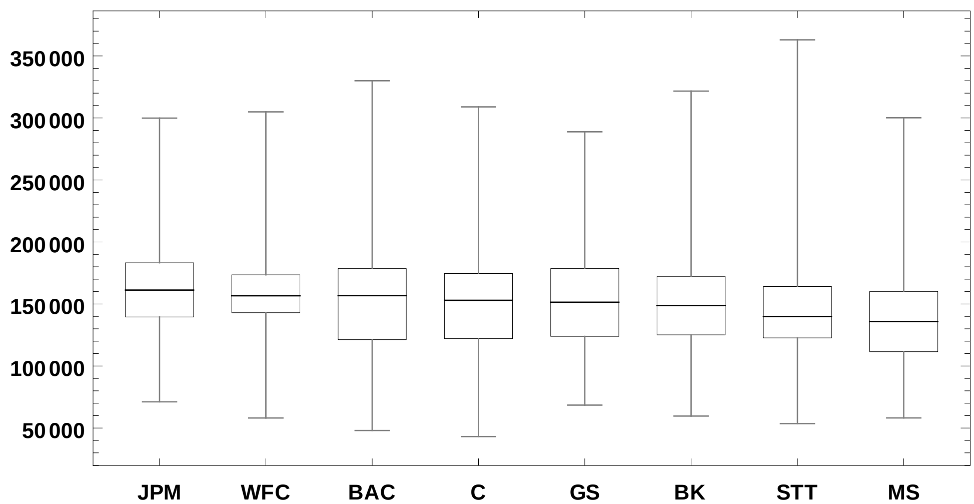
Three-month expected shortfall at the 95 percent confidence level, ratio to market capitalization, daily, Jan. 4, 2006 to Jan. 14, 2013. Vertical grid lines as in Figure 2.

Figure 6: Conditional systemic event probability 2006-2012



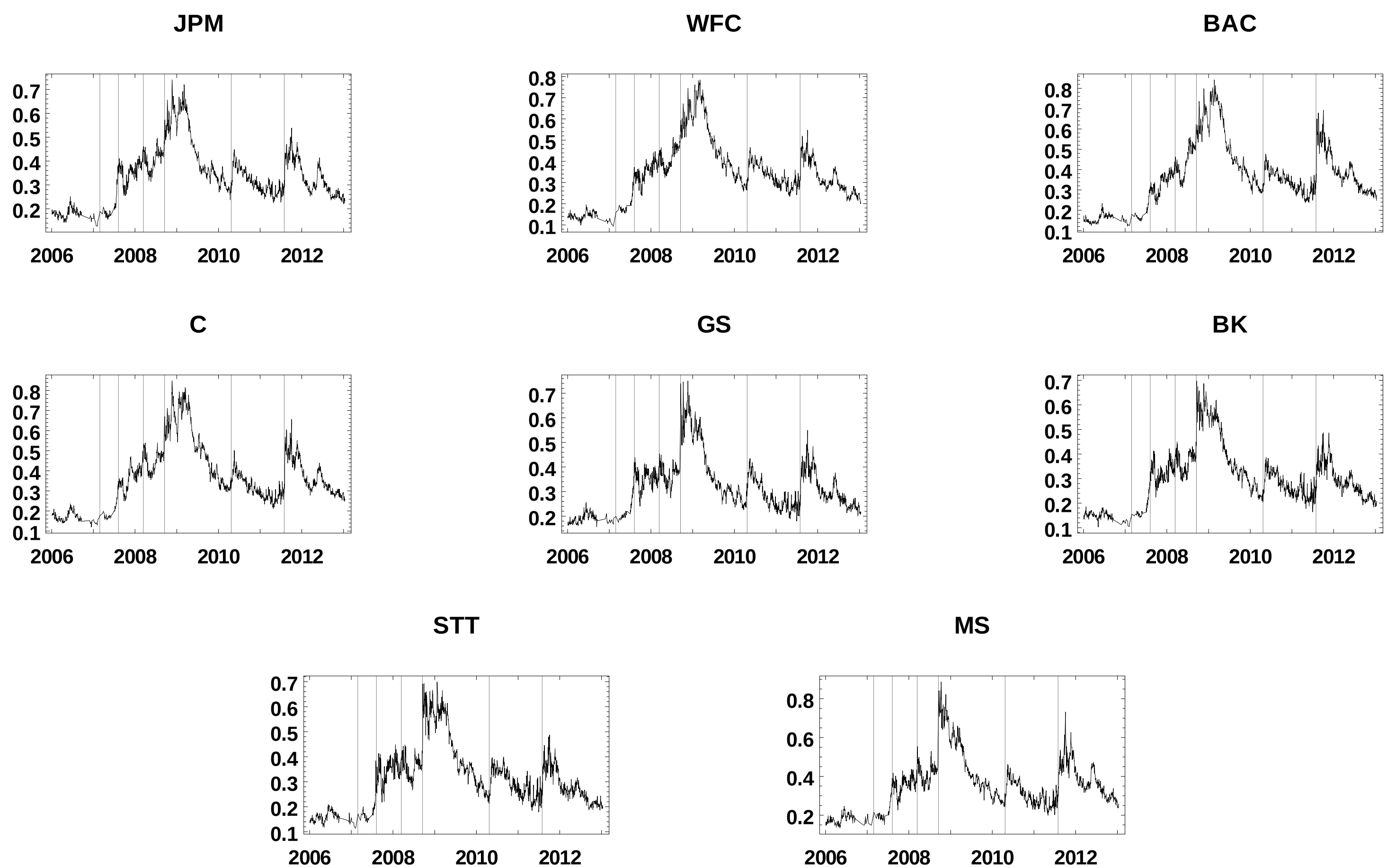
Conditioning event is a 25 percent market capitalization loss of the individual firm over the subsequent three months. Systemic risk event is a 25 percent market capitalization loss of the portfolio over the subsequent three months. Daily, Jan. 4, 2006 to Jan. 14, 2013. Vertical grid lines as in Figure 2.

Figure 7: System conditional expected shortfall 2006-2012



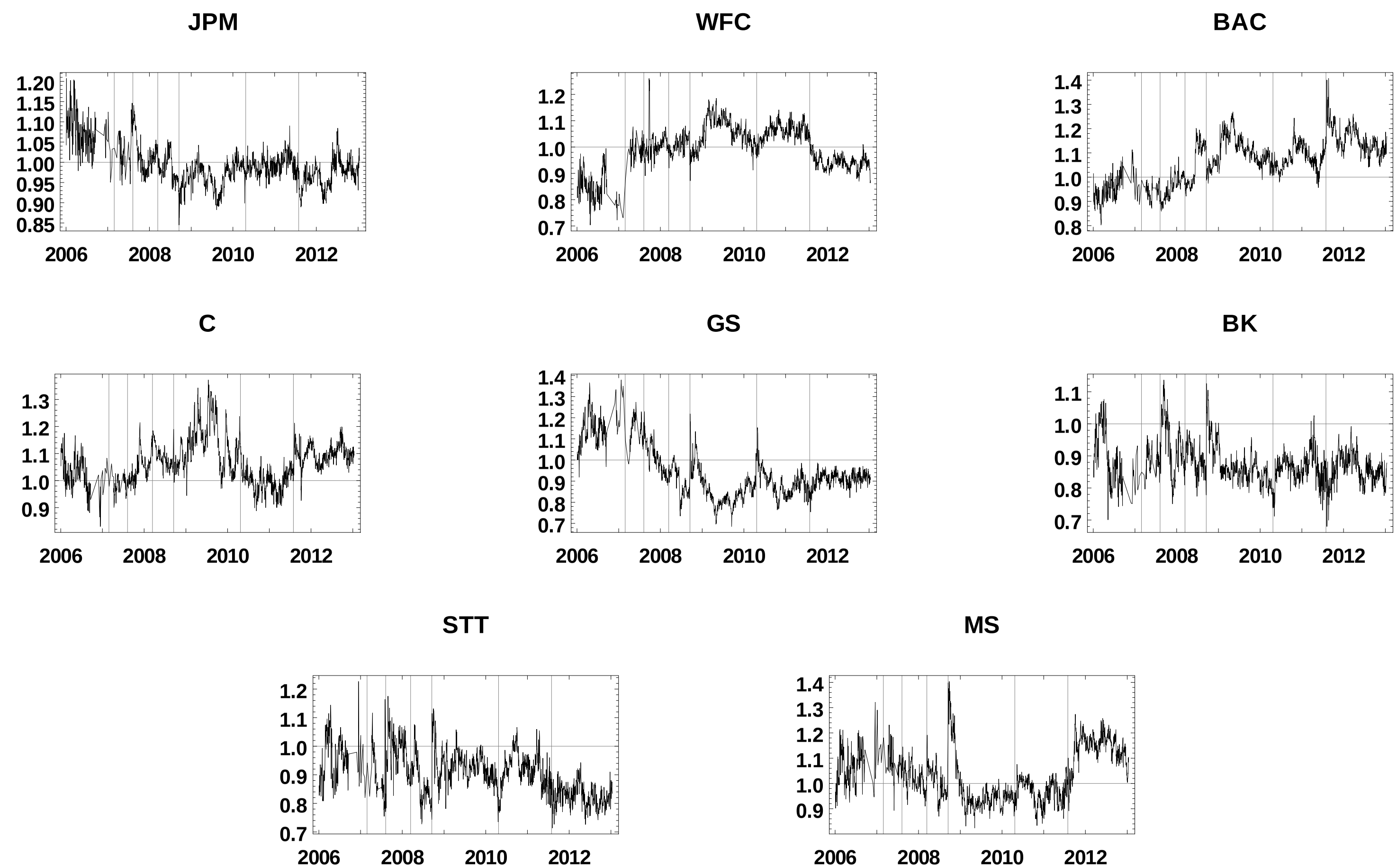
Three-month expected shortfall of the 8-firm portfolio at a 5 percent confidence level, millions of dollars. Conditioning event is a 25 percent market capitalization loss of the firm over the next three months. Daily, Jan. 4, 2006 to Jan. 14, 2013.

Figure 8: Conditional expected shortfall (return) 2006-2012



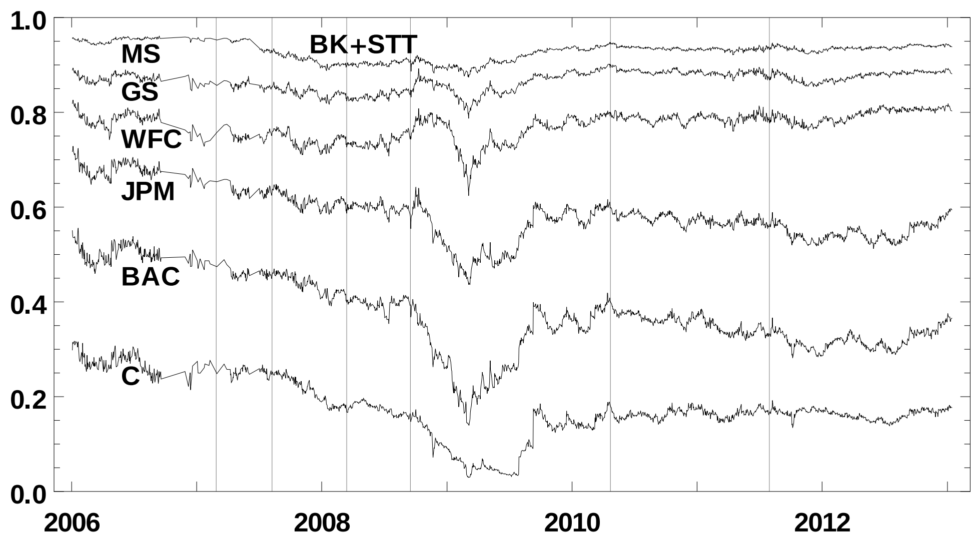
Three-month expected shortfall of the individual firm at a 5 percent confidence level, as a fraction of current forward market capitalization. Conditioning event is a 25 percent market capitalization loss of the 8-firm portfolio over the next three months. Daily, Jan. 4, 2006 to Jan. 14, 2013. Vertical grid lines as in Figure 2.

Figure 9: Conditional expected shortfall ratios 2006-2012



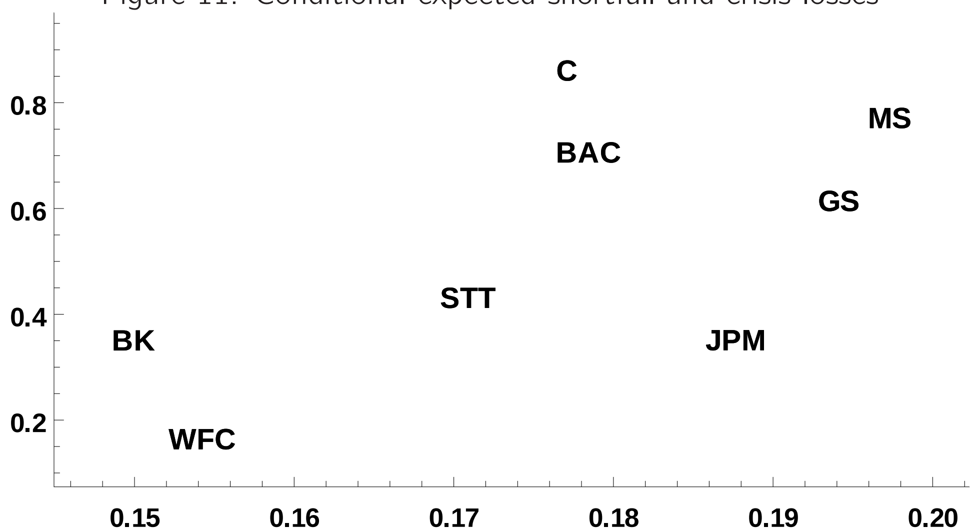
Ratio of conditional expected shortfall of the firm to the system expected shortfall, both at a 5 percent confidence level. Conditioning event is a 25 percent market capitalization loss of the 8-firm portfolio over the next three months. Daily, Jan. 4, 2006 to Jan. 14, 2013. Vertical grid lines as in Figure 2.

Figure 10: Expected shortfall elasticities 2006-2012



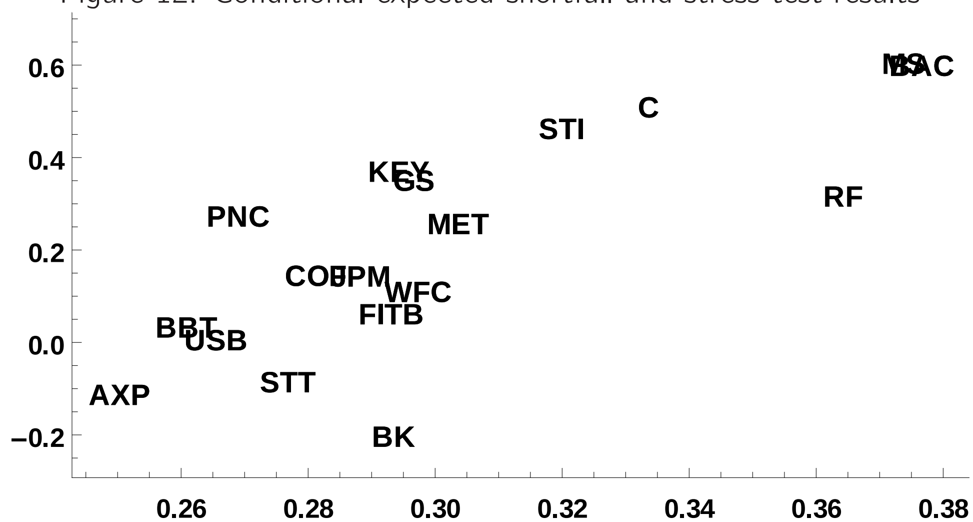
The elasticities are displayed cumulatively, so that each plot includes the shares of all the firms below it. Vertical grid lines as in Figure 2.

Figure 11: Conditional expected shortfall and crisis losses



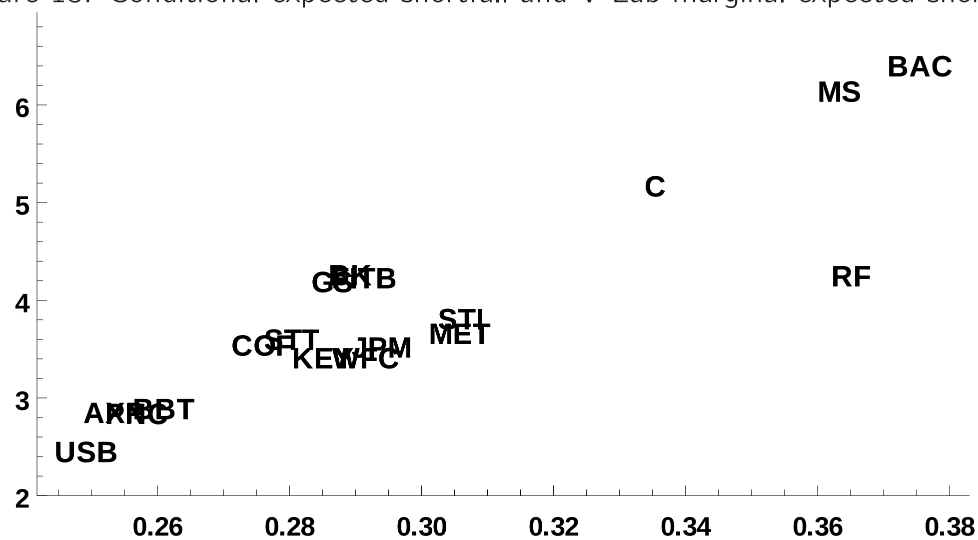
Values on the x-axis are firms' conditional expected shortfall at the 95 percent level (ratio to market capitalization) on July 3, 2008. Values on the y-axis are realized equity market losses between July 3 and Dec. 31, 2008.

Figure 12: Conditional expected shortfall and stress test results



Values on the x-axis are the firm's average conditional expected shortfall at the 95 percent level (ratio to market capitalization) between Feb. 10 and Mar. 8, 2012. Values on the y-axis are $-1\times$ the ratio of each firm's Net Income before Taxes, Table 4 of Board of Governors of the Federal Reserve System (2012), to average market capitalization between Feb. 10 and Mar. 8, 2012.

Figure 13: Conditional expected shortfall and V-Lab marginal expected shortfall



Values on the x-axis are the firm's average conditional expected shortfall at the 95 percent level (ratio to market capitalization), Apr. 2-30, 2012. Values on the y-axis are MES for Apr. 30, 2012 from `http://vlab.stern.nyu.edu/analysis/RISK.USFIN-MR.MES`.