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"Near-Coincident" Indicators of Systemic Stress

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Abstract

The G-20 Data Gaps Initiative has called for the IMF to develop standard measures of tail risk, which we identify in this paper with systemic risk. To understand the conditions under which tail risk is present, it is first necessary to develop a measure of what constitutes a systemic stress, or tail, event. We develop such a measure and uses it to assess the performance of eleven near-term systemic risk indicators as 'early' warning of distress among top financial institutions in the United States and the euro area. Two indicators perform particularly well in both regions, and a couple of other simple indicators do well across a number of criteria. We also find that the sizes of institutions do not necessarily correspond with their contribution to spillover risk. Some practical guidance for policies is provided.

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I. MOTIVATION

The repeated bouts of financial crises in recent years have focused a great deal of attention on systemic risk. While there is still no universally agreed definition of what constitutes systemic risk, the IMF, FSB and BIS define it as the potential for "disruption to the flow of financial services that is (i) caused by an impairment of all or parts of the financial system and (ii) has the potential to have serious negative consequences for the real economy."[2] A systemic event is the realization of this risk.

Recommendation 3 of the G-20 Data Gaps initiative has called on the IMF "to investigate, develop and encourage implementation of standard measures that can provide information on tail risks."[3] However, the definition above provides little practical guidance for empirical work that can help provide such information. Thus, there is a need for a concrete definition of systemic or tail events that can be used in attempts at systematic identification of measures that can help predict such events, that is, that can identify the conditions under which systemic *risk* is present.[4]

At the same time, the attempt to find systematic methods of forecasting systemic tail events should be approached with a high degree of caution and humility. The predictive track record of early warning systems is poor.[5] The Early Warning Exercise (EWE) of the IMF and the Financial Stability Board (FSB) thus does not aim to predict the timing of crises, but rather, identify underlying vulnerabilities that predispose a system to a crisis.[6]

The challenge of forecasting systemic events is heightened due to the extremely complex dynamics and potentially multiple causes of such events. As capital markets and many large financial institutions have become more globalized and as financial instruments have grown more complex and non-transparent, the transmission of shocks through complex feedback loops has often served to amplify and spread seemingly modest initial impulses. Systemic events generally feature negative externalities in which individual institutions take actions

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[2] See IMF-BIS-FSB (2009) and IMF (2011a).

[3] See IMF-FSB (2009).

[4] A tail event is one that has a very low probability of occurrence. Since for a system to survive long enough to become economically and financially significant, it must evolve towards some degree of broad stability over time. An event that has the potential to substantially disrupt that stability will, by definition, be rare. Hence, we identify tail events in this paper with systemic events, and use the two terms interchangeably.

[5] For example, Rose and Spiegel (2009) notes that not only are early warning systems poor at predicting the timing of crises, there are almost no variables, out of over 60 that they test, that can help predict the severity of crises. Interestingly, the one exception that they find, the size of the equity market run-up prior to the crisis, is closely linked to the systemic financial stress index we develop below. Also see Blancher and others (2013) for a framework that links monitoring tools to specific questions about systemic risk.

[6] The IMF and FSB jointly conduct the EWE with the aim of alerting senior international policymakers to the risks of globally systemic tail events. See IMF (2010) and IMF (2012a) for a description of the Early Warning Exercise.

that, in isolation, are in their own interest, but collectively work to undermine the stability of the system as a whole.[7]

A related challenge is to find good measures of 'interconnectedness' between financial institutions within a country. Interconnectedness between asset or liability positions (both on- and off-balance sheet) among financial institutions amplifies losses during a crisis through domino effects running from one institution's failure to solvency or liquidity problems in others (Sole and Espinoza-Vega, 2010). In the absence of data on these positions, however, investors in these institutions could withdraw positions in a number of institutions at the same time for fear that they have common exposures to a sector, like housing. Whatever the initial shock, interconnectedness amplifies the effect of any shock on the system (IMF, 2009, 2011a).

This is not to say that the general preconditions for systemic crisis are necessarily poorly understood. For instance, excessive and sustained credit creation appears to be an important precondition for financial crises, although attempts to find measures with accurate predictive power have met with limited success.[8] The recent definitive historical treatment of financial crises by Reinhart and Rogoff (2011) identified a set of factors associated with various types of crises, including high levels of indebtedness, asset price bubbles and capital inflows.[9] But they note that early warning signals still are not capable of pinpointing when bubbles will burst or the severity of the looming crisis.

Thus, it is true that conditions associated with crisis can remain in place for many years without such a crisis occurring, so that many early warning signals yield "false positives" or Type II error, and hence are not necessarily a useful guide to policy. Financial crises, though requiring a fertile high-risk environment in which to flower, are triggered by a loss of market confidence that is inherently difficult to predict.[10]

However, this suggests a promising, if more modest, approach to predicting the timing of financial crises. If such crises are triggered by a significant change in the market's view, then

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[7] Indeed, taking into account such externalities is a critical rationale for complementing traditional microprudential financial supervision with macroprudential supervision (IMF, 2011a).

[8] The credit-to-GDP gap advocated by Borio and Drehmann appears to work, at best, only in a limited set of advanced countries, while low thresholds of the change in the credit-to-GDP ratio tends to send out signals predicting too many crises that do not occur. See the discussion in IMF (2011b).

[9] Reinhart and Rogoff also emphasize the critical importance of data gaps, particularly the paucity of cross country data spanning long time periods, a deficiency that they made significant strides in overcoming. Importantly, they also note that "The greatest barrier to success [in establishing effective and credible early warning systems] is the well-entrenched tendency of policymakers and market participants to treat the signals as irrelevant archaic residuals of an outdated framework…."

[10] Paul McCulley famously coined the term "Minsky Moment," after economist Hyman Minsky, to describe the point at which markets lose confidence in the sustainability of a process of ever greater amounts of leverage provided against increasingly over-valued collateral. See McCulley (2008).

using market-based indicators should provide the earliest possible indicator that a systemic crisis may unfold. Since once market confidence is lost, a systemic event can occur rather quickly, market-based indicators will usually be of little utility in predicting financial crises far in advance. However, this does not mean that there is no point in tracking these indicators. This paper takes the position that even if a potential systemic event can be predicted only a few weeks or months in advance, monitoring what we call below "near-coincident indicators" can give policymakers time to implement previously mapped out crisis management responses that can significantly ameliorate, if not forestall, the worst potential consequences of a systemic crisis.

II. Systemic risk—Near-Coincident and Coincident Indicators

A large number of indicators have been proposed in the literature, especially since the beginning of the current crisis (see IMF (2009) and Office of Financial Research (2012) for surveys). The early-warning capacity of some of these indicators, constructed with high-frequency market-based data, is at best a few months ahead of the actual crisis events. Recognizing this feature, these indicators are termed "near-coincident" for the purpose of this paper, for the near-term nature of their early-warning properties.[11] The idea is that even though these indicators do not have early-warning capacity 2-3 years in advance of a financial crisis, policymakers could still look at them to prepare for contingencies (for instance, to release capital buffers that have already been built in advance, and to identify recapitalization needs at a time when the probability of a financial crisis is already very high).

The eleven indicators covered in this paper use various types of data based on both market and balance sheet information of a number of financial institutions. There are 17 institutions from the United States and 19 from the euro area (Table 1). Based on the type of data used in their construction, the indicators can be classified as equity market based, debt market based, balance sheet based or a combination of these (the interaction of these sources are shown in Figure 1). The VIX, and its euro area equivalent the VSTOXX, and the Credit Suisse Fear Barometer are the only purely equity market based indicators that are used in the analysis, while the JPoD and the Diebold-Yilmaz (Diebold and Yilmaz, 2009) are the only purely debt market based indicators.[12] A number of indicators, including the banking system's Distance-to-Default and the Systemic Contingent Claims Analysis, combine balance sheet and equity market data. Another set of indicators is constructed from data that have a more macroeconomic character. These indicators are the yield curve slope, the LIBOR-OIS spread and the Systemic Liquidity Risk Indicator (Severo, 2012).

[11] The discussion in this paper updates the results in IMF (2011b).

[12] The Diebold-Yilmaz indicator can be constructed on any high frequency variable, but is based on CDS spreads in this paper. Similarly, the marginal probabilities for the JPoD can be based on supervisory data or any market-based data on the probabilities of default for individual institutions. In this paper, CDS spreads are used. The indicators based on CDS spreads are based on a smaller subset of financial institutions due to data limitations.

It should be noted that each of these indicators has a different purpose but has been used mostly as an early warning indicator (Table 2).[13] For instance, the Systemic Liquidity Risk Indicator (SLRI) is a global indicator of violations in various arbitrage conditions across different asset classes and is meant to capture systemic liquidity risk. The VIX, the Chicago Board Options Exchange Volatility Index calculated from S&P 500 option prices, is meant to capture near-term market uncertainty. The Joint Probability of Distress (JPoD) and the Systemic Contingent Claims Analysis (SCCA) are measures that account for the varying interaction across institutions through time. They differ in the way these interactions are modeled, even though both approaches use non-parametric techniques. The JPoD and SCCA indicators move a lot during extreme events, and almost not at all during calmer periods. Both these measures yield the joint probability of default of institutions and the expected shortfall (or the loss) during tail events.[14] Some of the parametric approaches to distress dependence, like the Diebold-Yilmaz and the Conditional Value at Risk (CoVaR) are suited for assessing spillover-potential but do not provide information on the probability of default or joint default of the institutions.[15] However, the latter two indicators, as well as the JPoD and the SCCA, can inform policymakers about the systemic risk contribution of individual financial institutions.

A new coincident indicator to identify systemic events based on abnormal equity returns is proposed in this paper. Abnormally *large* negative equity returns in individual financial institutions are signs of distress in those institutions. In order to identify events that involved system-wide stress among financial institutions, abnormal (equity) returns are calculated for each of the institutions relative to the equity benchmark index of the institution's host country (for the United States the benchmark index is the S&P 500 index while other country-specific indices are used for the euro area institutions).

The constructed index is termed the systemic financial stress index (SFS). It is defined as the fraction of the number of financial institutions that are experiencing large negative abnormal returns—defined as abnormal returns lower than the 5th percentile (left) tail of the joint distribution of such returns on a given day, as well as cumulatively negative abnormal returns

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[13] See Schwaab, Koopman and Lucas (2011) for a discussion of different purposes of high frequency indicators.

[14] Indicators that allow the distress dependence between institutions (and across markets) to vary between calm and crisis episodes may be more suited for stress testing than as early warning indicators, as they capture the *impact* (rather than likelihood) of the failure of one institution on another institution or the whole system. The systemic CCA is one such indicator. Even though stress tests are problematic to use during systemic events, it is during these events that the systemic CCA registers actual spillovers between institutions and can gauge the contribution of each institution to systemic (spillover) risk and the capital required to cover losss.

[15] Diebold-Yilmaz decomposes the variance of returns and can be used to assign how much of the variance in one institution is due to the influence of another institution. The CoVaR gives a decomposition of the Value at Risk (VAR) at a given probability level. Since the probability level is fixed by assumption, CoVar gives no information on the likelihood of experiencing a large loss, only an estimate of the spillover from one institution to the system given the loss at a specified probability.

for the two weeks following that day.[16] For instance, an SFS of 0.10 in Figure 2 refers to 10 percent of the U.S. financial institutions experiencing large and persistent stresses. A subset of the observations in SFS is termed *extreme* SFS and has a value of 1 if 25 percent or more of the financial institutions are experiencing stress, that is, the SFS is greater than, or equal to, 0.25, and zero otherwise. Thus, extreme SFS can be used as a binary variable distinguishing tail events from other time periods. The corresponding SFS and extreme SFS for the euro area are shown in Figure 3.

The SFS is taken as a coincident indicator of stress to proxy for actual stressful events in a group of financial institutions. A number of event studies have tested the market response to actual events (Rodriguez-Moreno and Peña, 2011), such as various official interventions in financial institutions (IMF, 2009; and Aït-Sahalia and others, 2010). There are advantages of using the SFS over exogenous events such as official interventions.[17] First, the SFS yields a continuum of a large number of data points that range from no financial stress to extremely high financial stress, compared to the relatively small number of actual interventions that are usually related to extreme situations only. Second, the SFS can be easily updated with market-based data and forms a basis for a standardized measure of stress across institutions, countries, and time. Third, since it measures abnormal returns based on market prices relative to the overall index, it measures the market's response to financial institution-specific difficulties. The measure is therefore an indicator of the actual 'excess' stress in a group of financial institutions at any time.[18]

III. Testing for Early Warning

Data

The U.S. sample consists of 17 financial institutions (FIs) and the euro area sample of 19 financial institutions (see Table 1). The FIs are chosen based on size (total assets) and the limits of 17 and 19 are imposed because of computational limits to working with a larger number of institutions. For each institution in the sample, the data to construct the SFS consist of equity prices (Bloomberg). For the 11 indicators, the data consist of equity prices (Bloomberg), 5-year CDS premia (Bloomberg or Datastream, depending on which has better

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[16] Based on the joint distribution of all banks, the threshold for the U.S. banks is -6.7 percent, and that for the euro area banks is -5.9 percent.

[17] Event studies attempt to identify specific events as factors that can drive abnormal returns. For example, Rodriguez-Moreno and Peña (2011) uses a timeline of the crisis maintained by the Federal Reserve Bank of St. Louis (available at http://timeline.stlouisfed.org/). However, identifying the appropriate timing of such events is difficult since markets may frequently anticipate them, so that an event is often "priced in" prior to its occurrence.

[18] The monthly version of the SFS for the United States helps forecast current-year's GDP growth (as shown by Granger-Causality tests of the SFS and GDP growth forecasts from Consensus Forecasts) but not necessarily next years' GDP growth (see IMF, 2011b).

coverage) and implied asset values (Moody's KMV). In addition, country specific data collected from Bloomberg includes: 3-month interbank rates (U.S. dollar LIBOR and EURIBOR) and overnight index swap rates (OIS), 3-month and 10-year constant-maturity government bond yields, equity market implied volatility indices (VIX for the US and VSTOXX for the euro area), and the Credit Suisse Fear Barometer index based on S&P 500 index options.

The sample includes daily (5-day week) data from January 2003 to April 2011. The near-coincident systemic risk indicators are constructed with a daily frequency. However, for the three tests outlined below, daily series are transformed into weekly series using the transformation that would à priori give the highest risk signal, e.g. the maximum over the week for the JPoD or the minimum over the week for the distance-to-default, depending on how the risk signal is meant to be interpreted. This way, the indicators are given a chance to put up their best performance, albeit possibly at the cost of introducing noise.

Methodology

The performance of the 11 indicators in signaling the materialization of risk is judged by their scores on each of three tests:

Test 1: Granger Causality

The indicator should have the ability to forecast systemic financial stress at a reasonable horizon. In particular, the test uses the simple average of two scores.

- The first score, the *Granger Causality (GC)* p-value score, is based on four tests between the SFS and the near-coincident indicators that use weekly data to test whether the near-coincident indicators Granger cause the SFS at lag-lengths of 52 weeks, 26 weeks, 4 weeks and 1 week (equations 1.1-1.4).[19] The score is constructed by giving a positive weight only to those lags for which the p-values are less than 0.01 *and* where there is no reverse Granger-causality running from the SFS to the near-coincident indicator at that lag. For a lag that passes this test, the weight assigned to it is the length of the lag. The total p-value score is then the sum of the scores on each lag length divided by the sum of the lag lengths. For instance, in the yield curve row of Table 3, the first four columns indicate (as shown by a red number) that only the 52^{nd} and 26^{th} weeks lags have both a p-value less than 0.01 *and* no reverse causality running from the SFS to the yield curve (values with p-value less than 0.01 but that *do* have reverse causality are

[19] The p-value score indicates the probability of the null hypothesis (the near-coincident indicator does not Granger cause the SFS) is rejected. That is, a p-score less than 0.01 can be interpreted as saying that there is very strong evidence for in-sample forecasting power for a particular number of lags for a particular near-coincident indicator, beyond the SFS's own lags.

shown in black boldface). Thus, in columns 5-8 (the "Scores" columns), the 52nd and 26th week lags receive weights of 52 and 26, respectively, while the 4th week and 1st week lags (on which the p-values exceed 0.01) receive weights of zero. The p-value score for the yield curve is then calculated as the sum of the scores on each lag divided by the sum of the lags: (52+26+0+0)/(52+26+4+1)=0.94.

$$(1.1)\quad SFS_t = c + \sum_{s=1}^{52} \beta_s SFS_{t-s} + \sum_{s=1}^{52} \rho_s x_{t-s} + \varepsilon_t,$$

$$(1.2)\quad SFS_t = c + \sum_{s=1}^{26} \beta_s SFS_{t-s} + \sum_{s=1}^{26} \rho_s x_{t-s} + \varepsilon_t,$$

$$(1.3)\quad SFS_t = c + \sum_{s=1}^{4} \beta_s SFS_{t-s} + \sum_{s=1}^{4} \rho_s x_{t-s} + \varepsilon_t,$$

$$(1.4)\quad SFS_t = c + \sum_{s=1}^{1} \beta_s SFS_{t-s} + \sum_{s=1}^{1} \rho_s x_{t-s} + \varepsilon_t,$$

where x is the near-coincident indicator.

- The second score, the *lag-length score*, is based on running OLS regressions of the SFS on both the near-coincident indicator and the SFS with various specific lags in the same regression (lags of the 52nd week, 26th week, 4th week, and 1st week) and reporting the p-values of t-tests on the coefficients of each of the four lags of the near-coincident indicator, $\rho_{52}, \rho_{26}, \rho_4,$ and ρ_1, in the same regression (equation 2). The final lag-length score is based on a similar weighting scheme as the Granger Causality p-value score. Taking the yield curve row again, only the p-value of the near-coincident indicator at the 52-week lag is less than 0.01 and therefore the lag-length score is (52+0+0+0)/ 52+26+4+1)=0.63.

$$(2)\quad SFS_t = c + \sum_{s=1,4,26,52} \beta_s SFS_{t-s} + \sum_{s=1,4,26,52} \rho_s x_{t-s} + \varepsilon_t,$$

where x is the near-coincident indicator.

- The total score for the test is the simple average of the Granger-Causality p-value score and the lag-length score.

Test 2: Predicting Extreme Events

The near-coincident indicator should be capable of predicting extreme systemic financial stress events with reasonable accuracy. In particular, these events are measured with the extreme SFS, which as noted above is a binary variable that takes the value of 1 if the SFS ≥ 0.25 and 0 otherwise. Lags of the SFS and lags of the near-coincident indicator are used to predict the probability of extreme systemic financial stress, which is proxied by this binary variable, *y*. A logit regression for each set of lags—for 6 weeks, 4 weeks, and 1 week—is used for this purpose (equations 3.1-3.3). Scores are based on two components: the p-values of Wald-tests (that all lags are jointly significant) and the McFadden R-squares from each regression. For example, in Table 4 for the yield curve, the p-values and the McFadden R-squares for the 6-week lag are based on regression equation (3.3) and the Wald test that $\beta_1,...,\beta_6$ are jointly significant and similarly, for the other lags. The p-value score, column 5 in Table 4, is calculated as (1 *minus*) the average p-values, each weighted by the associated lag-length. The McFadden R-square score, column I in Table 4, is the lag-length-weighted average of the McFadden R-squares. The total score for this test is the simple average of these two scores.

$$(3.1)\ \text{Prob}(SFS_t \geq 0.25 \mid \text{X},\text{B}) = \frac{e^{\text{X'B}}}{1+e^{\text{X'B}}};\ where\ \text{X'B} \equiv c + \beta_1 SFS_{t-1} + \rho_1 x_{t-1}$$

$$(3.2)\ \text{Prob}(SFS_t \geq 0.25 \mid \text{X},\text{B}) = \frac{e^{\text{X'B}}}{1+e^{\text{X'B}}};\ where\ \text{X'B} \equiv c + \sum_{s=1...4} \beta_s SFS_{t-s} + \sum_{s=1...4} \rho_s x_{t-s}$$

$$(3.3)\ \text{Prob}(SFS_t \geq 0.25 \mid \text{X},\text{B}) = \frac{e^{\text{X'B}}}{1+e^{\text{X'B}}};\ where\ \text{X'B} \equiv c + \sum_{s=1...6} \beta_s SFS_{t-s} + \sum_{s=1...6} \rho_s x_{t-s}$$

where x is the near-coincident indicator.

Test 3: Early Turning Point

The indicator should have a turning point early enough so as to give policymakers time to deploy contingency measures. This is evaluated in the context of the current crisis and records the week in which the indicators switched from being in a tranquil mode to a more volatile mode. Most systemic risk indicators moved little before the crisis. However, nearer to systemic events, these indicators started moving, recording structural breaks. For this exercise, autoregressive regressions with 4 lags (AR(4)) are estimated for each of the indicators (equation 4) and the Quandt-Andrews break point (QABP) test (a test for identifying an unknown break point) is conducted for each of the regressions, testing for breaks both in the level (the constant term) and the persistence process (lagged coefficients in the AR terms). The QABP provides the possible breakpoint date for each of the near-coincident indicators for each test (level and persistence). Table 5 shows the dates of these turning points and ranks the near-coincident indicators based on their timeliness. If the turning points are statistically significant (at the 5 percent level), turning points are assigned a score based on how far ahead they occurred before the failure of Bear Stearns for the U.S. sample, and end-March 2009 (the peak of bank CDS spreads before problems in the periphery emerged) for the euro area sample, with earlier dates receiving higher ranks.

(4) $x_t = c + \sum_{s=1}^{4} \rho_s x_{t-s} + \varepsilon_t$,

where x is the near-coincident indicator.

The 11 near-coincident indicators of systemic risk are then ranked by the average score across all three tests. The three scores and the overall ranking is shown in Table 6 for the U.S. sample and Table 7 for the euro area sample.[20] Even though an aggregate score is provided, the paper emphasizes the results for the individual tests. This is because each of the indicators/models was originally meant to serve different purposes and hence it might not be fair to compare these indicators on an overall score.

Discussion of Results

United States

Several indicators performed consistently well across the tests, which is reflected in their high overall score (see Table 6 and Figure 5).[21] These indicators are the Diebold-Yilmaz, the distance-to-default (DD), and the time-varying CoVaR (T-CoVaR), each of which is ranked in the top three indicators in at least two of our three sub-tests.

The T-CoVaR is estimated conditionally on the LIBOR-OIS spread and the yield curve slope. These two simple indicators perform well on their own, but not as well as the T-CoVaR, in several of the sub-tests: the yield curve slope outperforms significantly the other indicators in predicting systemic stress and the LIBOR-OIS spread performs well in predicting extreme events and has a relatively early turning point. The good individual performance of the yield curve and the LIBOR-OIS, in combination with the use of these indicators in the construction of the overall well-performing time-varying CoVaR, suggest that these two simple measures may be good near term coincident indicators of forthcoming stress events by themselves.

Some of the other 'simple' risk indicators like the VIX and the LIBOR-OIS spread performed better, both on average and in most of the three sub-tests, than some of the complex risk indicators, like the JPoD and the SCCA, that take into account the dependence of institutions and interconnectedness. This may be due to the inability of market participants to accurately estimate exposures across institutions, sectors and countries, since such data are generally not available. Lack of such exposure data represents a major data gap which, if

[20] By testing the indicators *against* each other on their ability to predict multiple events mainly during crisis, the issue of "volatility bias" (Forbes and Rigobon, 2002) in the tests is avoided. This is because the heteroskedasticity (higher volatility during the crisis) in the data would bias correlation coefficients for all indicators so that the horserace puts all indicators on even ground.

[21] Table 6, as the tables with detailed results for the three individual tests (Tables 3-5), shows the detailed test results for the United States only. These results could vary a bit with those reported in IMF (2011b) due to slightly more stringent set of tests.

addressed, could provide the market with the means of assessing the dependencies across institutions and potentially produce better early warnings of impending financial stress. Indeed, such data could be used by authorities themselves to directly see such interdependencies even without these data being publicly released and incorporated into prices by market participants.

Some indicators do well in specific tests while doing poorly overall. For example, the JPoD is the best performer in predicting extreme events but does not do well in the other two sub-tests.[22] As cautioned earlier, results in each of the tests could also reflect the very purpose of the indicators and should deserve an equal, if not more, attention than the overall results.

Euro Area

Just as for the United States, the time-varying CoVaR and the Diebold-Yilmaz are two of the best performing near coincident indicators for the euro area, at least based on the indicators' overall scores.[23] The LIBOR-OIS spread is the best overall near coincident indicator for the euro area (see Table 7 and Figure 6).

Unlike the United States, the distance-to-default performs relatively poorly in the euro area, which is due to its poor performance in the turning point (persistence) sub-test. Although the turning point in persistence is fairly early, it is not statistically significant with a QABP test p-value of 0.32 and is, consequently, assigned a very low score. The SLRI performs better in the euro area than in the United States, possibly related to the U.S. dollar liquidity (funding) difficulties experienced by euro area banks during the crisis.

Robustness

The results appear robust to changes in the tests' specifications. The results' robustness was examined by perturbing the tests with small changes in their parameters and re-ranking the near-coincident indicators based on their new scores. Specifically, robustness tests included the following:

- For the JPoD the composition of the banking system was changed. For the United States, the JPoD indicators were recomputed based on a sample including Bear Stearns, a sample including Lehman Brothers, and a sample including only the U.S. financial institutions that did not fail during the financial crisis. The JPoD is time

[22] The performance of these indicators could also hinge on the data used as inputs—for instance, the individual PDs for the JPoD (in this paper, CDS spreads). A time-varying version of the JPoD (the CoPoD in Segoviano and Padilla, 2006) that estimates the PDs conditional on other market information like the LIBOR-OIS or the yield curve could perform better, but this has not been tried in this paper.

[23] For the euro area only the overall tests scores are shown here, the detailed euro area results for the individual tests are available from the authors upon requests.

consuming to compute when the sample size increases above 15 institutions.[24] Because of this computational limitation and the large number of potential candidates for inclusion in the euro area sample, this robustness test was not performed on the euro area JPoD.

- The definition of the extreme SFS was varied by using threshold levels of 33 percent and 20 percent, and then the logit regressions for predicting extreme systemic stress in the second sub-test were re-estimated using these new thresholds.

- Instead of a logit regression, extreme value and probit regressions were estimated for the second sub-test (i.e., the test for predicting extreme events).

The range of overall scores and the sub-scores across the test perturbations were computed for both the United States and the euro area (Figures 7 and 8). The ordering of some indicators like the VIX and the CSFB for the United States, and the JPoD and the yield curve for the euro area, are susceptible to change in the tests implemented above. However, there is little variation in the top two indicators for the United States and the euro area.

IV. Interconnectedness

Shocks to the financial system get amplified through the interconnections among institutions. This is true for both positive and negative shocks, although the effects could be asymmetric. So far, the discussion of systemic risk indicators in this paper has focused on their 'early warning' capacity or their ability to predict the likelihood of a systemic event. Some of these indicators, such as the CoVaR, JPod, SCCA, and Diebold-Yilmaz, also embed estimates of the "loss-given-distress"—some measure of 'loss' in the financial system if there is distress in any one institution.[25] The potential for such 'spillovers' or interconnectedness is related to the actual balance-sheet and off-balance sheet exposures between institutions—data that is usually not made available to the market—or to their exposure to a common shock, such as a shock to the housing market.

In the absence of actual inter-institution data on exposures, market prices that embed some incomplete knowledge and perceptions of such interconnections are used to estimate the potential for spillovers of risk from one institution to the system (Figure 9). Three of the indicators are derived from those discussed in the previous sections; the fourth is taken from Chan-Lau, Mitra and Ong (2012).[26] The spillover-coefficient of each institution is plotted

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[24] Although a version of the JPoD that can handle many more institutions is currently being tested.

[25] The specific interconnectedness measure associated with the JPoD is the Probability of Cascade Effects (PCE), which is the probability that at least one other bank in the sample of banks is in distress when a specific bank falls into distress. The PCE is derived from the same framework as the JPoD and embeds the same distress dependence between FIs as the JPoD (Segoviano and Goodhart, 2009).

[26] Chan-Lau, Mitra and Ong (2012) estimates the probability that one institution is in distress conditional on the rest of the institutions being in distress—the tail-dependence. In order to calculate the systemic importance of

(continued…)

against the size of its total assets as of 2007. The spillover-potential of Bear Stearns is highlighted to indicate the market's view of its systemic importance as of June 2007.

Interestingly, there is a striking disassociation between the size of firms and their perceived potential for systemic spillovers (Figure 9).[27] Based on data up to June 2007, at least two of the indicators—Diebold-Yilmaz and Chan-Lau, Mitra and Ong—pick up the disproportionately high spillover risk of Bear Stearns in June 2007. The other two show that Bear Stearns had the same spillover potential as Bank of America or Citigroup as of June 2007.[28] This evidence implies that we need to develop good proxies for contributions to systemic risk, apart from size.

Additionally, size appears to be a questionable indicator of institution's spillover potential, there is an urgent need for better data on actual, as opposed to perceived, interconnectedness. This need is being addressed by the work on recommendations 8 and 9 of the G-20 Data Gaps Initiative, on linkages between individual financial institutions and on a common draft template for systemically important global financial institutions, respectively.

V. Policy Implications and Conclusions

The discussion around the early-warning capacity of the indicators and measures of interconnectedness leads to the question: how can policymakers use this information in practice? Here are some issues to consider, based on the findings.

Choice of indicator. Policymakers should have a wide range of indicators at their disposal, rather than relying on one single indicator, bearing in mind that each indicator has its own purpose. However, the analysis in this paper provides some guidance to policymakers in choosing the best near-coincident measures of systemic tail risk for the United States and the euro area.

Indicator Thresholds. Policy tools could be based, at least in part, on certain values of indicators associated with those levels that signaled systemic stress in the past. For example, the authorities could request a drawdown of countercyclical capital buffers once an indicator, or set of indicators, exceeds a pre-specified threshold. Threshold levels could be set at those values of the near-coincident indicators observed at the turning points identified in the

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each institution in terms of "spilling over" to others, the number of significant spillover coefficients for one institution is taken as a fraction of the total number of potential spillover possibilities (into others) for all institutions.

[27] See IMF-BIS-FSB (2009), which provides guidance to assess the systemic importance of financial institutions, and includes both size and interconnectedness in the set of criteria.

[28] The spillover risk from Segoviano and Goodhart (2009) is loosely referred to as the JPoD, but is calculated by the Probability of Cascade Effects—the probability that at least one other bank is in distress if Lehman Brothers (or Bear Stearns) is in distress.

breakpoint tests (Tables 8 and 9). For two of the indicators, the yield curve slope and the Credit Suisse Fear Barometer, their levels at the turning points may be less informative for establishing the thresholds than the change in the indicators around the turning points.[29] Different thresholds may be appropriate in different regions. The turning point for the VIX, for instance, ranges from 18-24 for the United States and 23-27 for the euro area.

Other Uses of Near-Coincident Indicators. The tests performed in this paper were designed only to judge the early warning capacity of near-coincident indicators, but these indicators can also be used for other purposes. For instance, the CoVaR and Diebold-Yilmaz are meant to be cross sectional 'spillover' measures at a particular point in time, although they can be computed at multiple dates. In this regard, their time-varying versions also performed very well as near-term early warnings. The JPoD measures the probability of distress in the financial system and 'spillover' effects using a flexible non-parametric measure of interdependence. It did not perform well on average, but did so for extreme stress in the United States. On balance, it may be more suited as a 'coincident' measure.[30] The SLRI, which measures the simultaneous breakdown of several financial arbitrage relationships, is an indicator of systemic liquidity risk and appears more suited as a 'coincident', rather than a 'near-coincident' measure of systemic stress. Still, in the euro area, it performs in the middle of the range of indicators and is the best indicator of extreme events. The SCCA integrates both 'probability of distress' and the 'loss-given-distress' and may be more suitable for stress tests that determine the shortfall in regulatory capital (for covering credit risk), especially during crisis.[31]

In conclusion, this paper has developed a specific metric for a systemic financial stress (SFS) event that can be used as a standard coincident measure of a tail event. The SFS comes in two variants, including a continuous version (the percent of financial institutions whose daily

[29] The level of the yield curve slope may be associated with a number of market environments, some of which could be quite benign, however a sharp steepening of the yield curve is likely to reflect either a sharp increase in term premia, or a sharp decline in short term rates in a flight to quality, or an abrupt loosening of monetary policy. Therefore, steepening of the yield curve is likely to reflect increased systemic risk and this is used as the basis for its threshold. Selecting the threshold level for the Credit Suisse Fear Barometer is even less clear cut. The indicator measures the cost of out-of-the-money equity index put options, which provide insurance against large market declines, relative to the overall price of equity index options. *A priori* it would be expected that a high level of the indicator should signal high systemic financial stress. However, the empirical results presented here suggest the opposite, with the indicator peaking well in advance of the increase in the SFS in the United States and the euro area. This behavior may reflect investor complacency, which leads to a buildup in risky positions and increased systemic financial stress at some point in the future. Therefore, consistent with the empirical observations, the threshold for the Credit Suisse Fear Barometer is based on a decline in the indicator.

[30] For an application of the JPoD to measuring systemic stress see ECB (2008) and IMF (2009).

[31] For an example based on U.K. stress tests, see http://www.centralbanking.com/central-banking/news/2115987/imf-modelling-liquidity-risk-capital-hike-jobst and IMF (2011c).

returns are in the 5th percentile left tail), or a discrete version termed “extreme SFS” that takes the value one when the SFS is 0.25 or greater and zero otherwise. Unlike the types of events used in event studies, the SFS is continuous, unambiguous, and can easily be updated with market-based data. It can serve as a standardized measure of stress across institutions, countries, and time.

The paper then ran a battery of tests on near-coincident indicators to see which best helped predict systemic tail events based on a range of criteria. The main caveat is that all these tests are in-sample forecasting exercises. Because there was one crisis episode—broken up into several stress events for the purpose of this exercise—and some relevant market data (CDS spreads for instance) only became available for a large number of institutions during this episode, the paper could not perform out-of-sample analysis.

The paper also suggests that the SFS and extreme SFS could meet the G-20 Data Gaps Initiative recommendation to develop standard measures of tail risk. We show that these two indicators can be used as coincident indicators of systemic events.

Table 1: Financial Institutions

Unites States	*Euro area*	
Bank of America	Bank Austria	Austria
Bank of New York Mellon	Erste Group Bank	Austria
BB&T	Raiffeisen Bank	Austria
Bear Stearns	Dexia	Belgium
Citigroup	KBC Groep	Belgium
Goldman Sachs	BNP Paribas	France
JPMorgan Chase	Crédit Agricole	France
Lehman Brothers	Société Générale	France
Merrill Lynch	Commerzbank	Germany
Morgan Stanley	Deutsche Bank	Germany
PNC	Hypo Real Estate	Germany
State Street	Allied Irish Banks	Ireland
SunTrust	Bank of Ireland	Ireland
US Bancorp	Intesa Sanpaolo	Italy
Wachovia	UniCredit	Italy
Washington Mutual	ING Groep	Netherlands
Wells Fargo	Banco Popular	Spain
	Banco Santander	Spain
	BBVA	Spain

Table 2. Near-Coincident Indicators of Financial Stress

Indicator	What is it?	Purpose	Method	Pros	Cons	Reference
Yield Curve slope	The difference between the yield on 10-year Treasury bonds and 3-month Treasury bills	In the U.S., has been shown to predict recessions.	Observed directly from market interest rates.	Very simple concept; available for a large number of countries.	Too aggregated, does not provide information on the source of stress.	Estrella, 2005
Time-varying Conditional Value-at-Risk (CoVaR)	The value-at-risk of the financial system conditional on institutions being under distress.	Measures the loss in the financial system if one institution is in distress.	The time-varying CoVaR is based on the returns of the market-value of assets, and is estimated by quantile regressions of the returns of the financial system on the returns of an institution and systemic state variables. For the purpose of this paper, the yield-curve and the Libor-OIS spread are used as the systemic state variables.	Very flexible and intuitive; amenable to a wide variety of data	Depends on the choice of systemic state variables; the quantiles are estimated with linear regressions which may not accurately capture the underlying relationship (although alternative, but more demanding, estimations are possible).	Adrian and Brunnermeier, 2010
Rolling CoVaR	The value at risk of the financial system conditional on institutions being under distress.	Measures the loss in the financial system if one institution is in distress.	Same as above, but without conditioning on systemic variables . The time variation comes from 400-day rolling quantile regressions, with daily updating	Very flexible and intuitive; amenable to a wide variety of data	The rolling regressions make the indicators too backward-looking.	Adrian and Brunnermeier, 2010
Joint Probability of Distress (JPoD)	Measures the joint probability of distress of all institutions by estimating a multivariate density from the data and modeling distress-dependence by the CIMDO-copula function	Time-varying probability of systemic financial risk (credit risk).	Constructs a non-linear, time-varying measure of "tail dependence" using a multivariate distribution of individual institutions' probability distributions of their implied asset value movements.	Nonlinear distress-dependence; form of copula given by the data; multiple outputs: probability of default and spillovers	Sensitive to the inputs of the individual institutions'' probability of default.	Segoviano and Goodhart, 2009
Credit Suisse Fear Barometer	Measures investor sentiment, and the number represented by the index prices zero-premium collars that expire in three months.	Measure of investor sentiment by implicitly measuring skewness in equity returns.	The collar is implemented by the selling of a three-month, 10 percent out-of-the-money S&P 500 call option and using the proceeds to buy a three-month out-of-the-money S&P 500 put option of equal value.	Easy to compute from observed equity prices.	Occasionally exhibits counterintuitive performance.	Tom and Davitt, 2009
Distance to default (DD)	The number of standard deviations the banking system is away from the default point--at which the liabilities of the banks are just equal to the market value of assets.	Time varying measure of bank (credit) risk.	Based on the Merton (1974) model where default occurs when the value of a firm's assets falls below the promised debt payments and the firm cannot service its debt. Both equity and debt are modeled as derivative securities with values contingent on the value of the underlying assets. Firm equity can be viewed as a call option on the assets with an exercise price equal to the promised debt payments.	Simple way to measure and analyze credit risk.	Dependence structure not modeled but can construct rolling correlations from the data.	De Nicolo and Kwast, 2002
Diebold-Yimaz (DY)	A time-varying measure of outward spillovers of all institutions.	Size of spillovers over time	Based on the matrix of variance decompositions from a 80-week rolling VAR of financial institutions' CDS returns.	Time-varying distress-dependence	Does not explicitly model tail-dependence; rolling window estimation yields central moments and makes the measure backward-looking	Diebold and Yilmaz, 2009
VIX	Chicago Board Options Exchange Volatility Index calculated from S&P 500 option prices.	Measure of market uncertainty. It measures the market's expectation of future volatility over the next 30-day period.	Option-implied volatility calculated from cross-section of option prices.	Easily available.	Too aggregated, does not provide information on the source of stress.	Chicago Board Options Exchange, 2009
LIBOR-Overnight Indexed Swap (OIS) spread	Measure of the risk of default associated with lending to other banks in the LIBOR market.	Measure of counterparty risk in the interbank market; liquidity risk.	Observed directly from market interest rates.	Readily available for a large number of large countries.	Too aggregated, does not provide information on the source of stress; LIBOR based on quotes submitted by a panel of banks rather than on actual rates interbank transactions and may inaccurately represent conditions in the money market.	Taylor and Williams, 2008
Systemic Liquidity Risk Indicator (SLRI)	Measures the breakdown of arbitrage conditions in major markets	Global indicator of systemic liquidity stress.	First principal component of a number of arbitrage violations in international financial markets.	Easy to construct; measures liquidity conditions across markets.	Too aggregate, does not provide information on the sources of stress.	Severo, 2011
Systemic Contingent Claims Approach (CCA)	Measures the joint dependence of various financial institutions during crisis	A measure of interconnectedness; measures expected shortfall due to credit risk	Non-parametric copula approach to dependence-modeling.	Nonlinear distress-dependence.	Potentially affected by government injections and dilutions.	Gray and Jobst, 2010

Sources: The table is partly based on IMF (2009).

Table 3. Test 1—Granger Causality of Systemic Risk Measures to the Event Indicator for the U.S. Sample

	p-Values for Granger Causality Tests with Various Lags 1/				Scores 2/					p-Values for t-Test at Each Lag 3/					
	52 weeks	26 weeks	4 weeks	1 week	52 weeks	26 weeks	4 weeks	1 week	Granger Causality p-Value score	52 weeks	26 weeks	4 weeks	1 week	Lag-length score	Total Score
Credit Suisse Fear Barometer	0.122	0.716	0.072	**0.007**	0	0	0	**1**	0.01	0.24	0.48	0.04	0.95	0.00	0.01
Time-varying CoVaR	**0.000**	**0.000**	**0.000**	**0.000**	**52**	**26**	**4**	**1**	1.00	0.65	0.63	0.11	0.11	0.00	0.50
Rolling CoVaR	0.011	0.021	0.243	**0.001**	0	0	0	**1**	0.01	0.63	0.57	0.96	0.58	0.00	0.01
DD banks	0.078	0.750	**0.000**	**0.000**	0	0	**4**	0	0.05	0.02	0.46	0.29	0.86	0.00	0.02
Systemic Liquidity Risk Index	**0.000**	**0.000**	**0.000**	**0.000**	0	0	0	0	0.00	0.86	0.09	0.17	0.17	0.00	0.00
Diebold-Yilmaz	**0.000**	0.049	**0.002**	**0.000**	**52**	0	**4**	**1**	0.69	0.01	0.22	0.64	0.06	0.00	0.34
JPoD	**0.001**	**0.000**	**0.000**	**0.000**	0	0	0	0	0.00	0.05	0.44	**0.01**	0.08	0.05	0.02
Systemic CCA	**0.000**	**0.000**	0.116	0.053	0	0	0	0	0.00	0.43	0.72	0.43	0.38	0.00	0.00
Libor-OIS spread	**0.000**	**0.000**	**0.000**	**0.000**	0	0	**4**	**1**	0.06	0.03	0.61	**0.00**	0.09	0.05	0.05
VIX	**0.000**	**0.000**	**0.000**	**0.000**	0	0	**4**	**1**	0.06	0.26	0.45	0.32	**0.01**	0.01	0.04
Yield curve	**0.000**	**0.000**	0.097	0.070	**52**	**26**	0	0	0.94	**0.00**	0.32	0.24	0.70	0.63	0.78

Note: Black boldface values are significant at 1 percent level. Red boldface values are those with no two-way causality and significant at the 1 percent level.

1/ Granger Causality (GC) tests with lag-lengths specified in each column.

2/ Equal to the number of lags if the p-value is less than 0.01 and no two way causality, 0 otherwise.

3/ Based on ordinary least squares regression that regresses the Systemic Financial Stress (SFS) indicator on various lags of itself and the risk indicators; the p-values are for the t-tests for each of the lags in the same regression. The lag-length score is the weighted average of the p-values if the p-value is less than or equal to 0.01.

Source: Authors' estimates.

Table 4. Test 2—Forecastability of Extreme Events for U.S. Sample: Logit Regressions

	p-Values for Sum of Lags of Indicators Equal to 0			Weighted average p-values	p-Value Score	McFadden R-squares			McFadden R2 Scores	Total Score
	6 weeks (weight = 6)	4 weeks (weight = 2)	1 week (weight = 1)			6 weeks (weight = 6)	4 weeks (weight = 2)	1 week (weight = 1)	weighted avg F - H	average E and I
Indicator	A	B	C	D	E=1-D	F	G	H	I	J
Credit Suisse Fear Baromet	**0.000**	**0.000**	**0.000**	0.00	1.00	0.32	0.29	0.19	0.30	0.65
Time-varying CoVaR	**0.000**	**0.000**	**0.000**	0.00	1.00	0.41	0.35	0.36	0.39	0.69
Rolling CoVaR	0.368	0.093	**0.002**	0.27	0.73	0.26	0.21	0.13	0.23	0.48
DD banks	**0.001**	**0.000**	**0.000**	0.00	1.00	0.36	0.34	0.31	0.35	0.68
Systemic Liquidity Risk Inde	0.036	**0.006**	**0.000**	0.03	0.97	0.29	0.27	0.20	0.27	0.62
Diebold-Yilmaz	**0.000**	**0.000**	**0.000**	0.00	1.00	0.32	0.26	0.19	0.29	0.64
JPoD	0.043	0.033	0.022	0.04	0.96	0.62	0.52	0.21	0.55	0.76
Systemic CCA	0.750	0.530	0.079	0.63	0.37	0.28	0.22	0.12	0.25	0.31
Libor-OIS spread	**0.003**	**0.000**	**0.004**	0.00	1.00	0.37	0.34	0.26	0.35	0.67
VIX	0.021	**0.001**	**0.000**	0.01	0.99	0.31	0.29	0.23	0.30	0.64
Yield curve	0.686	0.528	0.158	0.59	0.41	0.29	0.24	0.12	0.26	0.33

Note: Black boldface values are significant at 1 percent level.

Source: Authors' estimates.

Table 5. Test 3—Turning Points for the U.S. Sample: Quandt-Andrews Breakpoint Tests on Persistence and Level

	Persistance			Level			
Indicator	Break date	p-Value	Rank Score (higher the better)	Break date	p-Value	Rank Score (higher the better)	Total Score
Credit Suisse Fear Barometer	30-Apr-2007	0.097	0.1	30-Apr-2007	0.077	0.1	0.1
Time-varying CoVaR	**6-Aug-2007**	0.000	0.5	**6-Aug-2007**	0.000	0.5	0.5
Rolling CoVaR	26-Feb-2007	0.967	0.1	**24-Sep-2007**	0.013	0.4	0.2
DD banks	**9-Jul-2007**	0.031	0.9	**9-Jul-2007**	0.000	1.0	1.0
Systemic Liquidity Risk Index	6-Aug-2007	0.111	0.1	**6-Aug-2007**	0.002	0.5	0.3
Diebold-Yilmaz	**16-Jul-2007**	0.000	0.8	**16-Jul-2007**	0.000	0.9	0.9
JPoD	**24-Sep-2007**	0.021	0.4	9-Jul-2007	0.647	0.1	0.2
Systemic CCA	**6-Aug-2007**	0.000	0.5	23-Jul-2007	0.255	0.1	0.3
Libor-OIS spread	**30-Jul-2007**	0.000	0.7	**6-Aug-2007**	0.000	0.5	0.6
VIX	**9-Jul-2007**	0.008	0.9	**23-Jul-2007**	0.000	0.8	0.9
Yield curve	**27-Aug-2007**	0.000	0.5	**6-Aug-2007**	0.000	0.5	0.5

Note: Black boldface values are significant at 5 percent level.

Source: Authors' estimates.

Table 6. Overall Results—Performance of Near-Coincident Risk Indicators for the United States

Indicator	Forecasting Stress (Granger Causality)	Forecasting Extreme Event (Logit)	Turning Point (Breakpoint)	**Average**
Diebold-Yilmaz	0.34	0.64	0.86	**0.62**
Time-varying CoVaR	0.50	0.69	0.50	**0.56**
DD banks	0.02	0.68	0.95	**0.55**
Yield curve	0.78	0.33	0.45	**0.52**
VIX	0.04	0.64	0.86	**0.51**
Libor-OIS spread	0.05	0.67	0.59	**0.44**
JPoD	0.02	0.76	0.23	**0.34**
Systemic Liquidity Risk Index	0.00	0.62	0.27	**0.30**
Credit Suisse Fear Barometer	0.01	0.65	0.09	**0.25**
Rolling CoVaR	0.01	0.48	0.23	**0.24**
Systemic CCA	0.00	0.31	0.32	**0.21**

Notes: The scores are based on tests carried over the period from January 2003 to April 2011 for the forecasting of stress and forecasting of extreme events tests and a sample from November 2004 to March 2008 for the turning point test. The JPoD is estimated on a sample including Bear Stearns and is estimated up to the failure of Bear Stearns in March 2008.

Sources: Authors' estimates.

Table 7. Performance of Near-Coincident Risk Indicators for the Euro Area

Indicator	Forecasting Stress (Granger Causality)	Forecasting Extreme Event (Logit)	Turning Point (Breakpoint)	**Average**
Libor-OIS spread	0.50	0.71	0.75	**0.65**
Time-varying CoVaR	0.32	0.72	0.60	**0.55**
Diebold-Yilmaz	0.01	0.67	0.95	**0.54**
JPoD	0.47	0.53	0.60	**0.53**
Systemic Liquidity Risk Index	0.00	0.75	0.60	**0.45**
VIX	0.48	0.70	0.15	**0.44**
Credit Suisse Fear Barometer	0.01	0.66	0.55	**0.41**
DD banks	0.00	0.72	0.45	**0.39**
Yield curve	0.34	0.41	0.10	**0.28**
Systemic CCA	0.00	0.46	0.15	**0.20**

Notes: The scores are based on tests carried over the period from January 2003 to April 2011 for the forecasting of stress and forecasting of extreme events tests and a sample from November 2004 to March 2009 for the turning point test. VIX for the euro area refers to the implied volatility index of the EURO STOXX 50 index.
Sources: Authors' estimates.

Table 8. Thresholds for Near-Coincident Risk Indicators in the United States

	Persistence turning point		Level turning point			
Risk indictaor	Date of turning point	Indicator value at turning point	Date of turning point	Indicator value at turning point	Threshold	Concern if indicator value
Credit Suisse Fear Barometer	30-Apr-2007	25.52	30-Apr-2007	25.52	-3.91	**falls by more** than threshold in short period of time (threshold based on change in indicator during week of level breakpoint)
Time-varying CoVaR	6-Aug-2007	7.17	6-Aug-2007	7.17	7.2	**higher** than threshold (threshold range based on persistence and level breaks)
DD banks	9-Jul-2007	8.91	9-Jul-2007	8.91	8.9	**lower** than threshold (threshold range based on persistence and level breaks)
Systemic Liquidity Risk Index	6-Aug-2007	-0.48	6-Aug-2007	-0.48	-0.48	**higher** than threshold
Diebold-Yilmaz	16-Jul-2007	0.83	16-Jul-2007	0.83	0.83	**higher** than threshold
JPoD	24-Sep-2007	0.0004	9-Jul-2007	0.0002	0.0002 - 0.0004	**higher** than threshold (threshold range based on persistence and level breaks)
Systemic CCA	6-Aug-2007	0.22	23-Jul-2007	0.15	0.15 - 0.22	**higher** than threshold (threshold range based on persistence and level breaks)
Libor-OIS spread	30-Jul-2007	18.50	6-Aug-2007	48.30	18.5 - 48.3	**higher** than threshold (threshold range based on persistence and level breaks)
VIX	9-Jul-2007	17.57	23-Jul-2007	24.17	18 - 24	**higher** than threshold (threshold range based on persistence and level breaks)
Yield curve	27-Aug-2007	0.54	6-Aug-2007	-0.01	0.48	**increases by more** than threshold in short period of time (threshold based on change in indicator during week of level breakpoint)

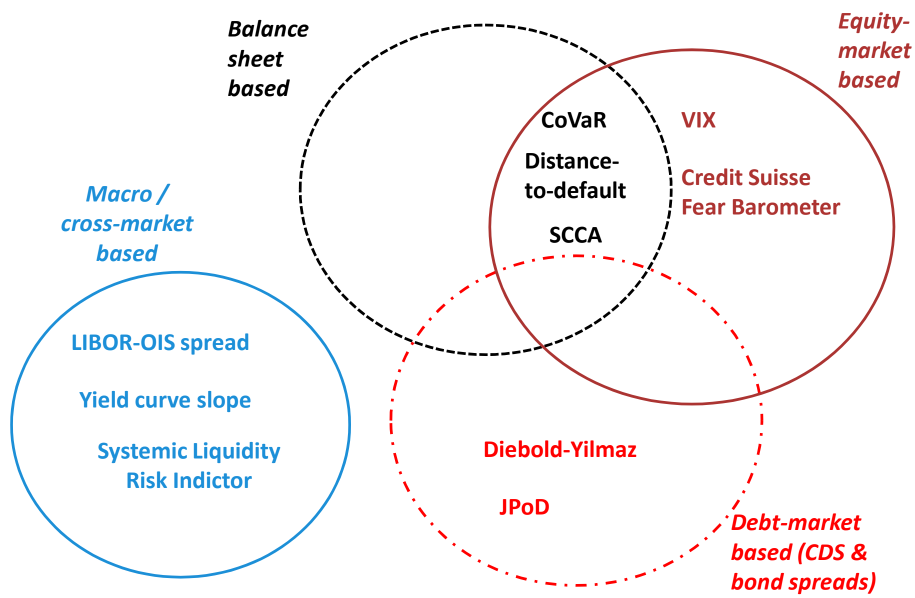
Notes: Turning points estimated over sample from November 2004 to March 2008.
Source: Authors' estimates.

Table 9. Thresholds for Near-Coincident Risk Indicators in the Euro Area

Risk indicator	Persistence turning point: Date of turning point	Persistence turning point: Indicator value at turning point	Level turning point: Date of turning point	Level turning point: Indicator value at turning point	Threshold	Concern if indicator value
Credit Suisse Fear Barometer	30-Apr-2007	25.22	30-Apr-2007	25.22	-3.91	**falls by more** than threshold in short period of time (threshold based on change in indicator during week of level breakpoint)
Time-varying CoVaR	14-Apr-2008	1.81	6-Aug-2007	0.90	0.9 - 1.8	**higher** than threshold (threshold range based on persistence and level breaks)
DD banks	7-May-2007	6.94	9-Jul-2007	7.32	6.94 - 7.32	**lower** than threshold (threshold range based on persistence and level breaks)
Systemic Liquidity Risk Index	14-Jan-2008	-0.47	23-Jun-2008	0.03	-0.47 - 0.03	**higher** than threshold (threshold range based on persistence and level breaks)
Diebold-Yilmaz	25-Jun-2007	0.74	25-Jun-2007	0.74	0.74	**higher** than threshold
JPoD	7-Apr-2008	0.00	7-Jan-2008	0.00	0.0002 - 0.0005	**higher** than threshold (threshold range based on persistence and level breaks)
Systemic CCA	8-Oct-2007	0.18	30-Jun-2008	7.01	0.18 - 7.01	**higher** than threshold (threshold range based on persistence and level breaks)
Libor-OIS spread	6-Aug-2007	14.92	6-Aug-2007	14.92	14.92	**higher** than threshold
VIX	2-Jun-2008	23.41	30-Jun-2008	26.79	23 - 27	**higher** than threshold (threshold range based on persistence and level breaks)
Yield curve	27-Oct-2008	1.44	15-Sep-2008	0.08	0.43	**increases by more** than threshold in short period of time (threshold based on change in indicator during week of level breakpoint)

Notes: Turning points estimated over sample from November 2004 to March 2009. VIX for the euro area refers to the implied volatility index of the EURO STOXX 50 index.
Source: Authors' estimates.

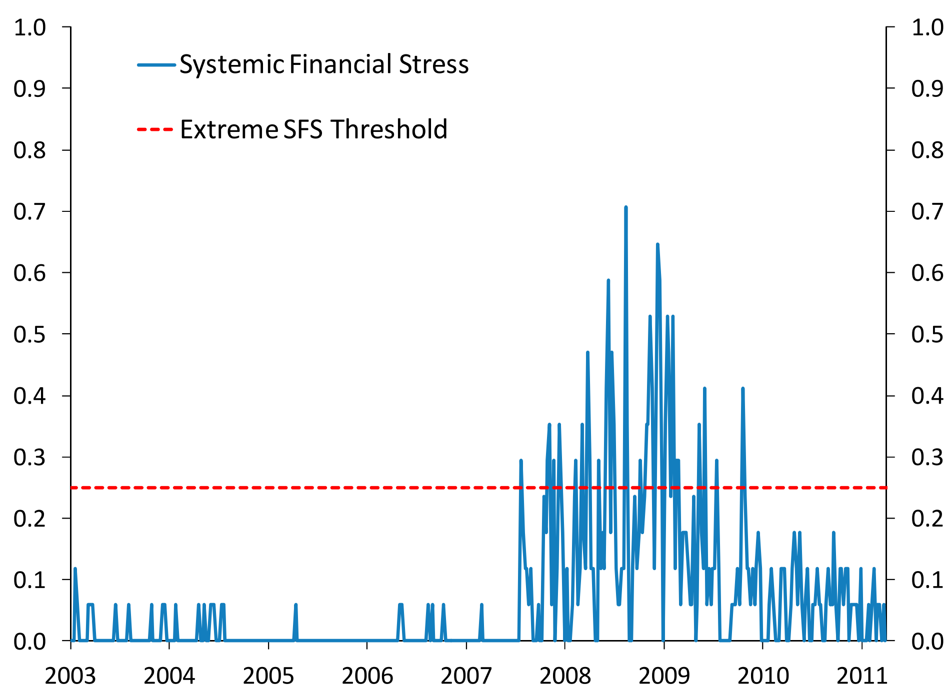
Figure 1. Data Requirements for Near-Coincident Indicators



Source: Authors’ presentation.

Figure 2. Systemic Financial Stress in the United States

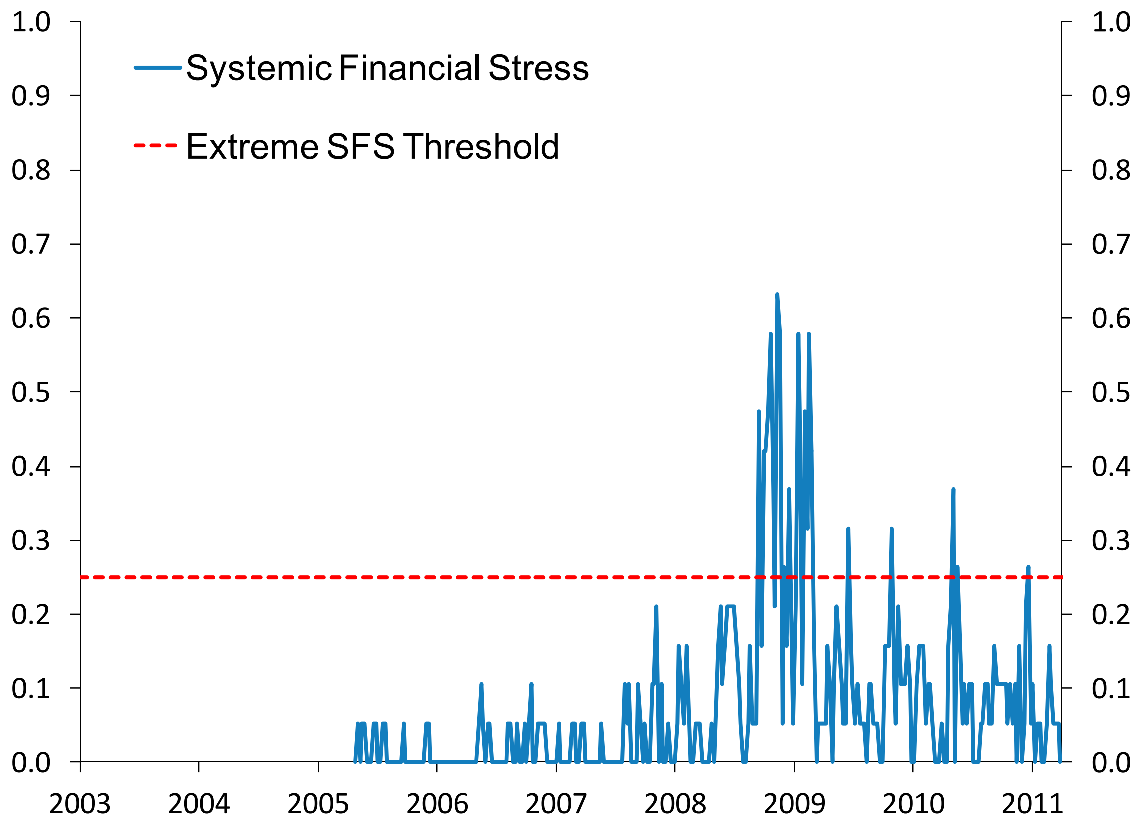
(Fraction of U.S. financial institutions experiencing large and persistent negative abnormal returns)



Source: Authors’ estimates.

Figure 3. Systemic Financial Stress in the Euro Area

(Fraction of euro area financial institutions experiencing large and persistent negative abnormal returns)



Source: Authors' estimates.

Figure 4. "Near Coincident" Risk Indicators for the United States

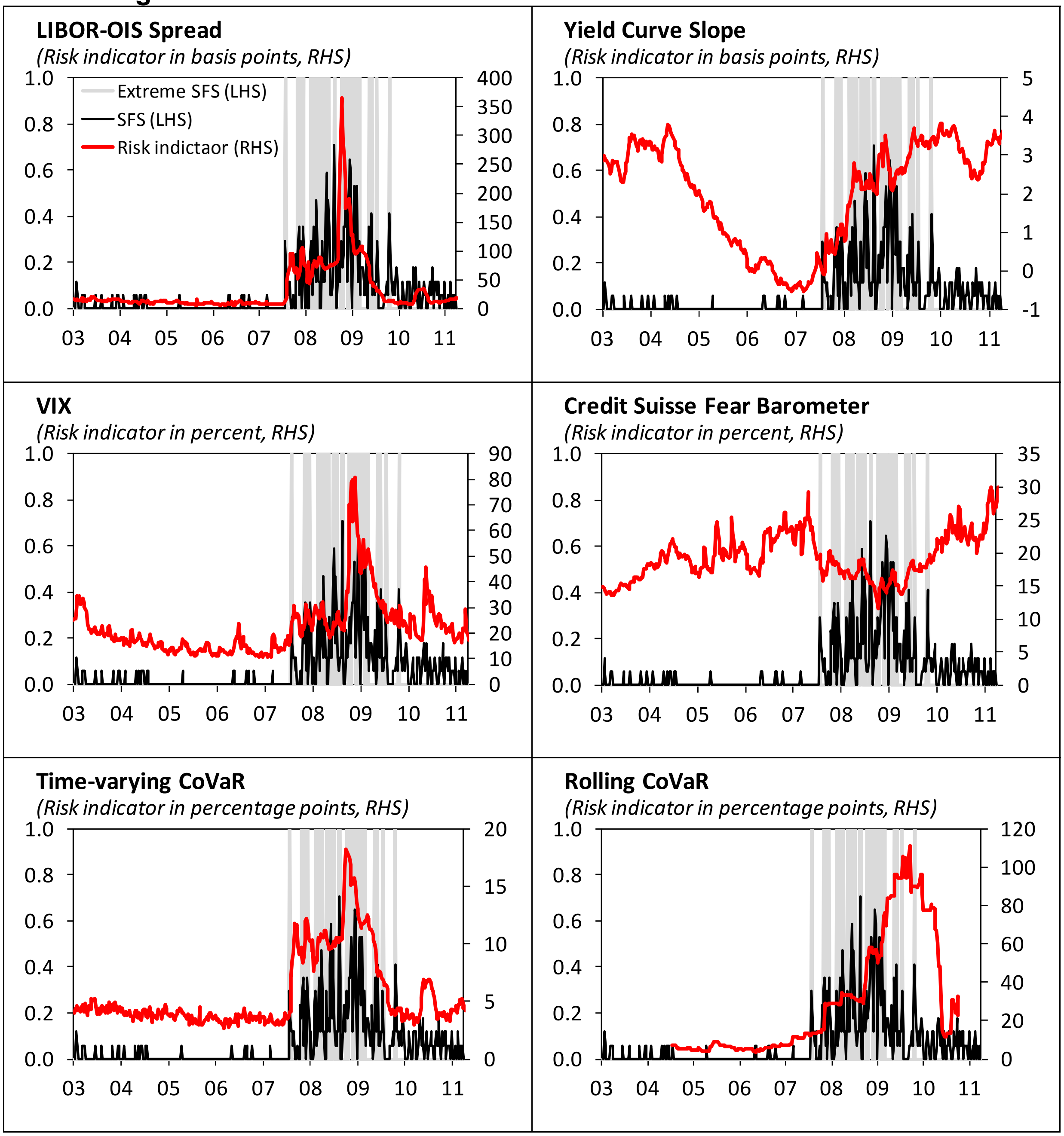
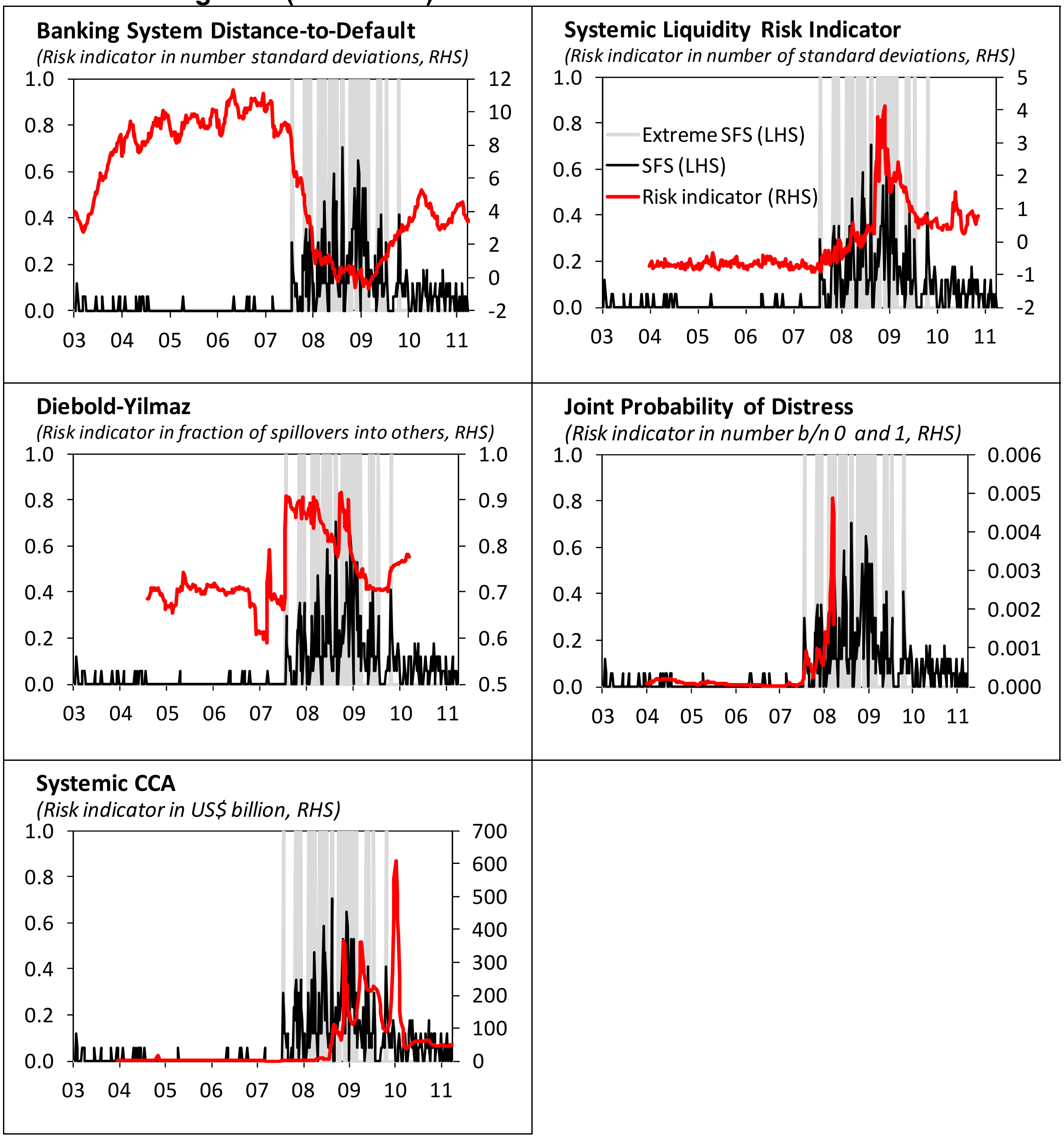
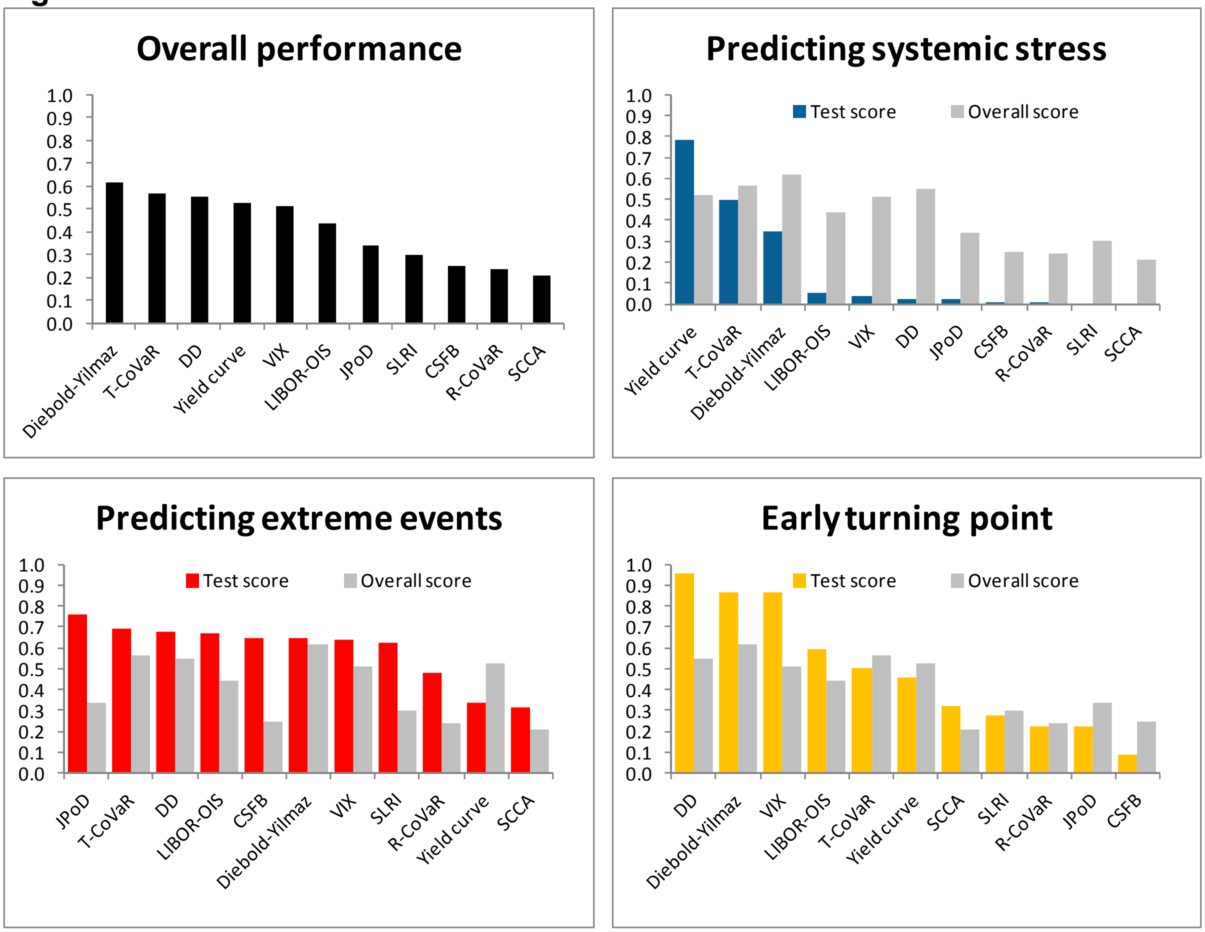


Figure 4 (continued). "Near Coincident" Risk Indicators



Sources: Bloomberg; Authors' estimates; see Table 2 for detailed sources on each near-coincident risk indicator.

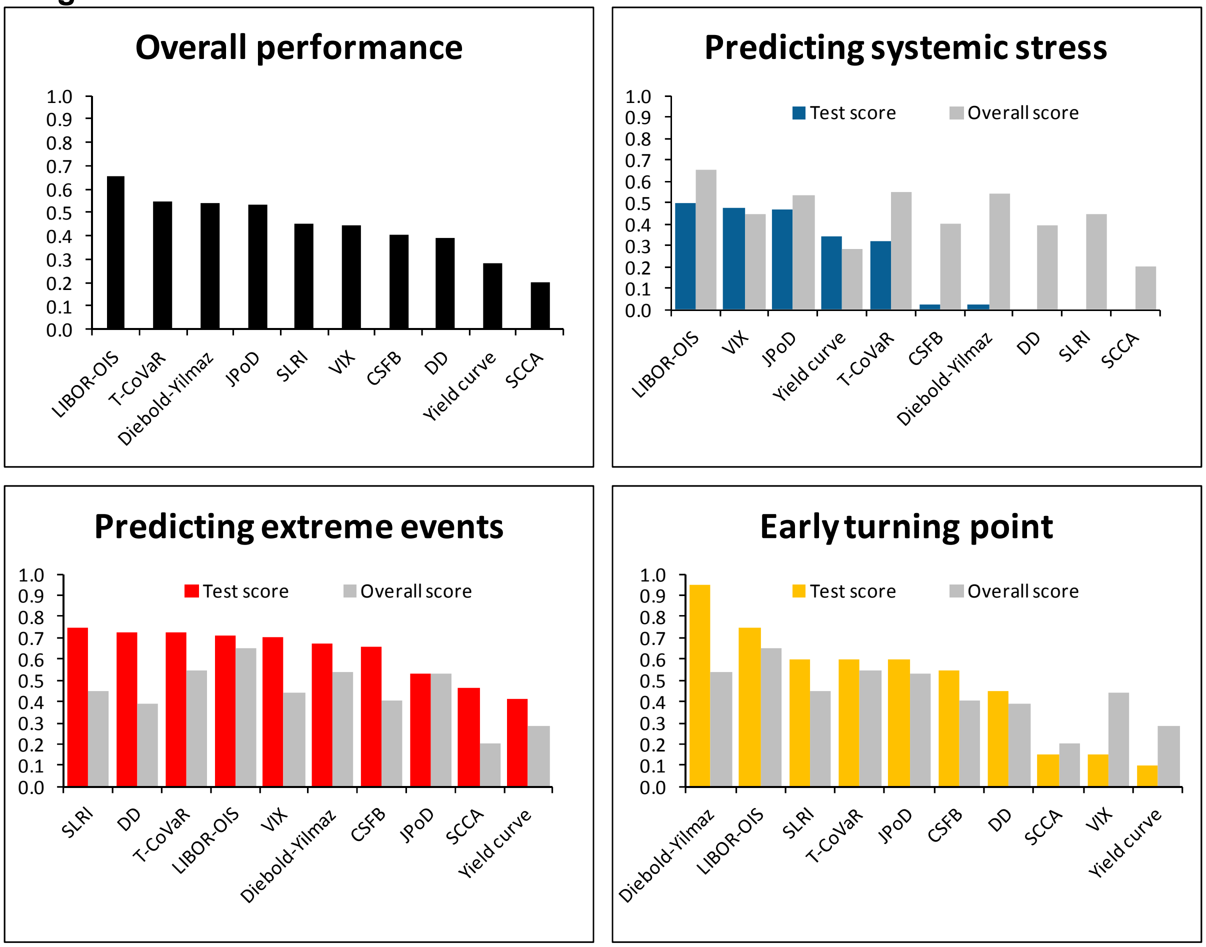
Figure 5. Performance of Near-Coincident Risk Indicators for the United States



Notes: T-CoVaR = time-varying CoVaR, DD = distance-to-default, Yield curve = 10-year/3-month slope, LIBOR-OIS = 3-month interbank rate over OIS, JPoD = joint probability of distress, SLRI = systemic liquidity risk indicator, CSFB = Credit Suisse Fear Barometer, R-CoVaR = rolling CoVaR, SCCA= systemic contingent claims analysis.

Sources: Authors' estimates.

Figure 6. Performance of Near-Coincident Risk Indicators for the Euro Area



Notes: T-CoVaR = time-varying CoVaR, DD = distance-to-default, Yield curve = 10-year/3-month slope, LIBOR-OIS = 3-month interbank rate over OIS, JPoD = joint probability of distress, SLRI = systemic liquidity risk indicator, CSFB = Credit Suisse Fear Barometer, R-CoVaR = rolling CoVaR, SCCA= systemic contingent claims analysis. VIX for the euro area refers to the implied volatility index of the EURO STOXX 50 index.
Sources: Authors' estimates.

Figure 7. Variation in Overall Score of U.S. Near-Coincident Risk Indicators Across Robustness Tests

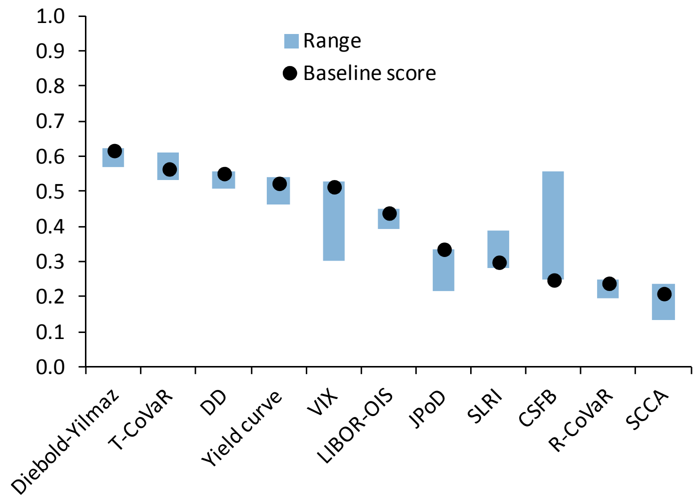
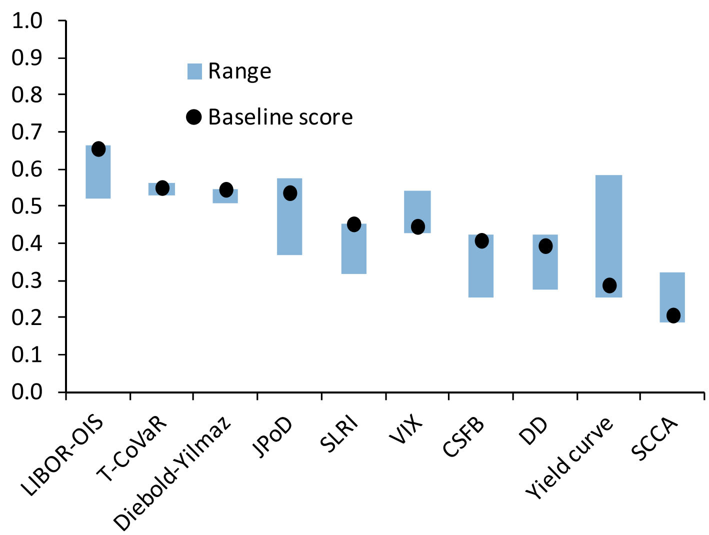
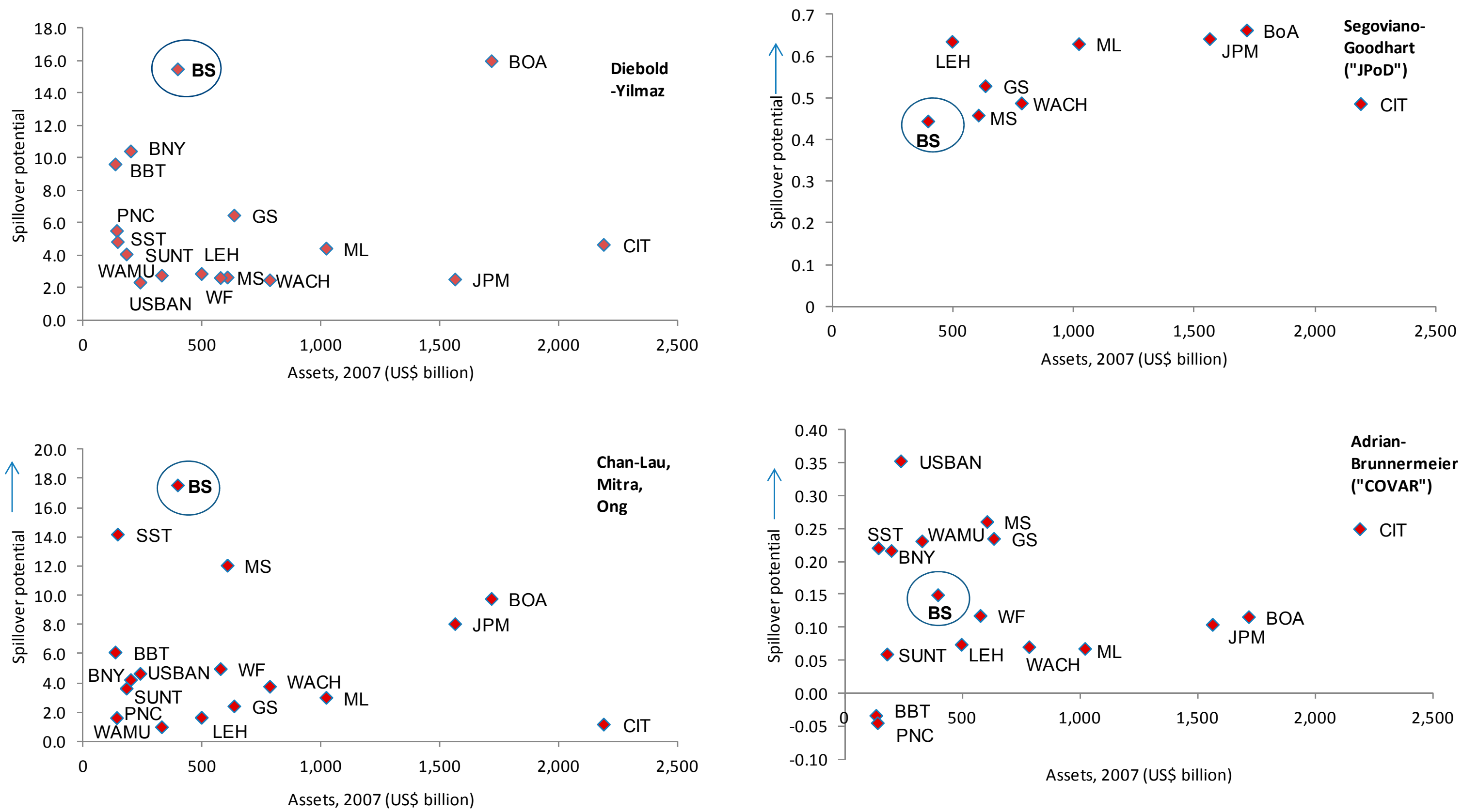


Figure 8. Variation in Overall Score of Euro Area Near-Coincident Risk Indicators Across Robustness Tests



Notes: T-CoVaR = time-varying CoVaR, DD = distance-to-default, Yield curve = Euro area 10-year/3-month government yield curve slope, VIX = S&P 500 implied volatility index, LIBOR-OIS = Euro 3-month interbank rate over OIS, JPoD = joint probability of distress, SLRI = systemic liquidity risk indicator, CSFB = Credit Suisse Fear Barometer, SCCA= systemic contingent claims analysis. VIX for the euro area refers to the implied volatility index of the EURO STOXX 50 index.
Source: Authors' estimates.

Figure 9. Interconnectedness: Spillover Risk for U.S. Financial Institutions in 2007



Notes: See Table 2 for explanation of each indicator. All the charts are based on the static version of the spillover indices, using daily data from 12/30/2002-06/30/2007, except for the JpoD, which is based on the end-June 2007 value from the rolling probability that at least one other bank will default if a certain bank defaults. All the four indices are based on the concept of "contribution"—the contribution of a particular bank to potential spillovers to other banks. "Chan-Lau, Mitra, Ong" is based on the method discussed in Chan-Lau, Mitra, Ong (2012). Bank name abbreviations: BOA = Bank of America, BNY = Bank of New York Mellon, BBT = BB&T, BS = Bear Stearns, CIT = Citigroup, GS = Goldman Sachs, JPM = JPMorgan Chase, LEH = Lehman Brothers, ML = Merrill Lynch, MS = Morgan Stanley, PNC =PNC; SST = State Street, SUNT = Sun Trust, USBAN = US Bancorp, WACH= Wachovia, WAMU = Washington Mutual, WF = Wells Fargo. Source: Authors' estimates

References

Adrian, Tobias and Markus Brunnermeier, 2010, "CoVaR," Federal Reserve Bank of New York Staff Reports.

Aït-Sahalia, Yacine, Jochen Andritzky, Andreas Jobst, Sylwia Nowak, and Natalia T.Tamirisa, 2009, "How to Stop a Herd of Running Bears? Market Response to Policy Initiatives during the Global Financial Crisis," IMF Working Paper, September 2009.

Bisias, Dimitrios, Mark Flood, Andrew W. Lo, and Stavros Valavanis, 2012, "A Survey of Systemic Risk Analytics," Office of Financial Research Working Paper 1, January.

Blancher, Nicolas, Srobona Mitra, Hanan Morsy, Akira Otani, Tiago Severo, and Laura Valderrama, *forthcoming,* 2013, "SysMo—Practical Guidance on the Toolkit for Systemic Risk Monitoring," IMF Working Paper.

Borio, Claudio, and Mathias Drehmann, 2009, "Assessing the Risk of Banking Crises—Revisited," BIS Quarterly Review, March, pp. 29–44.

Chan-Lau, Jorge, Srobona Mitra, and Li Lian Ong, 2012, "Identifying Contagion Risk in the International Banking System: An Extreme Value Theory Approach," International Journal of Finance and Economics Vol. 17 (4), October.

Chicago Board Options Exchange, 2009, The CBOE Volatility Index - VIX, available at http://www.cboe.com/micro/VIX/vixwhite.pdf.

Gray, Dale F. and Jobst, Andreas A., 2010, "New Directions in New Directions in Financial Sector and Sovereign Risk Management," *Journal of Investment Management*, Vol. 8, No. 1, pp. 23–38.

De Nicolò, Gianni and Myron Kwast, 2002, "Financial Risk and Consolidation: Are They Related?" *Journal of Banking and Finance*, Vol. 26, no. 5, pp. 861–80.

Diebold, Francis X. and Kamil Yilmaz, 2009, "Measuring Financial Asset Return and Volatility Spillovers, With Application to Global Equity Markets," *Economic Journal*, Vol.119, pp.15–71.

Tom, Edward K. and Dennis Davitt, 2009, "Fear Factor: The Credit Suisse Fear Barometer (CSFB)," Credit Suisse Equity Derivatives Strategy, April 13.

Estrella, Arturo, 2005. "Why Does the Yield Curve Predict Output and Inflation?" Economic Journal 115, no. 505 (July): 722–44.

European Central Bank, 2008, "The Euro Area Financial System," Financial Stability Review, December, pp. 100–05.

Forbes, K and R. Rigobon, 2002, "No Contagion, Only Interdependence: Measuring Stock Market Comovements," *Journal of Finance*, Vol LVII, No. 5, October.

International Monetary Fund, Bank of International Settlements, Financial Stability Board (IMF-BIS-FSB), 2009, "Guidance to Assess the Systemic Importance of Financial Institutions, Instruments, and Markets: Initial Considerations," Report to the G-20 Finance Ministers and Governors (October).

International Monetary Fund Staff and Financial Stability Board Secretariat (IMF-FSB), 2009, "The Financial Crisis and Information Gaps," Report to the G-20 Finance Ministers and Central Bank Governors (October).

International Monetary Fund, 2009, "Detecting Systemic Risk," Chapter 3 in *Global Financial Stability Report*, World Economic and Financial Surveys (Washington, April).

__________, 2010, "The IMF-FSB Early Warning Exercise: Design and Methodological Toolkit", available at www.imf.org/external/np/pp/eng/2010/090110.pdf, September.

__________, 2011a, "Macroprudential Policy—An Organizing Framework," IMF Policy Paper, April.

__________, 2011b, "Towards Operationalizing Macroprudential Policy—When to Act?" Chapter 3 of Global Financial Stability Report, September.

__________, 2011c, United Kingdom: Stress Testing the Banking Sector Technical Note, IMF Country Report 11/227, July.

__________, 2011d, "How to Address the Systemic Part of Liquidity Risk," Chapter 2 of the Global Financial Stability Report, April.

__________, 2012a, "Factsheet: IMF-FSB Early Warning Exercise", available at http://www.imf.org/external/np/exr/facts/ewe.htm, March.

McCulley, Paul, 2008, "PIMCO Global Central Bank Focus: A Perfervid Moment," available at http://www.pimco.com/EN/Insights/Pages/GCBF%20Jan%202008.aspx, January.

Office of Financial Research, 2012, "A Survey of Systemic Risk Analytics," Working Paper Number 1, U.S. Department of Treasury, January.

Reinhart, Carmen M. and Kenneth Rogoff, 2011, "This Time is Different: Eight Centuries of Financial Folly", Princeton, NJ: Princeton University Press

Rodriguez-Moreno, Maria, and Juan Ignacio Peña, 2011, "Systemic Risk Measures: The Simpler the Better?" available at SSRN: http://ssrn.com/abstract=1681087, February.

Rose, Andrew K. and Mark M. Spiegel, 2009, "Predicting Crises, Part II: Did Anything Matter (to Everybody)?" FRBSF Economic Letter, available at http://www.frbsf.org/publications/economics/letter/2009/el2009-30.html, 28 September.

Schwaab, Bernd, Siem Jan Koopman, and Andre Lucas, 2011, "Systemic Risk Diagnostics: Coincident Indicators and Early Warning Signals," ECB Working Paper No. 1327 (Frankfurt: European Central Bank).

Segoviano, Miguel and Charles Goodhart, 2009, "Banking Stability Measures," IMF Working Paper No. 09/04 (Washington: International Monetary Fund).

Segoviano, Miguel and Pablo Padilla, 2006, "Portfolio Credit Risk and Macroeconomic Shocks: Applications to Stress Testing Under Data-Restricted Environments," IMF Working Paper No. 06/283 (Washington: International Monetary Fund).

Severo, Tiago, 2012, "Using Violations of Arbitrage to Measure Systemic Liquidity Risk and the Cost of Liquidity Insurance," IMF Working Paper 12/194 (Washington: International Monetary Fund)

Solé, Juan and Marco Espinoza-Vega, 2010, "Cross-Border Financial Surveillance: A Network Perspective," IMF Working Paper No. 10/105 (Washington: International Monetary Fund).

Taylor, John B. and John C. Williams, 2009, "A Black Swan in the Money Market," *American Economic Journal: Macroeconomics*, American Economic Association, Vol. 1(1), pp.58–83, January.