The reciprocal relationship between systemic risk and real economic activity

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The Reciprocal Relationship Between Systemic Risk and Real Economic Activity*

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Abstract

The contribution of this paper to the literature is three-fold: (1) it empirically uncovers the directionality and persistence of systemic risk surrounding "the great recession"; (2) it quantifies the reaction of the macro-economy to financial (banking) system shocks; and (3) it unearths feedback effects from the macro-economy to the (in)stability of a banking system. These contributions are attained by looking at the extremal dependence structure among banks, by presenting a multivariate framework for identifying and modeling their joint-tail distributions, and by constructing an aggregate system-wide distress index, a risk-stability index, which quantifies the systemic risk of a bank.

JEL Classification: C10, E44, F15, F36, F37

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1 Introduction

The recent financial crisis has highlighted the need to better understand the drivers of systemic (financial) risk and its reciprocal relationship with real economic activity. Therefore, spotting macro-systemic-risk linkages through a reliable and well-behaved framework can make it possible to devise macro-prudential tools and policies. Recently, both policymakers and academics have begun to discriminate between the "size" of a financial institution and its systemic importance. For example, Bernanke (2009) focuses on financial institutions that are "too interconnected to fail", while Rajan (2009) uses the term "too systemic to fail". Despite this divergence in terminology, during periods of severe distress, there is an incentive to prevent the collapse of risk factors (e.g. financial institutions, and/or exchange rates) because such failures can pose significant risks to the financial system, and consequently to the broader real economy. Accordingly, a trend has developed towards focusing on the macro-prudential perspective of banking regulation (see Aspachs et al., 2007; Goodhart et al., 2005, 2006; Lehar, 2005). However, as the 'great recession' has highlighted, policymakers and academics do not fully understand how risk spreads within and between financial systems, or which institutions can become systemically important or too interconnected to fail. Moreover, there is insufficient knowledge about the effects and desirability of particular regulatory macro-prudential measures. Accordingly, the contribution of this paper is three-fold: first, it empirically uncovers the directionality and persistence of distress surrounding "the great recession"; second, it quantifies the reaction of the macro-economy to financial system shocks; and third, the paper unearths feedback effects from the macro-economy to the (in)stability of a banking system.

The literature on contagion and systemic risk in the banking system can be classified into two categories: (i) direct channels, such as interbank markets, that systemically link banks; (ii) indirect channels, such as similar portfolio holdings in bank balance sheets. Studies in the first category focus on the contagion effect; that is, an extreme event in one risk factor may cause an extreme event in other risk factors. Specifically, Allen and Gale (2000) and Dasgupta (2004), focus on modeling the interbank market; while Cifuentes et al. (2005) go a step further, and consider two channels: (1) similar portfolio holdings, and (2) mutual credit exposure. This latter study shows that contagion propagates through changes in asset prices; that is, the indirect channel dominates. The second category focuses on the modeling of systemic risk and indirect channels. Luganoff and Schreft (2001) assume that the return of one bank's portfolio depends on the portfolio allocation of other banks. Given this assumption, they show that crises spread due to forward-looking behavior. De Vries (2005) starts from the fat-tail property of the underlying assets shared by banks, and argues that this creates the potential for a systemic breakdown (for comprehensive surveys on systemic risk modeling, see De Bandt and Hartmann, 2000; Allen et al., 2009).

Recent developments in multivariate EVT ($mEVT$) provides the opportunity to investigate extreme co-movements, which go to the heart of this paper. For instance, $mEVT$ has been applied to measure risk contagion across different financial markets in Longin and Solnik (2001), Hartman et al. (2004), and Poon et al. (2004); while Hartmann et al. (2007) apply multivariate EVT to the analysis of bilateral relations within the banking system. More recently, the Global Financial Stability Report published by the IMF in April 2009 has moved beyond bivariate relations by looking at the interconnection of financial distress within a system consisting of three banks (International Monetary Fund, 2009).

Several measures of systemic risk have recently appeared in empirical studies. For instance, Segoviano and Goodhart (2009) construct a metric for financial stability, which they call the PAO ("probability that at least one bank becomes distressed"). However, the PAO only reflects the probability of having at least one extra distress, without specifying the size of the systemic impact. Zhou (2010) extends the PAO measure by proposing a "systemic impact index" (SSI), which measures the expected number of bank failures in a banking system given that one particular bank fails. The difference between the PAO and the SSI is that the latter is more explicit about "systemic impact". The research herein applies the multivariate extreme value theory ($mEVT$) methodology to a portfolio composed of 30 banks from around the world, and calculates a risk-stability index (RSI) based on Garita and Zhou (2009) and Zhou (2010). This index quantifies systemic risk in a financial system, and for the purposes herein, is based on forward-looking price information stemming from credit default swap (CDS) spreads. One advantage of utilizing this risk-stability index, is that it reveals the importance of different risk factors (e.g. banks) in causing systemic risk, where the potential for a systemic breakdown of the financial system can be either weak or strong (see De Vries, 2005), depending on whether the "conditional probability of joint failure" fades away or remains asymptotically (see Garita and Zhou, 2009). Accordingly, the international monetary and financial system can be described as being relatively stable in the former case, while in the latter case it is more fragile.

The results indicate that, on average, Asian banks create slightly more instability to the financial system, very closely followed by U.S. banks, and then by European banks. Second, an increase of the RSI lowers the federal funds rate, while increasing the slope of the term structure. This result suggests that monetary policy reacts to financial instability concerns. The results of the panel VAR also indicate that a higher conditional probability of joint failure, and an increased sensitivity of market participants to higher failure risk deteriorates the general market by lowering the returns to the $S\&P500$. Moreover, the perception of market participants that the VIX is the "fear index" is corroborated by the results, since a positive shock to the risk-stability index increases the implied volatility of the market. Third, the paper unearths feedback effects from the macro-economy to the (in)stability of a banking system. These latter set of results indicate that “leaning against the wind” can help reduce the systemic risk of a financial system. Last but not least, the results show that an improvement in the returns to the $S\&P500$, as well as a reduction of market volatility, reduces the sensitivity of market participants to failure risk.

The remainder of the paper evolves as follows: Section 2 will discuss the measures of dependence employed herein. Section 3 provides and discusses the results stemming from the Risk-Stability Index, and also looks at the directionality of contagion and the persistence of distress surrounding "the great recession". Section 4 takes advantage of the time-series properties of the Risk-Stability Index, and estimates a panel VAR that links the instability of a financial system to the macro-economy. Lastly, section 5 concludes.

2 Measures of Dependence

2.1 Multivariate EVT: tail dependence

To assess VaR at a low probability level p, univariate EVT can be used to model the tail behavior of a "loss". However, since the focus herein is on "systemic risk", I omit the details on univariate risk modelling (for a formal analysis of univariate EVT, see Embrechts et al., 1997). Multivariate EVT ($mEVT$) takes into account more than the tail behavior of each individual risk factor, since it also looks at the extreme co-movements among them. Moreover, this approach makes it possible to find (possible) contagion effects stemming from "distress" in one risk factor in relation to other risk factors in a system. Let $X = (X_1, ..., X_d)$ denote the losses of d individual risk factors, where each risk factor X_i follows a univariate EVT setup with its own tail index α_i and scale function $a_i(t)$. Therefore, for any $x_1, x_2, ..., x_d > 0$, as $\delta \to 0$, we have:

$$\frac{P(X_1 > VaR_1(x_1\delta),\ or\ X_2 > VaR_2(x_2\delta),\ or, ..., or\ X_d > VaR_d(x_d\delta))}{\delta} = L(x_1, x_2, ..., x_d) \qquad (1)$$

where VaR denotes the value-at-risk of X_i, and L is a finite positive function. The L-function characterizes the co-movement of extreme events that X_i exceeds a high threshold $VaR_i(x_i\delta)$. $(x_1, x_2, ..., x_d)$ controls the level of the level of high threshold, which in turn controls the direction of extreme co-movements. However, this time around the values will be delimited between 1 and the number of risk factors d; the estimation procedure follows Huang (1992). Following Hartman et al. (2004), assume a system of two banks with loss returns X and Y. From the definition in (1) we have

$$\lim_{\delta \to 0} \frac{P(X > VaR_x(x\delta),\ or\ Y > VaR_y(y\delta))}{\delta} = L(x, y) = L(1, 1) \text{ for } x = y = 1 \qquad (2)$$

As noted by De Haan and Ferreira (2006), $1 \leq L(1, 1) \leq 2$. A value for $L(1, 1)$ equal to 1 indicates complete tail dependence. If $L(1, 1)$ equals 2, then it indicates tail independence. In the case there is an interest in looking at a multidimensional setting (e.g. the effects of one bank's failure on the rest of the financial system), as is the case in this paper, then equation (2) can be modified accordingly. For an exposition of how the L-function is connected to the modern instrument of dependence modeling - the copula - see Zhou (2010).

Risk-Stability Index (RSI)

Building on the $mEVT$ framework previously discussed, I construct a risk-stability index based on Garita and Zhou (2009) and Zhou (2010). As stated in the introduction, this index makes it possible to quantify the effect that a "failure" of any risk factor can have on an entire financial system, be it economy-wide or worldwide. For expositional purposes on the construction of the RSI, assume that a financial system consists of three banks. From equation (1) we know that

$$\frac{P(X_1 > VaR_1(x_1\delta),\ \text{or } X_2 > VaR_2(x_2\delta),\ \text{or } X_3 > VaR_3(x_3\delta))}{\delta} = L(x_1, x_2, x_3)$$

For bank X_i, the RSI is defined as:

$$RSI = \lim_{\delta \to 0} E(\text{number of crises in } X_2 \text{ and } X_3 \mid X_1 \text{ is in crisis}) \tag{3}$$

Denote $\Phi = 1\{X_i > VaR_i(\delta)\}$ as X_i being in crisis, for $i = 1, 2, 3$. Using this to rewrite (3), we obtain:

$$RSI_1 = \lim_{\delta \to 0} E(\Phi_2 + \Phi_3 \mid \Phi_1 = 1) \tag{4}$$

Note that the above expression can be rewritten as the sum of two expectations as follows:

$$E(\Phi_2 \mid \Phi_1 = 1) + E(\Phi_3 \mid \Phi_1 = 1) \tag{5}$$

Rewriting (5) in terms of probabilities, and by using equation 11 (see the Appendix) we get:

$$\begin{aligned} RSI_1 &= \lim_{\delta \to 0} \frac{P(\Phi_2 = 1 \ \&\ \Phi_1 = 1)}{P(\Phi_1 = 1)} + \frac{P(\Phi_3 = 1 \ \&\ \Phi_1 = 1)}{P(\Phi_1 = 1)} \\ &= \lim_{\delta \to 0} \frac{2\delta - P(\Phi_2 = 1 \text{ or } \Phi_1 = 1)}{\delta} + \frac{2\delta - P(\Phi_3 = 1 \text{ or } \Phi_1 = 1)}{\delta} \end{aligned} \tag{6}$$

By using equation (1) in the above expression, it is easy to show that:

$$RSI_1 = 2 * (d-1) - \sum_{i \neq j} L_{i,j}(1,1) \tag{7}$$

or in the three-bank example:

$$\begin{aligned} RSI_1 &= 2 - L(1,1,0) + 2 - L(1,0,1) \\ &= 4 - L(1,1,0) - L(1,0,1) \end{aligned}$$

An RSI close to $d-1$ means that risk-factor i has a high influence on the financial system, while an RSI close to 0 implies a negligible influence of risk-factor i on the financial system.

3 Empirical Results

3.1 Empirical Setup and Data

The well-being of the banking sector is (arguably) reflected in credit default swap spreads, since CDS spreads are a type of insurance against credit risk.[1] However, it is worth pointing out that there are those who argue against the reliability of CDS spreads as a trustworthy indicator of a firms' financial health. The main criticism being that CDS spreads may overstate a firm's "fundamental" risk when: (*i*) the CDS market is illiquid, and (*ii*) when the financial system is frothing with risk aversion. Even though these types of arguments might be accurate, they can become self-fulfilling factors if they have a real effect on the eagerness of the market to finance a particular firm (Segoviano and Goodhart, 2009). Consequently, this can lead to a real deterioration of a firm's financial health, as we have experienced throughout the 2007-2010 financial crisis. Additionally, even though CDS spreads may overshoot, they do not generally

[1] A CDS is similar to a put option written on a corporate bond, and like a put option, the buyer is protected from losses incurred by a decline in the value of the bond stemming from a "credit event". Accordingly, the CDS spread can be viewed as a premium on the put option, where payment of the premium is spread over the term of the contract. More specifically, CDS spreads are considered as determinants of default risk as well as liquidity risk (Das and Hanouma, 2006; Hull et al., 2004). Moreover, a long stream of research, starting with Merton (1974), has established a strong link between credit risk markets and equity markets.

stay wide of the mark for long, where the direction of the move is by and large a good distress signal. Therefore, the analysis to follow is based on an artificially constructed financial system composed of 30 banks from around the world. These banks are included because they are the most important banks in various countries for which CDS spreads are available for the longest time period. The daily CDS spreads (all at 5-year maturity in USD) range from February 1, 2002 until July 22, 2010, and are obtained from Markit. The chosen banks are listed in Table 1 alongside the descriptive statistics of their CDS spreads.

From Table 1, we can observe that all daily CDS spreads exhibit high kurtosis relative to the kurtosis of the normal distribution, which is 3. This indicates that the CDS spreads may follow a heavy-tailed distribution. Moreover, the skewness of the CDS spreads is positive, indicating that the heavy-tailedness comes from the right-hand side of the distribution - high premiums paid by the protection buyer to the seller. Interestingly, from the descriptive statistics, we can also discern a large variation on the market perception of riskiness of the banks. The top four risky banks in the list $-$ Woori, Shinhan, Hana, and Morgan Stanley $-$ are approximately two to three times more risky than the "safest" banks, DBS and HSBC.

Before proceeding with the analysis, it is imperative to calculate the number of high-ordered statistics k, by using an estimator for the $L(1,1)-$function. The standard approach in the literature is to look at the $L(1,1)-function$ for different k, and for all the bilateral relationships, with the aim to "let the tail speak for itself".[2] The solution to this trade-off for each bilateral relationship yields a $k = 45$, which implies a quantile of $\delta = \frac{k}{n} = 9\%^3$. Moreover, in order to quantify the evolution of "(in)stability", a 500 day sub-sample moving (weekly) window is used to construct a time-series for the Risk-Stability Index (see Table 2 in the Appendix for the descriptive statistics of the RSI).

[2] This is the same technique as for choosing the tail-index with a Hill-plot (see Hill, 1975), in which we have a trade-off between "too small" or "too large" k. If k is "too small", then we choose too few observations and the variance of the estimator is large. If on the other hand, k is "too large", then we are incorporating "non-extreme" observations (i.e. observations from the middle of the distribution), and therefore we would impose a bias to the estimator.

[3] I also performed the analysis with a 200 day sub-sample moving (weekly) window. The quantile for this exercise was $\delta = \frac{20}{200} = 10\%$. Moreover, the results that follow stayed relatively unchanged.

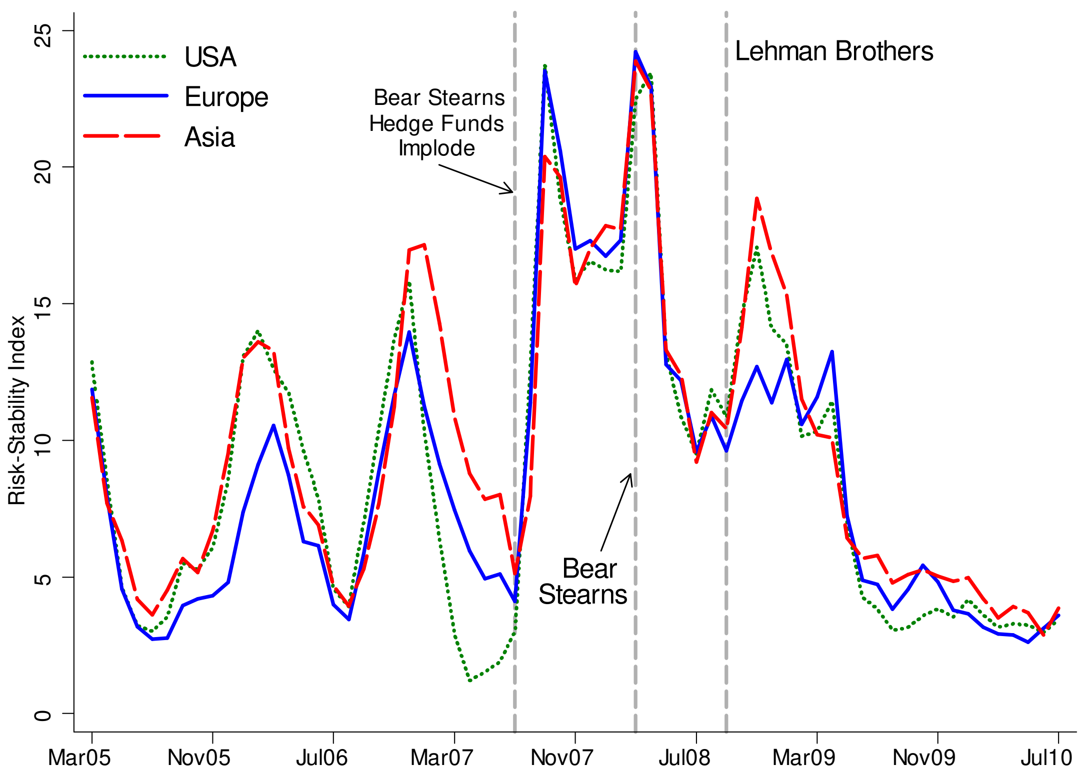
Table 1: Descriptive Statistics of CDS Spreads (in bps) for 30 Major Banks

Bank	N	Mean	SD	Skew.	Kurt.	Min	Max
BBVA	2206	45.65	51.08	1.93	7.22	7.77	308.05
BNP Paribas	2207	32.59	31.40	1.37	4.15	5.33	170.74
BOA	2207	60.68	66.65	1.86	6.67	8.09	400.25
Citi	2207	93.48	127.22	2.23	8.25	7.31	697.62
Credit Suisse	2176	54.85	49.55	1.41	4.61	9.01	267.19
DBS	2173	40.05	38.76	1.87	6.56	4.06	223.06
Deutsche Bank	2207	47.22	42.91	1.22	3.39	9.44	205.11
Erste	2042	71.78	88.58	1.89	6.93	9.90	503.73
Goldman Sachs	2207	84.31	84.24	2.20	8.37	18.49	633.10
Hana	2060	115.23	125.76	2.36	8.77	13.25	863.00
HSBC	2207	40.60	41.02	1.45	4.44	5.06	212.31
IBK	2010	102.77	116.39	2.42	9.30	12.60	848.13
ING	2190	44.20	41.45	1.44	4.19	4.37	205.20
JPMorgan	2207	58.81	42.00	1.32	4.55	11.41	250.23
KDB	2206	95.35	105.44	2.71	11.33	12.32	841.40
KEXIM	2206	94.16	104.30	2.71	11.31	11.93	832.18
Kookmin	2190	106.76	112.05	2.50	10.01	12.40	857.39
Lehman Brothers	1727	71.42	79.97	3.10	15.20	18.41	739.64
Mizuho	2014	56.42	44.17	0.61	2.09	5.88	180.83
Morgan Stanley	2207	108.37	140.60	3.73	24.97	18.14	1478.20
Nomura	2044	84.41	107.77	2.12	7.11	8.79	487.87
Santander	2207	48.87	47.18	1.35	4.47	7.55	267.29
Scotia	1703	49.67	51.23	1.24	3.00	9.12	169.74
Shinhan	1981	116.43	127.13	2.29	8.39	13.66	852.86
SocGen	2207	40.64	41.79	1.20	3.30	5.86	220.48
Standard Chart.	2176	54.22	60.57	2.25	8.91	5.44	365.87
Tokyo Mitsu.	2207	61.86	50.40	0.85	2.70	5.77	218.00
UBS	2207	52.39	69.27	1.87	6.32	3.96	372.25
Unicredito	1969	49.34	51.94	1.48	4.80	7.30	291.43
Woori	1996	129.99	136.69	2.21	8.12	12.27	881.67

3.2 Distress to Financial System

As previously mentioned, the risk-stability index makes it possible to quantify how the "failure" of a bank can affect a financial system, be it economy-wide or worldwide.[4] In simple terms, the risk-stability index gives an estimation of the number of risk-factors that would "catch a cold", given that a specific risk-factor "sneezes". Therefore, a risk-stability index (equation 7) close to $d-1$ means that risk-factor i has a high influence on the financial system, while an RSI close to 0 implies a negligible effect of risk-factor i on a portfolio (or financial system).

Figure 1: Risk-Stability Index Time-Series Surrounding the "Great Recession". Average RSI for Asia, Europe, United States. The vertical dashed lines indicate, from left to right: Implosion of Bear Stearns' Hedge Funds, and when SMBS' were uncovered in Europe; Collapse of Bear Stearns; Collapse of Lehman Brothers.



An immediate result that stands out from Figure 1 is the severity of the banking crisis surrounding "the great recession". As the RSI indicates, the global financial system was severely

[4]More generally, the RSI can also be used to quantify the effect that a "failure" of any risk-factor (e.g. stocks, or currencies) can have on any portfolio.

unstable surrounding the events related to demise of Bear Stearns, and the discovery of sub-prime mortgage backed securities around the world. The collapse of Lehman Brothers also had a significant impact in exacerbating systemic risk; however, this impact was slightly less severe than the shocks emanating from the gradual collapse of Bear Stearns. The RSI also indicates that in the two years prior to the beginning of "the great recession", the banking system was already experiencing severe bouts of distress (in contrast to the period beginning in the summer of 2009, when systemic risk had declined and remained, thereafter, at a low level). Last but not least, it is worth pointing out that throughout the entire period shown in Figure 1, banks tended to affect about 9 other banks, on average; this implies an average infection rate of 31% (Asian banks have an infection rate of 34%, while European and U.S. banks have an infection rate of 30% each). Once the crisis began, around the summer of 2007, the average infection rate, up to the summer of 2009, increased to 45% on average. However, looking at averages masks the fact that systemic risk and financial instability can arise from anywhere, irrespective of risk-factor and/or geographical location. (For an graphical overview for each individual bank, see Figures $2-4$).

Delving deeper into the individual banking reveals that for the US banking system (see Figure 2), and more specifically for Bank of America, Citi, and JPMorgan, the higher levels of systemic risk started with the bankruptcy of New Century Financial (at the time the largest sub-prime mortgage lender in the United States). However, Figure 2 also shows that for Goldman Sachs, Lehman Brothers, and Morgan Stanley, it was the implosion of the Bear Stearn Hedge funds (the "High-Grade Structured Credit Strategies Enhanced Leverage Fund", and the "High-Grade Structured Credit Fund") that led to higher systemic risk. The collapse of Lehman Brothers was most harshly felt by Goldman Sachs, Morgan Stanley, and Citi (see Figure 2).

For both European and Asian banks, Figures 3 and 4 show that the implosion of the Bear Stearn Hedge Funds, and the discovery of sub-prime mortgage backed securities (SMBS) in portfolios of banks and hedge funds around the world, is what led to the dramatic increase in systemic risk (ultimately being felt as a "credit-crunch"). Interestingly, the collapse of Lehman Brothers only seems to have moderately affected European banks. However, this event did create a large increase in systemic risk for Asian banks. The next section delves deeper in the directionality of systemic risk.

3.3 Directionality of Distress

In this subsection, I aim at uncover the directionality of distress by employing, for tractability purposes, 8 periods of 500 days each (with a one-year overlap). The results of this particular exercise are presented through Figure 5, which shows how the directionality of contagion to the financial system has evolved through the time surrounding "the great recession". This is accomplished by looking at how many banks will experience a "tail-event" at time t, given that bank "i" experienced a "tail-event" at $t-1$.

Figure 5: Directionality of Contagion - the figure shows the consequences to the banking system conditional on bank i "failing" one period before (see footnote 5 for period coding). For example, $1-2$ (on the x-axis) shows the repercussion to the system in period 2, given that bank i "fails" in period 1.

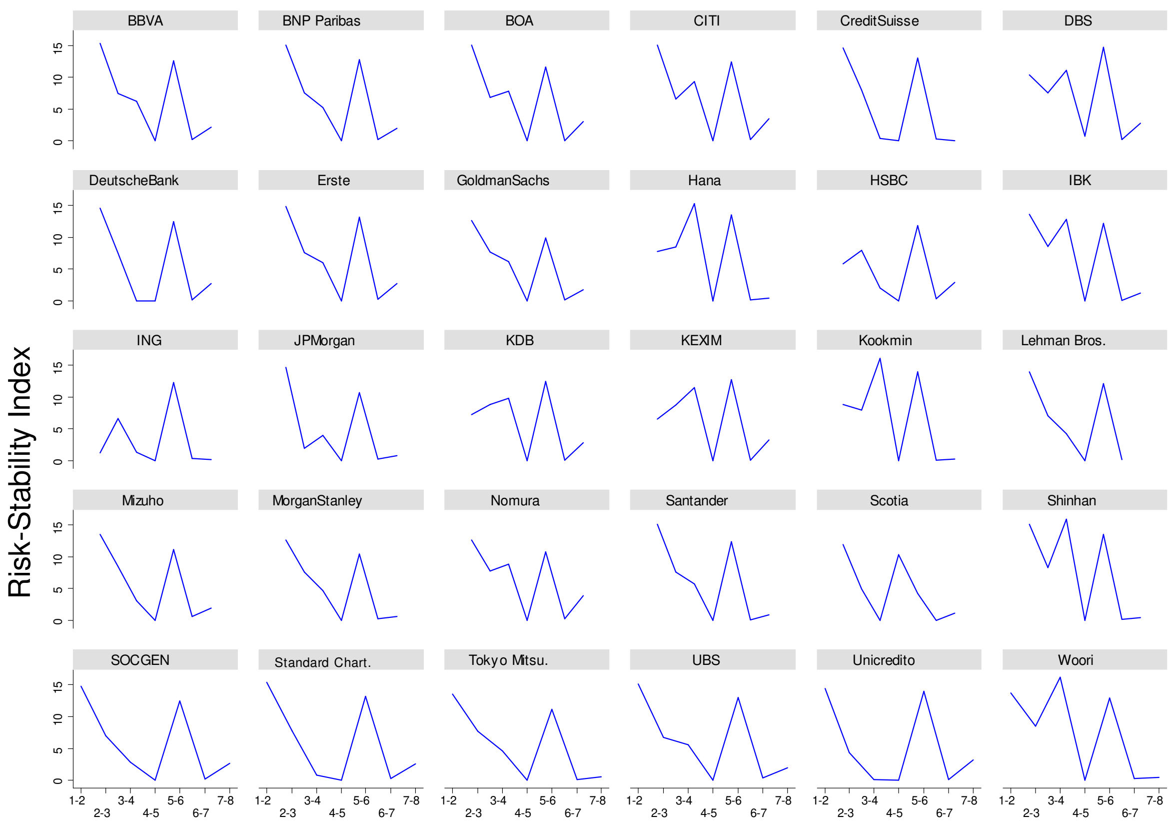


Figure 5[5] confirms that banks also affect the financial system with a lag; however, they do so at irregular intervals and with different magnitudes. This implies that the system is constantly under stress, where the source of the stress varies from period to period. Figure 5 also shows that the systemic impact of a tail-event in the banking system was higher in the year preceding "the great recession", since if a bank had "failed" in period 5, at least ten other banks would have experienced the same tail-event one period later. These results are corroborated by the facts discussed in sub-section 3.2, where we discovered that systemic risk began to build around the beginning of 2007. Interestingly, the lagged effect of the failure of Lehman Brothers is somewhat negligible, less than five banks suffered (a period later) because if its collapse.

3.4 Persistence of Distress

In order to capture the persistence of distress for bank i in a financial system, we need to capture systemic risk in a bivariate setting (in this case, systemic risk with itself).[6] I do this through the conditional probability of joint failure, which is a special measure of two-dimensional tail dependence (see the appendix, and Garita and Zhou, 2009), displayed here as Figure 6.

The result stemming from the CPJF, and as shown in Figure 6, indicate that, during the "great recession", the Japanese bank Mizuho experienced the most persistence of distress with an average $CPJF$ of 78%. In 2006, Mizuho started incurring massive losses on subprime investments; and in 2008, it lost more than US$6 billion on subprime investments, the most among Japan's top banks. Mizuho was followed by Lehman Brothers ($average\ CPJF = 36\%$) from the USA, which displayed an increasing pattern of persistence of distress as the crisis progressed. By the time it collapsed in September 2008, Lehman Brothers was fully systemic with itself. At the lower end of persistence are the Swiss banks CreditSuisse ($average\ CPJF = 4\%$) and UBS ($average\ CPJF = 5\%$), followed by ING ($average\ CPJF = 5\%$), Unicredito ($average\ CPJF = 5\%$), and JPMorgan ($average\ CPJF = 6\%$).

[5] The x-axis of Figure 5 is coded as follows: 1 = Feb 1, 2002 to Jan 1, 2004; 2 = Jan 16, 2003 to Dec 15, 2004; 3 = Jan 1, 2004 to Nov 30, 2005; 4 = Dec 16, 2004 to Nov 15, 2006; 5 = Dec 2, 2005 to Nov 1, 2007; 6 = Nov 20, 2006 to Oct 17, 2008; 7 = Nov 6, 2007 to Oct 5, 2009; 8 = Aug 19, 2008 to July 22, 2010.

[6] All other bilateral results stemming from the CPJF are available upon request.

Figure 6: Persistence of Distress - the figure shows the consequences to bank i, given that it experienced a "tail-event" one period before (see footnote 5 for period coding).

Table 3 indicates that banks are highly interlinked especially within geographical borders. For example, Asian banks tend to experience the most persistence of distress on average, with a 22% conditional probability of joint failure at time t, given that the same Asian bank experienced distress at $t-1$. Within Asia, Korean banks have a propensity to create and experience higher systemic risk for themselves ($CPJF = 25\%$). Asian (Korean) banks are followed by U.S. banks with a 16% CPJF, and then by European banks with an 10% CPJF, on average. These set of results corroborate Hartmann et al. (2007), who argued that in a more integrated banking system (e.g. the United States) area-wide systemic risk is higher, and that the lower overall spillover risk in Europe is due to the weak extreme cross-border linkages.

From Table 3 we can also discern how banks are affecting each other across regions. The Figure indicates that Asian banks are the most contagious for Europe ($CPJF = 18\%$), followed by US banks ($CPJF = 17\%$). However, US banks do not lag that far behind their Asian counterparts, since when a US bank experiences a "tail-event" in period $t-1$, a European or Asian bank will experience the same tail event in period t with a CPJF of 17%, on average. Lastly, European banks seem to be the less contagious for both Asian and US banks ($average\ CPJF = 11.5\%$).

Table 3: Directionality of Bilateral Contagion - Average CPJF Within and Across Regions

	Asia Banks$_t$	Asia-ex-Kor-Banks$_t$	Kor. Banks$_t$	Europe Banks$_t$	US Banks$_t$
Asia Banks$_{t-1}$	0.22	0.21	0.22	0.18	0.17
Asia-ex.Kor-Banks$_{t-1}$	0.19	0.21	0.18	0.14	0.14
Kor. Banks$_{t-1}$	0.23	0.21	0.25	0.20	0.20
Europe Banks$_{t-1}$	0.12	0.11	0.13	0.10	0.11
US Banks$_{t-1}$	0.18	0.15	0.20	0.16	0.16

4 VAR Analysis

This section implements a panel-data vector autoregression methodology (see Holtz-Eakin et al., 1988; Love and Ziccino, 2006) in order to uncover the feedback effect from the banking system to the rest of the economy. This procedure merges the traditional VAR and panel-data methodologies, by allowing for endogeneity and for unobserved individual heterogeneity. However, when applying the VAR approach to panel data, it is crucial that the underlying structure be the same for each cross-sectional unit (Love and Ziccino, 2006). Since this constraint is likely to be violated in practice, one way to overcome the restriction is to allow for "individual heterogeneity"; that is by introducing fixed effects in the levels of the variables. However, due to the lags of the dependent variables, the fixed effects are correlated with the regressors; therefore, the usual approach of "mean differencing" would create biased coefficients. Therefore, in order to avoid this problem, the panel VAR methodology uses forward mean-differencing, also known as the "Helmert procedure" (see Arrellano and Bover, 1995; Love and Ziccino, 2006). This transformation preserves the orthogonality between the transformed variables and the lagged regressors; thereby allowing the use of the lagged regressors as instruments and the estimation of the coefficients through a system GMM.

The impulse-response functions describe the reaction of one variable to the innovations in another variable in the system, while holding all other shocks equal to zero. However, since the actual variance–covariance matrix of the errors is unlikely to be diagonal, it is necessary to decompose the residuals in such a way that they become orthogonal, in order to isolate shocks to one of the variables in the system. The usual convention is to adopt a particular ordering and allocate any correlation between the residuals of any two elements to the variable that comes first in the ordering.[7] The identifying assumption is that the variables that come earlier in the ordering affect the following variables contemporaneously, as well as with a lag, while the variables that come later affect the previous variables only with a lag. In other words, the variables that appear earlier in the system are more exogenous, and the ones that appear later are more endogenous. Finally, to analyze the impulse-response functions we need an estimate of their confidence intervals. Since the matrix of impulse-response functions is constructed from the estimated VAR coefficients, their standard errors need to be taken into account. Accordingly, the standard errors of the impulse response functions and the confidence intervals are generated through Monte Carlo simulations.

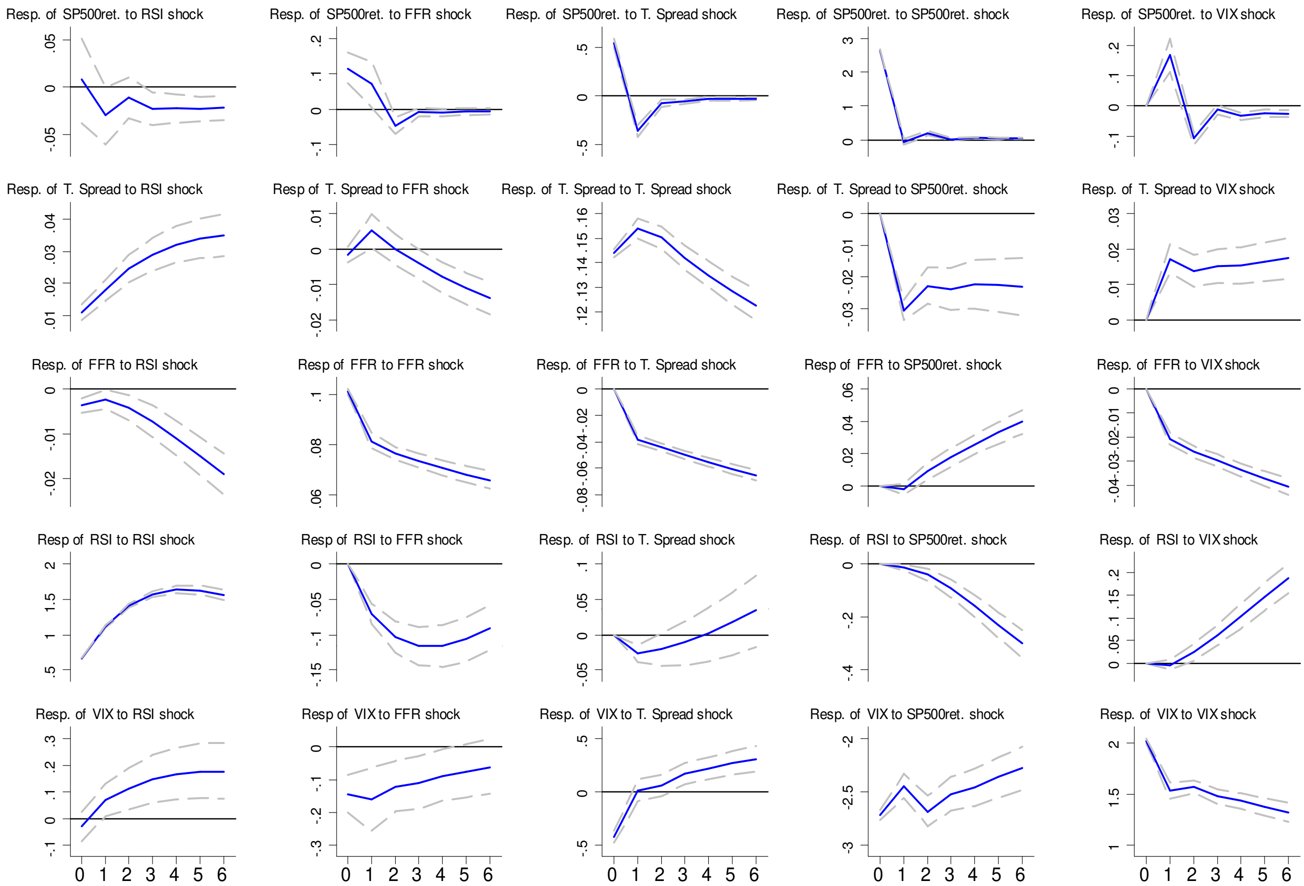
The panel VAR employs the RSI time-series (see Figures $1-4$), and the following financial market variables (from St.Louis FRED and CBOE): the short rate (effective federal funds rate), the term spread (diff. between 10-year and 3-month Treasury constant maturity rates), the market return (returns on the $S\&P500$), and the VIX, which is the implied market volatility. The number of lags in the panel VAR system equals 2, and is selected through the Schwarz Bayesian Information Criteria.

The reaction of the macroeconomy and the market to banking system shocks are as follows (see column 1 in Figure 7): an increase of the risk-stability index lowers the federal funds rate, while increasing the slope of the term structure; this suggests that monetary policy reacts to financial instability concerns. The results of the panel VAR also indicate that a higher conditional probability of joint failure, and an increased sensitivity of market participants to higher failure

[7] The procedure is known as the Choleski decomposition of the variance–covariance matrix of residuals, and is equivalent to transforming the system into a "recursive" VAR (see Hamilton, 1994).

risk deteriorates the general market, by lowering the returns to the $S\&P500$. Last but not least, the perception of market participants that the VIX is the "fear index" is corroborated by the results, since a positive shock to the risk-stability index increases the implied volatility of the market.

Figure 7: Impulse-Responses of a one standard deviation shock for 2-lag Panel VAR (errors are 5% on each side generated by Monte Carlo with 1000 replications). RSI = risk-stability index; FFR = effective federal funds fate; T.Spread = difference between 10 year and 3 month treasury constant maturity Rate; SP500 ret = returns on the SP500; VIX = implied volatility of the market.



As is well known, the VAR framework allows for a feedback effect (see row 4 in Figure 7) from the macro-economy and the general financial market to the banking system. This feedback effect shows that an increase in the federal funds rate (used as a proxy for the global interest rate) reduces the risk-stability index. This indicates that "leaning against the wind" decreases the instability of the financial (banking) system. Moreover, the results also indicate that an improvement in the returns to the $S\&P500$, as well as a reduction of the VIX (i.e. of market volatility), reduces the sensitivity of market participants to failure risk. The variance decomposition (Table 4) confirms the above-mentioned results. More specifically, the RSI explains about 5.5% of interest rate movements, especially at longer horizons (30 weeks). However, the RSI only has marginal explanatory power of the returns to the $S\&P500$ and the VIX. On the other hand, the returns to the $S\&P500$ explain more of the risk-stability index variation than any other variable (especially at longer time horizons), followed by the VIX.

Table 4: Variance Decomposition - variation in the row variable explained by column variable

	Step-Ahead	RSI	FFR	T.Spread	SP500ret	VIX
RSI	10	0.947	0.003	0.001	0.040	0.013
FFR	10	0.025	0.470	0.290	0.110	0.110
T.Spread	10	0.046	0.007	0.900	0.030	0.014
SP500ret	10	0.001	0.003	0.060	0.930	0.006
VIX	10	0.003	0.001	0.010	0.710	0.270
RSI	20	0.810	0.004	0.004	0.140	0.043
FFR	20	0.050	0.230	0.340	0.230	0.144
T.Spread	20	0.060	0.020	0.820	0.060	0.035
SP500ret	20	0.001	0.003	0.060	0.930	0.006
VIX	20	0.002	0.001	0.030	0.710	0.260
RSI	30	0.760	0.006	0.006	0.180	0.054
FFR	30	0.050	0.150	0.350	0.300	0.160
T.Spread	30	0.060	0.040	0.730	0.110	0.060
SP500ret	30	0.001	0.003	0.06	0.930	0.006
VIX	30	0.002	0.001	0.040	0.700	0.250

Note: RSI = Risk Stability Index; FFR = Effective Fed Funds Rate; T. Spread = Diff. between 10 year and 3 month treasury constant maturity rate; VIX = implied volatility of the market.

5 Conclusion

The macro-prudential view, which elicits explicit supervision of "asset prices" and the stability of the financial system, has by now gained wide acceptance among economists. Nonetheless, implementing macro-prudential regulation depends, largely, on the operational feasibility. Despite this "obstacle", the research herein offers a good foundation and a useful starting point towards understanding the rapport between financial (in)stability, systemic risk, and the real economy.

Accordingly, the contribution of this paper to the literature has been three-fold: first, it empirically uncovers the directionality and persistence of distress surrounding “the great recession”, where the results indicate that, on average, Asian banks create slightly more instability to the financial system, very closely followed by U.S. banks, and then by European banks. Second, it quantifies the reaction of the macro-economy to financial system shocks. An increase of the RSI lowers the federal funds rate, while increasing the slope of the term structure. This result suggests that monetary policy reacts to financial instability concerns. The results of the panel VAR also indicate that a higher conditional probability of joint failure, and an increased sensitivity of market participants to higher failure risk deteriorates the general market by lowering the returns to the $S\&P500$. Moreover, the perception of market participants that the VIX is the "fear index" is corroborated by the results, since a positive shock to the risk-stability index increases the implied volatility of the market. Third, the paper unearths feedback effects from the macro-economy to the (in)stability of a banking system. These latter set of results indicate that “leaning against the wind” can help reduce the systemic risk in/of a financial system. Last but not least, the results show that an improvement in the returns to the $S\&P500$, as well as a reduction of market volatility, reduces the sensitivity of market participants to failure risk.

The paper has also underscored that systemic risk varies from period to period, thus supporting the idea that financial (in)stability is a continuum. Therefore, the monitoring of financial stability within and between economies should be a counter-cyclical continuous process. This analysis must be wide-ranging, probing all risk-factors that influence the financial system; furthermore, it should be intended at the early detection of financial vulnerabilities, which can arise (from) anywhere and at any time, as this paper has quantified.

Another aspect that continues to be debated by academics and regulators is whether regulation should be aimed at institutions that are either "too big to fail" or "too interconnected to fail". While not directly tested herein, it seems that "too big to fail" is not a major factor in explaining the instability of a financial system. However, "too interconnected to fail", does seem to be of more importance. This is something that future research will have to uncover.

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Appendix

Conditional Probability of Joint Failure

Garita and Zhou (2009) define the "conditional probability of joint failure" (CPJF), which is a special measure of two-dimensional tail dependence, as follows: given that at least one risk-factor "fails", the CPJF is defined as the conditional probability that the other risk-factor will also "fail". Let $X = (X_1, X_2, ..., X_d)$ represent the losses of $d-$number of individual risk factors, then, the corresponding VaR (value at risk) at probability level δ of any two variables are $VaR_i(\delta)$ and $VaR_j(\delta)$. We then define:

$$CPJF_{i,j}=\lim_{\delta\to 0} P(X_i > VaR_i(\delta) \text{ and } X_j > VaR_j(\delta) | X_i > VaR_i(\delta) \text{ or } X_j > VaR_j(\delta)) \tag{8}$$

which can be rewritten as

$$CPJF_{ij} = E[\kappa|\kappa \geq 1] - 1 \tag{9}$$

where

$$E[\kappa|\kappa \geq 1] = \lim_{\delta\to 0} \frac{P(X_i > VaR_i(\delta)) + P(X_j > VaR_j(\delta))}{1 - P(X_i \leq VaR_i(\delta), X_j \leq VaR_j(\delta))} \tag{10}$$

is the dependence measure introduced by Embrechts et al. (2000), and first applied by Hartman et al. (2004). Under the $mEVT$ framework, the limit in (8) and (10) exists (see De Haan and Ferreira, 2006, Ch. 7). A higher CPJF between two risk-factors indicates that a "failure" of these two institutions is more likely to occur at the same time; moreover, the CPJFs may vary, which highlights the different linkages during crisis periods. In the two-dimensional case, the CPJF can be written as

$$\begin{aligned} CPJF &= \lim_{\delta\to 0} \frac{P(X_1 \text{ } and \text{ } X_2)}{P(X_1 \text{ } or \text{ } X_2)} = \lim_{\delta\to 0} \frac{P(X_1) + P(X_2) - P(X_1 \text{ } or \text{ } X_2)}{P(X_1 \text{ } or \text{ } X_2)} \\ &= \lim_{\delta\to 0} \frac{\delta + \delta - L(1,1) * \delta}{L(1,1) * \delta} \\ &= \frac{2}{L(1,1)} - 1 \end{aligned} \tag{11}$$

The CPJF always lies between 0 and 1. If it is zero, then the probability of joint failure is negligible; however, if it is one, then the "failure" of a risk factor in a portfolio will always go hand in hand with the downfall of the other risk factor. An important point to keep in mind before proceeding, is that conditional probabilities do not necessarily imply causation; however, this set of bilateral conditional probabilities of joint failure do provide important insights into the interlinkages and the likelihood of contagion between risk-factors in a portfolio (e.g. banks in a financial system).

Risk-Stability Index Descriptive Statistics and Graphs

Table 2: RSI Descriptive Statistics for 30 Major Banks

Bank	**Mean**	**SD**	**Skew.**	**Kurt.**	**Min**	**Max**
BBVA	7.92	5.85	1.02	3.42	0.78	26.09
BNP Paribas	9.23	5.66	0.79	2.98	0.96	26.29
Bank of America	8.96	5.84	0.62	2.56	1.09	25.62
Citi	9.04	6.13	0.55	2.34	1.24	25.78
Credit Suisse	8.99	5.81	0.71	2.94	0.56	25.96
DBS	9.07	5.41	0.63	2.77	1.07	26.29
Deutsche Bank	8.67	5.39	0.90	3.37	1.04	25.96
Erste	9.23	6.20	0.67	2.41	1.33	26.29
Goldman Sachs	8.55	5.56	0.71	2.73	0.42	25.58
Hana	10.37	5.38	0.72	2.59	2.67	25.96
HSBC	9.09	5.81	0.80	2.86	1.47	26.11
IBK	10.30	5.47	0.64	2.48	2.42	25.64
ING	7.91	5.94	1.01	3.39	0.40	26.29
JPMorgan	8.55	5.59	0.85	3.03	1.31	25.44
KDB	10.34	5.33	0.64	2.42	2.62	25.64
KEXIM	10.25	5.42	0.65	2.46	2.51	25.64
Kookmin	10.53	5.36	0.62	2.50	2.56	25.96
Lehman Brothers	8.30	6.39	0.49	2.34	0.00	25.62
Mizuho	9.62	5.70	0.52	2.42	1.02	26.29
Morgan Stanley	8.76	5.77	0.79	2.88	0.31	25.78
Nomura	8.74	6.04	0.70	2.71	0.56	25.89
Santander	8.96	5.92	0.72	2.91	0.87	26.09
Scotia	4.93	3.96	0.99	4.10	0.00	20.38
Shinhan	10.52	5.51	0.61	2.33	2.20	25.96
SocGen	9.27	5.62	0.79	2.97	1.62	26.07
Standard Chart.	9.76	5.69	0.60	2.63	1.60	26.29
Tokyo Mitsu.	9.90	5.65	0.44	2.30	1.82	26.29
UBS	9.77	5.59	0.61	2.77	0.80	26.04
Unicredito	7.19	5.87	1.14	3.60	0.24	26.29
Woori	10.45	5.67	0.51	2.25	2.60	25.96
Total	9.11	5.77	0.68	2.71	0.00	26.29

Figure 2: Risk-Stability Index Time-Series for Individual US Banks. The vertical dashed lines indicate, from left to right: Bankruptcy of New Century Financial; Implosion of Bear Stearns' Hedge Funds; Collapse of Bear Stearns; Collapse of Lehman Brothers.

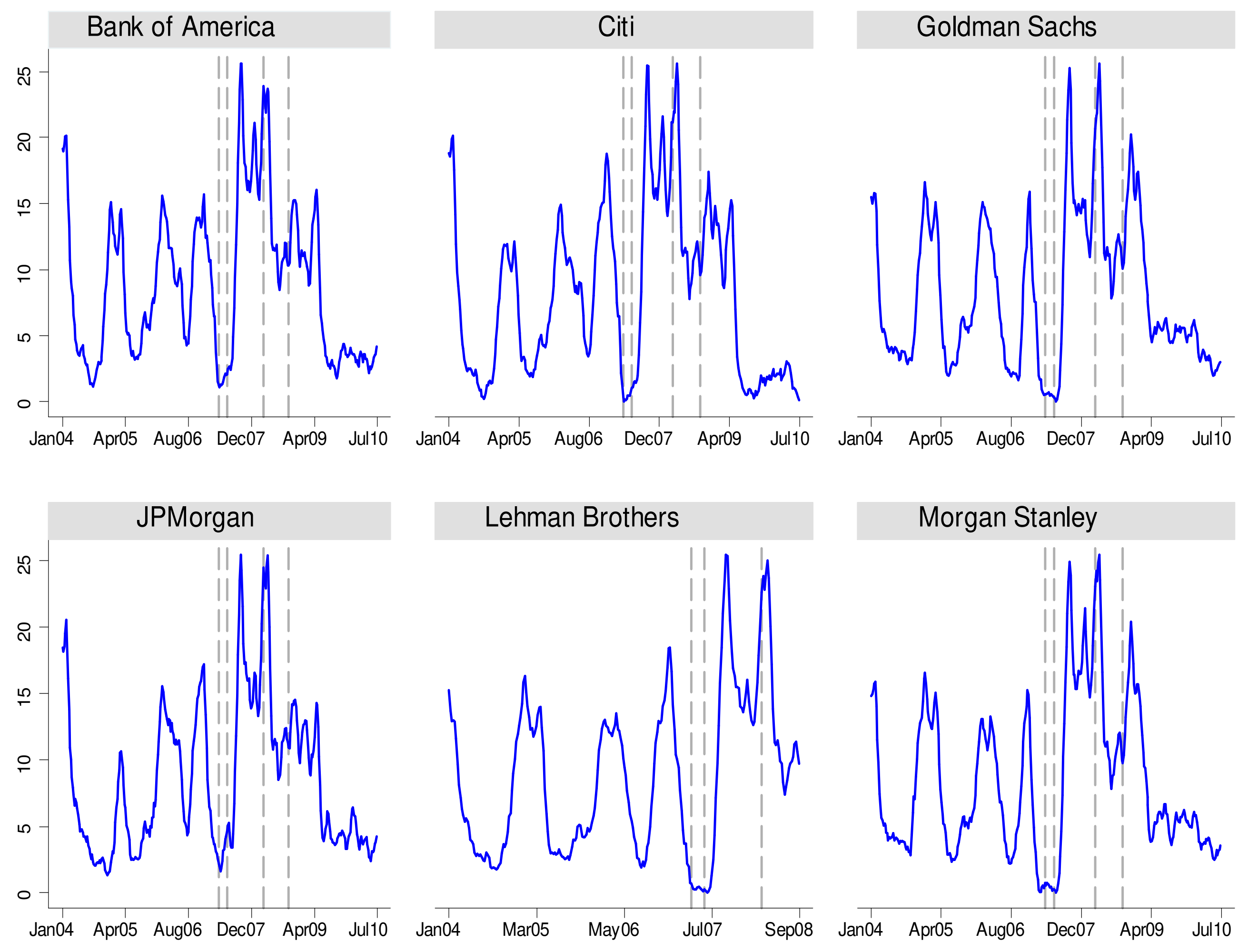

Figure 3: Risk-Stability Index Time-Series for Individual European Banks. The vertical dashed lines indicate, from left to right: Bankruptcy of New Century Financial; Implosion of Bear Stearns' Hedge Funds; Collapse of Bear Stearns; Collapse of Lehman Brothers.

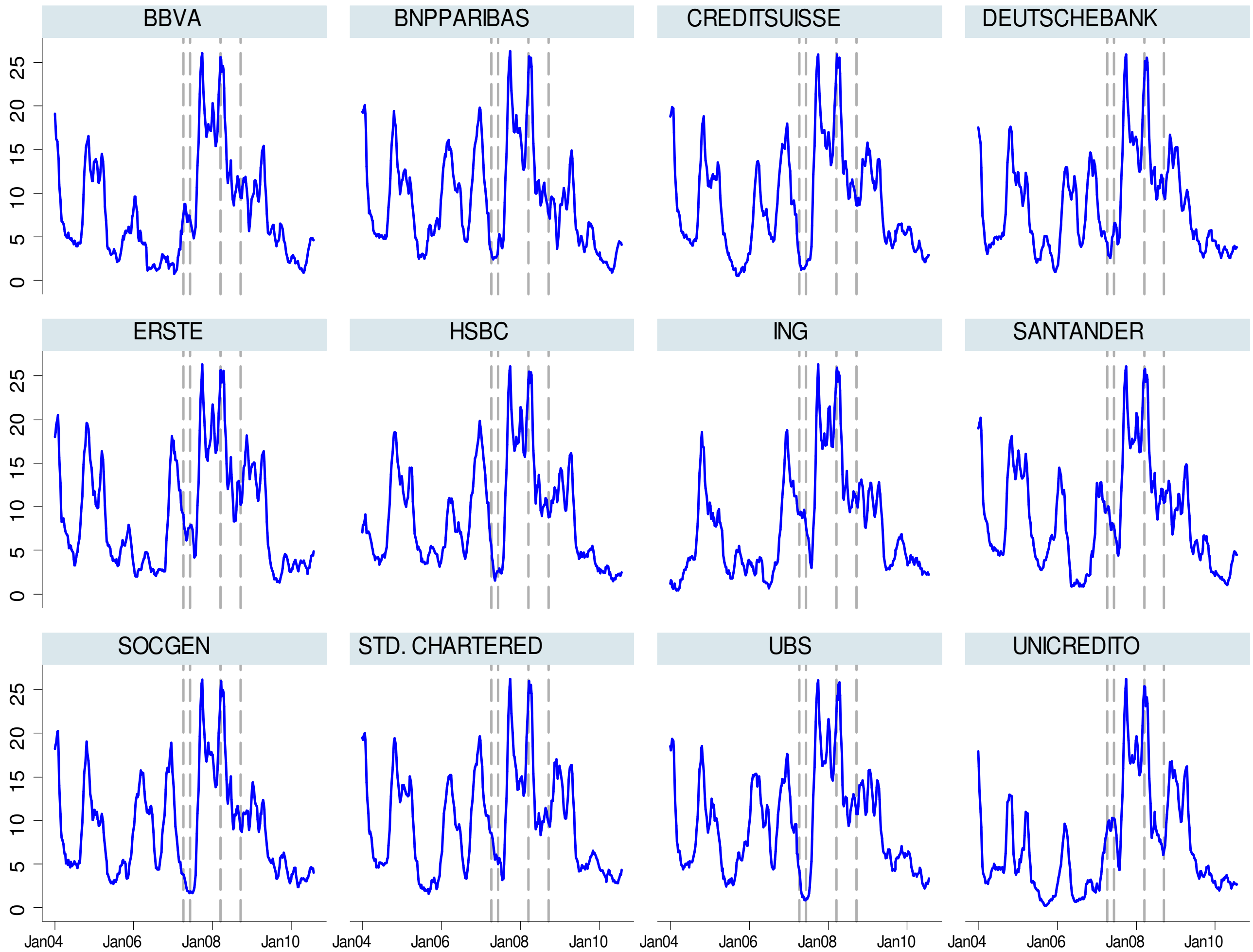

Figure 4: Risk-Stability Index Time-Series for Individual Asian Banks. The vertical dashed lines indicate, from left to right: Bankruptcy of New Century Financial; Implosion of Bear Stearns' Hedge Funds; Collapse of Bear Stearns; Collapse of Lehman Brothers.