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Abstract

This paper defines a risk-stability index (RSI) that takes into account the extreme dependence structure and the conditional probability of joint failure (CPJF) among risk factors in a portfolio. In combination, both the RSI and CPJF provide a valuable tool for analyzing risk from complementary perspectives; thereby allowing the measurement of (*i*) common distress of risk factors in a portfolio, (*ii*) distress between specific risk factors, and (*iii*) distress to a portfolio related to a specific risk factor. With an application to a financial system comprised of 18 banks from around the world, the results herein show that financial stability must be viewed as a continuum, since risk varies from period to period. The risk-stability index indicates that U.S. banks tend to cause the most stress to the global financial system (as defined herein), followed by Asian and European banks. The results also show that Asian banks seem to experience the most persistence of distress, followed by U.S. and European banks. The panel VAR results show that monetary policy should "lean against the wind", since it has a significant effect in reducing the (potential) instability of a financial system.

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1 Introduction

Banks are directly connected and are the most important financial intermediaries in an economy. This might sound like an understatement, but it has taken a severe financial crisis for economists and regulators to appreciate that it is true and that the malfunctioning of such connections can have dire consequences for any financial system. For example, the asset side of a bank's balance sheet contains common exposures in the interbank deposit market. Therefore, large losses due to exogenous causes, like a large company breaking an agreement to pay back its (syndicated) loan, leads to a succession of events instantaneously distressing a substantial fraction of the banking sector. Moreover, since banks perform related activities, they are also ultimately coupled due to their common exposition *vis-à-vis* similar macro-risk drivers like the short-term interest rate and cross-market rebalancing effects. This means that the asset side of a banks' balance sheet clings to the same risk factors albeit in different proportions, where the pressure to diversify risk is the underlying motive for "risk-sharing" rather than "risk-concentration". Paradoxically, while diversification reduces the frequency of individual bank failures (i.e. smaller shocks can be easily borne by the system), it makes the banking system prone to systemic breakdowns in case of very large (non-macro) shocks.

On the other hand, the liability-side of balance sheets is even more alike than the asset side, since the liability side largely consists of bank deposits. Accordingly, short-term interest rate movements encourage substitution between asset categories; and therefore, can quickly change the size of deposits held by the public. Diamond and Dybvig (1983) point out that a vital role of banks is to offer deposits that are more liquid than the assets under management. The main reason banks create liquid deposits, when compared to the assets they hold, is for insurance purposes; that is, they force depositors to share the risk of liquidating early, even if it is at a loss. The Diamond and Dybvig (1983) model shows that offering these demand deposits gives way to "bank runs" if too many depositors withdraw; and for this reason, the values of bank portfolios co-move (either through contagion following an idiosyncratic shock, or owing to a macroeconomic shock such as tighter monetary policy). To solve the problems associated with a bank run, deposit guarantee funds have been installed, and financial authorities have committed considerable effort to monitoring and regulating the banking industry, where in recent times there has been a trend towards focusing on the macro-prudential perspective of banking regulation (see Aspachs et al., 2007; Goodhart et al., 2005, 2006; Lehar, 2005). However, there remain important questions to be answered *vis-à-vis* the stability of any financial system. As the current crisis has highlighted, regulators and academics do not fully understand how risk is distributed within a financial system, and there is "insufficient" knowledge about the effects and desirability of regulatory measures.

If we economists were able to know the risk exposure of different risk factors, then we would be able to better assess the impact of adverse shocks to the system. However, we do not have an accepted quantification or time-series for measuring financial stability. Despite this shortcoming, what is most frequently employed as an alternative is an "after the fact" assessment of whether a crisis has occurred. This dichotomous measure is then used to gauge whether common risk factors preceded, perhaps even causing, such crises, and then to evaluate which official responses have best mitigated the crisis in question. However, such an approach is fraught with shortcomings. Specifically, the deficiency of having a continuous scale makes it unfeasible to calculate (*i*) the relative riskiness of a system in non-crisis periods, and/or (*ii*) the strength of a crisis once it occurs, with any accuracy. If the former could be quantified, it may allow for early corrective action as the menace of a systemic crisis increases. On the other hand, quantification of the latter can smooth the progress of decision making *vis-à-vis* the most suitable course of action to fight the crisis. As Segoviano and Goodhart (2009) state "a precondition for improving the analysis and management of financial (banking) stability is to be able to construct a metric for it". Segoviano and Goodhart (2009) do 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. The financial stability perspective taken herein is that multiple financial institutions (i.e. risk factors) "fail" due to a common risk exposure.[1] That is, when financial institutions are exposed to similar risks, multiple institutions may be affected when this risk materializes; often such crises are explained through contagion effects.

The well-being of the banking sector, as designated by the balance sheet items, is (arguably) reflected in credit default swap spreads, since CDS's are a type of insurance against credit risk.[2] 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 2008-2009 financial crisis. Additionally, even though CDS spreads may overshoot, they do not generally stay wide of the mark for long, where the direction of the move is by and large a good distress signal (see Figures 1 and 2).

[1] See deBandt and Hartmann (2000) and Allen et al. (2009) for comprehensive surveys on systemic risk modeling.

[2] 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.

Figure 1: Daily CDS Spreads (in basis points) of 8 Major Asian Banks (February 12, 2003 - September 8, 2009)

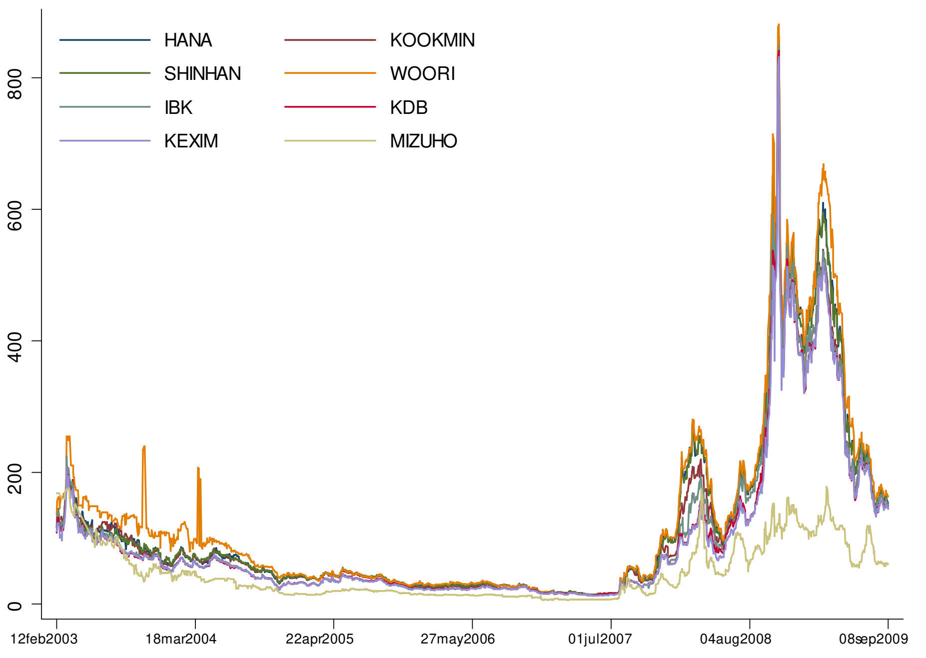
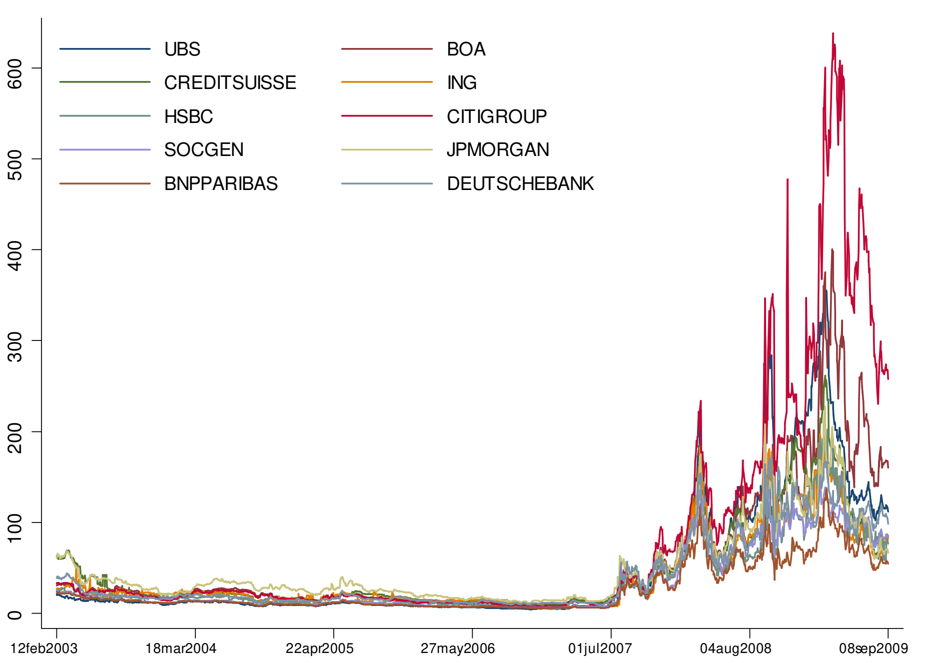


Figure 2: Daily CDS Spreads (in basis points) of 10 Major European and U.S. Banks (February 12, 2003 - September 8, 2009)



Accordingly, the aim herein is to take advantage of the aforementioned properties of the banking sector in order to epitomize the likelihood for systemic risk. Moreover, this paper endeavors at going further than the conventional "shock-transmission" approach, which is the epicenter of many existing frameworks. As an alternative, the focus herein is on spotting and dealing with the build-up of weaknesses preceding downward corrections in markets, problems with institutions, or failures in financial infrastructure. The conjecture inherent in this approach is that the shocks that may ultimately cause such adjustments are (usually) considered less relevant when viewed in isolation, and therefore, are often overlooked. This also accords with the view that financial stability is a continuum (Houben et al., 2004), in which "imbalances" may develop and then either fritter away or build up to the point of moving any financial system away from stability.

The starting point in this approach is the stylized fact that the return series of financial assets are fat-tailed distributed; therefore, the commonly maintained assumption that returns are normally distributed leads to an underestimation of risk. Hence, given the focus on extreme co-movements of risk, I will allow for fat-tails to capture the univariate risk properties. For the multivariate analysis, the normal distribution based correlation concept is also of limited value, since regular dependence and tail dependence are independent (see Garita and Zhou, 2009). For these and the above-mentioned reasons, the research herein will calculate the conditional probability of joint failure (CPJF) and a risk-stability index (RSI) derived from multivariate extreme value theory ($mEVT$), which quantifies systemic risk in a financial system.[3]

This index is based on forward-looking price information stemming from credit default swap (CDS) spreads, which are easily available in real time and on a daily basis; moreover, it is also economically instinctive, since it is comparable to a notional premium (i.e. to a risk-weighted deposit insurance plan that protects against harsh losses in the banking system). This new index also has the property that it increases when the conditional probability of joint failure and the dependence structure increase. In other words, higher systemic risk (i.e. an increase in the risk-stability index) reflects an elevated sensitivity by market participants *vis-à-vis* higher failure risk, as well as their view that the conditional probability of joint failure is higher. In addition, the risk-stability index 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.[4]

[3] Chen Zhou, of De Nederlansche Bank, deserves most credit for the construction of this index, although any errors remain mine.

[4] It is imperative to point out that random variables are asymptotically independent or asymptotically dependent despite their correlation. Moreover, the dependency of random variables, if they are asymptotically independent,

By applying a multivariate extreme value theory ($mEVT$) methodology to a portfolio composed of 18 banks from around the world during period February 12, 2003 until September 8, 2009, the results obtained in this paper show that extreme dependence in non-crisis times can be higher than during crisis times, and that risk varies from period to period; this supports the idea that financial stability must be viewed as a continuum. The results also indicate that, bilaterally, banks are highly interlinked both within and across borders; however, as previously mentioned, this interlinkage varies from period to period. The results stemming from the risk-stability index show that U.S. banks tend to cause the most stress to the global financial system (as defined herein), followed by Asian and European banks. When it comes to contagion or "domino-effects", U.S. banks seem to be the most contagious, followed by Asian banks, and then by European banks. The persistence of distress is also an important variable that must be taken into account when analyzing financial stability; accordingly, the results herein show that Asian banks seem to experience the most persistence of distress, followed by U.S. banks, which are in turn followed by European banks. The panel VAR results show that monetary policy can help reduce instability in the financial system.

The remainder of the paper will evolve as follows: Section 2 will discuss measures of dependence and introduce the concepts of "conditional probability of joint failure" (CPJF) and the risk-stability index (RSI). Section 3 provides empirical results for the CPJF through a distress dependence matrix, while section 4 provides the estimates for the risk-stability index. Section 5 looks at "domino-effects" and at the directionality of contagion. Section 6 takes advantage of the time-series properties of the Risk-Stability Index, and estimates a panel VAR. Lastly, section 7 concludes.

2 Measures of Dependence

In order to understand the dependence between two normally distributed random variables, it is sufficient to know the mean, variance and correlation coefficient. However, the correlation coefficient is not a useful statistic for financial data for various reasons. First, economists are interested in the risk-return trade-off for which the correlation measure is only an intermediate step; that is, the correlation coefficient measures dependence during normal times, and it is largely dominated by the moderate observations rather than the extreme observations. Boyer et al. (1997) show that even if the normal distribution is applicable, verifying "the market speak" of increased-correlations during crisis times, can be illusory at best. To make the point more precise, Forbes and Rigobon (2002) show that even after adjusting for heteroskedastic biases (i.e. increases in variance), "there was virtually no increase in unconditional correlation coefficients" during times of crisis. Second,

will eventually die out as the credit spreads become extreme.

the definition of the correlation coefficient depends on the assumption of finite variance; however, the distribution of financial data (e.g. asset returns) is not multivariate normally distributed, that is, the tails of the return distributions are "fat". Thirdly, the multivariate normal-based correlation does not measure very well the extreme dependence of financial data; therefore, what is required is a measure for the tail dependence.[5]

2.1 Univariate EVT and Value-at-Risk (VaR)

Univariate extreme value theory makes assumptions on the tail of the distribution function, where we only consider the heavy-tail case. Let X denote the loss generated from a certain risk factor; for example, if R is the return of a certain asset then we can take $X = -R$. Also, denote F as the distribution function of X, and suppose that X follows a heavy-tailed distribution; that is we have that

$$\lim_{t \to \infty} \frac{1 - F(tx)}{1 - F(t)} = x^{-\alpha} \tag{1}$$

where $\alpha > 0$ is the *tail index*. This implies that $1 - F(t) = t^{-\alpha} l(t)$, where $l(t)$ is a slowly varying function defined as

$$\lim_{t \to \infty} \frac{l(tx)}{l(t)} = 1$$

In the narrow case where $l(t)$ is almost a constant (i.e. $l(t) \to A$ as $t \to \infty$), then the tail of the distribution function of X has the following representation

$$P(X \geq x) = Ax^{-\alpha}[1 + o(1)]$$

as $x \to \infty$. This simply means that the tail distribution of X is approximately Pareto distributed.[6] Denote $VaR(\delta)$ as the Value-at-Risk of X at tail probability level δ; that is, $P(X > VaR(\delta)) = \delta$. From the EVT setup, we have that

$$\delta = (VaR(\delta))^{-\alpha} l(VaR(\delta))$$

which implies

$$VaR(\delta) = \left(\frac{a(\delta)}{\delta} \right)^{1/\alpha} \tag{2}$$

[5] There exist a few indicators that capture tail-dependence stemming from multivariate extreme value analysis (see Embrechts et al., 2000; Hartman et al., 2004); most are based on Huang (1992).

[6] See Hyung and de Vries (2002, 2005) for a similar setup.

where $a(\delta) = l(VaR(\delta))$ is called the *scale function*. It can be verified that $a(\delta)$ is a slowly varying function as $\delta \to 0$. Thus, for small δ, $a(\delta)$ can be regarded as a constant function.[7] In order to estimate the VaR, it is necessary to estimate the tail index α, in addition to the scale function a. Suppose we have a sample of observations $X_1, X_2, ..., X_n$. By ranking them, we get the ordered statistics $X_{n,1} \leq X_{n,2} \leq ... \leq X_{n,n}$. Hill (1975) proposed an estimator (now known as the *Hill estimator*) to estimate the tail index α as follows

$$\widehat{\alpha}_H = \left(\frac{1}{k} \sum_{i=1}^{k} \log X_{n,n-1+1} - \log X_{n,n-k} \right)^{-1}$$

where $k = k(n)$ is a suitable intermediate sequence such that $k(n) \to \infty$ and $k(n)/n \to 0$ as $n \to \infty$. From the *Hill estimator*, we observe that only k high-ordered statistics are used for estimation. Applying (2) with $\delta = k/n$, we get

$$VaR(k/n) = \left(\frac{a(k/n)}{k/n} \right)^{1/\alpha}$$

Since a remains at a constant level when δ approaches zero, for small δ, $a(\delta)$ can be well approximated by $a(k/n)$, and together with (2) we have

$$\frac{VaR(\delta)}{VaR(k/n)} \approx \left(\frac{k/n}{\delta} \right)^{1/\alpha}$$

Notice that the non-parametric estimation of $VaR(k/n)$ is $X_{n,n-k}$. This allows us to attain a suitable estimator of $VaR(\delta)$ as

$$\widehat{VaR}(\delta) = \left(\frac{k/n}{\delta} \right)^{1/\widehat{\alpha}} X_{n,n-k}$$

It is worth pointing out that the definition of VaR is exactly the same as the quantile of a certain distribution function.[8] In the case $a(\delta) \sim A$, where A is the scale, we then have an estimator for A as

$$\widehat{A} = \widehat{\alpha}(k/n) = \frac{k}{n} \left(\widehat{VaR}(k/n) \right)^{\widehat{\alpha}} = \frac{k}{n} (X_{n,n-k})^{\widehat{\alpha}}$$

We can link the VaR estimator to the estimator of the scale A as follows

$$\widehat{VaR}(\delta) = \left(\frac{\widehat{A}}{\delta} \right)^{1/\widehat{\alpha}}$$

[7] In case $l(t) \sim A$, we get $a(\delta) \sim A$, as $\delta \to 0$.

[8] Weissman (1978) was the first to propose this as a quantile estimator.

Hence the estimation of VaR is determined by the estimations on the tail index α and the scale function $a(k/n)$. This can be viewed as a solution from the Pareto approximation:

$$\delta = P(X > VaR(\delta)) \approx A(VaR(\delta))^{-\alpha}$$

Within the univariate EVT setup, the tail index plays a more prominent role for the analysis of extreme risks, although both the tail index and the scale function (or scale parameter) play a role in VaR evaluation. Suppose we have two risk factors X and Y with tail indices α_1 and α_2, and scale functions $\alpha_1(\delta)$ and $\alpha_2(\delta)$, respectively. If $\alpha_1 > \alpha_2$, then $1/\alpha_2 - 1/\alpha_1 > 0$. Hence, we have that

$$\lim_{\delta \to 0} \frac{VaR_X(\delta)}{VaR_Y(\delta)} = \lim_{\delta \to 0} \delta^{1/\alpha_2 - 1/\alpha_1} \frac{a_1(\delta)^{1/\alpha_1}}{a_2(\delta)^{1/\alpha_2}} = 0$$

Here it is assumed that $\frac{a_1(\delta)^{1/\alpha_1}}{a_2(\delta)^{1/\alpha_2}}$ is a slowly varying function as $\delta \to 0$. This implies that X is less risky that Y. In other words, the risk factor with higher tail index exhibits less risk at the extremes. In the case the tail indices are equal, we have $\alpha_1 = \alpha_2 = \alpha$, which implies that

$$\lim_{\delta \to 0} \frac{VaR_X(\delta)}{VaR_Y(\delta)} = \lim_{\delta \to 0} \left(\frac{a_1(\delta)}{a_2(\delta)} \right)^{1/\alpha}$$

Thus comparing the scale functions is important for the comparison of the $VaRs$. Following Zhou (2009), I herewith present two properties of the scale function under the assumption of equal tail indices. Given that the tail indices for X and Y are α, as $\delta \to 0$:

1. $a_{cX}(\delta) \sim c^\alpha a_X(\delta)$, for all $c > 0$;

2. $a_{X+Y}(\delta) \sim a_X(\delta) + a_Y(\delta)$, if X and Y are independent.

The second property follows from Feller's convolution theorem (see Feller, 1971, section VIII.8). Parallel to this, when we have the scale parameters A_X and A_Y, we then have that:

1. $A_{cX} \sim c^\alpha A_X$, for all $c > 0$;

2. $A_{X+Y} \sim A_X + A_Y$, if X and Y are independent.

2.2 Multivariate EVT: tail dependence

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 *vis-à-vis* other risk factors in a system. As an example of a two-dimensional case, assume a system of two banks, with loss returns X and Y. Following de Haan and Ferreira (2006), the two-dimensional EVT assumes that there exists a $G(x, y)$ such that

$$G(x, y) = \lim_{\delta \to 0} \frac{P(X > VaR_x(\delta) * x,\ or\ Y > VaR_y(\delta) * y)}{\delta} \tag{3}$$

we can express the marginal tail indices as follows:

$$if\ y = +\infty,\ then\ G(x, +\infty) = \lim_{\delta \to 0} \frac{P(X > VaR_x(\delta) * x)}{\delta} = \lim_{\delta \to 0} \frac{P(X > VaR_x(\delta) * x)}{P(X > VaR_x(\delta))} = x^{-\alpha_1}$$

$$if\ x = +\infty,\ then\ G(+\infty, y) = \lim_{\delta \to 0} \frac{P(Y > VaR_y(\delta) * y)}{\delta} = \lim_{\delta \to 0} \frac{P(Y > VaR_y(\delta) * y)}{P(Y > VaR_y(\delta))} = y^{-\alpha_2}$$

by using these marginal tail indices, we can remove the marginal information by simply changing x into $x^{-\frac{1}{\alpha_1}}$ and y into $y^{-\frac{1}{\alpha_2}}$, yielding

$$G(x, y) = \lim_{\delta \to 0} \frac{P(X > VaR_x(\delta) * x^{-\frac{1}{\alpha_1}},\ or\ Y > VaR_y(\delta) * y^{-\frac{1}{\alpha_2}})}{\delta} \tag{4}$$

Notice that $VaR_x(x\delta) \approx VaR_x(\delta) * x^{-\frac{1}{\alpha_1}}$ and $VaR_y(y\delta) \approx VaR_y(\delta) * y^{-\frac{1}{\alpha_1}}$, which allows us to write (3) as follows:

$$\lim_{\delta \to 0} \frac{P(X > VaR_x(x\delta),\ or\ Y > VaR_y(y\delta))}{\delta} = L(x, y) = L(1, 1) \text{ for } x = y = 1 \tag{5}$$

Through (5) we can notice that the marginal information, which is summarized by the tail indices α_1, α_2, has no influence on $L(x, y)$. In other words, the two-dimensional EVT condition models the marginals through one-dimensional EVT and it models the tail dependence through the $L(x, y)$ function. 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 (5) can be modified accordingly. Let $X = (X_1, ..., X_d)$ denote the losses of d individual risk factors (e.g. banks). Each risk factor X_i follows the 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:

$$\frac{P(X_1 > VaR_1(x_1\delta),\ or\ X_2 > VaR_2(x_2\delta),\ or, ..., or\ X_d > VaR_d(x_d\delta))}{\delta} = L(x_1, x_2, ..., x_d) \tag{6}$$

However, this time around the values will be delimited between 1 and the number of risk factors d. The estimation procedure follows Huang (1992).

2.3 Conditional Probability of Joint Failure

A special measure of two-dimensional tail dependence is the "conditional probability of joint failure" (CPJF). This measure is defined as in Garita and Zhou (2009) 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:

$$CPJF_{i,j} = \lim_{\delta \to 0} P(X_i > VaR_i(\delta) \text{ and } X_j > VaR_j(\delta) | X_i > VaR_i(\delta) \text{ or } X_j > VaR_j(\delta)) \quad (7)$$

which can be rewritten as

$$CPJF_{ij} = E[\kappa | \kappa \geq 1] - 1 \quad (8)$$

where

$$E[\kappa | \kappa \geq 1] = \lim_{\delta \to 0} \frac{P(X_i > VaR_i(\delta)) + P(X_j > VaR_j(\delta))}{1 - P(X_i \leq VaR_i(\delta), X_j \leq VaR_j(\delta))} \quad (9)$$

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 (7) and (9) exists (see de Haan and Ferreira, 2006, Ch. 7). Clearly, 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 between risk-factors may vary, which highlights the different linkages during crisis periods. In the two-dimensional case, the CPJF can be written as

$$\begin{aligned} CPJF &= \lim_{\delta \to 0} \frac{P(X_1 \ and \ X_2)}{P(X_1 \ or \ X_2)} \\ &= \lim_{\delta \to 0} \frac{P(X_1) + P(X_2) - P(X_1 \ or \ X_2)}{P(X_1 \ or \ X_2)} \\ &= \lim_{\delta \to 0} \frac{\delta + \delta - L(1,1) * \delta}{L(1,1) * \delta} \\ &= \frac{2}{L(1,1)} - 1 \end{aligned} \quad (10)$$

2.4 Risk-Stability Index

Building on the *mEVT* framework previously discussed, I construct a risk-stability index (RSI).[9] This index makes it possible to quantify the effect that a "failure" of any risk factor (e.g. bank) can have on an entire financial system, be it economy-wide or world-wide. In other words, the risk-stability index gives an estimation of the number of risk-factors that would "fail", given that a specific risk-factor "fails". This index, therefore, allows any economist to pin-point which risk-factor failure will have the most adverse effect on a financial system. For expositional purposes on the construction of the RSI, assume that the financial system consists of three banks. From equation (6) 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:

$$RSI = \lim_{\delta \to 0} E(\text{number of crises in } X_2 \text{ and } X_3 \mid X_1 \text{ is in crisis}) \tag{11}$$

Denote $I_i = 1\{X_i > VaR_i(\delta)\}$ as X_i being in crisis, for $i = 1, 2, 3$. Using this to rewrite (11), we obtain:

$$RSI_1 = \lim_{\delta \to 0} E(I_2 + I_3 \mid I_1 = 1) \tag{12}$$

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

$$E(I_2 \mid I_1 = 1) + E(I_3 \mid I_1 = 1) \tag{13}$$

Rewriting (13) in terms of probabilities, and by using (10) we get:

$$\begin{aligned} RSI_1 &= \lim_{\delta \to 0} \frac{P(I_2 = 1 \ \&\ I_1 = 1)}{P(I_1 = 1)} + \frac{P(I_3 = 1 \ \&\ I_1 = 1)}{P(I_1 = 1)} \\ &= \lim_{\delta \to 0} \frac{2\delta - P(I_2 = 1 \text{ or } I_1 = 1)}{\delta} + \frac{2\delta - P(I_3 = 1 \text{ or } I_1 = 1)}{\delta} \end{aligned} \tag{14}$$

By using equation (6) in the above expression, it is easy to show that:

$$RSI_1 = 2 * (d - 1) - \sum_{i \neq j} L_{i,j}(1, 1) \tag{15}$$

or in our three-bank example:

[9] This index can easily be applied to any asset return. For example, it can be used to analyze exchange rates as in Garita-Zhou (2009a,b).

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

A risk-stability index (equation 15) 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. In other words, the higher the index, the higher the instability of the financial system.

2.5 Data

Choosing the data is more often than not a subjective approach, since one has to choose between having a maximum number of risk-factors, and having a maximum amount of (time) observations. The analysis to follow is based on 18 major banks (8 Asian banks, 7 European banks, and 3 U.S. banks), for which the decision to include these banks was made on the amount of observations. Accordingly, the daily CDS spreads (denominated in US dollars for South Korean and U.S. banks, in Euros for European banks, and in Japanese Yen for Japanese banks, all at 5-year maturity) range from February 12, 2003 until September 8, 2009, and are obtained from Markit. According to Markit, the spreads do not represent any actual spreads at which a security has been traded, nor do they represent any offer to buy or sell such securities at those spreads. However, each contributor to Markit provides data from their official books and from feeds to automated trading systems, and other pricing sources on a daily basis. The data that Markit receives undergoes a rigorous cleaning process where they test for "stale, flat curves, outliers and inconsistent data"; thereby, ensuring that the data meets the highest standard and reliability. In order to show the evolution of "(in)stability" over time, a 200-day sub-sample moving (weekly) window is used to construct a time-series for both the CPJF and the Risk-Stability Index. The choice of a 200-day sub-sample window simply relates to the fact that this is, in my opinion, the minimum amount of observations required to calculate the tail-index and the extreme dependence structure (the $L(1,1)$ function); while at the same time, it allows the construction of a longer time-series. This time-series will also be employed in a panel VAR (see section 6) to uncover feedback effects between the financial sector and the economy.

3 Distress Dependence Matrix and CPJF

Before proceeding with the analysis, it is imperative to calculate the number of high-ordered statistics k, by using an estimator for $L(1,1)$ and plotting the results of $L(1,1)$ for different k and for all the bilateral relationships. This is the same technique as for choosing the tail-index with a Hill-plot, 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 our estimator. The solution to this trade-off is to make a "Hill-plot" (see Hill, 1975), and to let the tail speak for itself. The solution to this trade-off for each bilateral relationship yields a $k = 20$, which implies a quantile of $\delta = \frac{k}{n} = 10\%$ (these results are available upon request)[10].

As is well known, assessing the exact point in time when "liquidity risk" turns to "solvency risk", is difficult at best, and disentangling these risks is a complex issue. Additionally, note that more often than not, CDS not only cover the event of default of an underlying asset, but they also cover a wider set of "credit events" (e.g. downgrades). I consider the combined effects of these factors, which are inherent in CDS spreads, to encapsulate "distress" or "failure" risk (i.e. large losses and the possible default of a specific bank). Thus, the definition of "distress" or "failure" risk used in this paper is broader than "default", "credit", or "liquidity" risks.[11]

As shown in section 2.3, I measure systemic risk in a bivariate setting through the conditional probability of joint failure (CPJF). 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 banks in a portfolio (i.e. in a financial system). For each 200-day period under analysis, I estimate the bilateral conditional probability of joint failure for each pair of banks in the portfolio.

3.1 Common Distress in "Local" Banking Systems

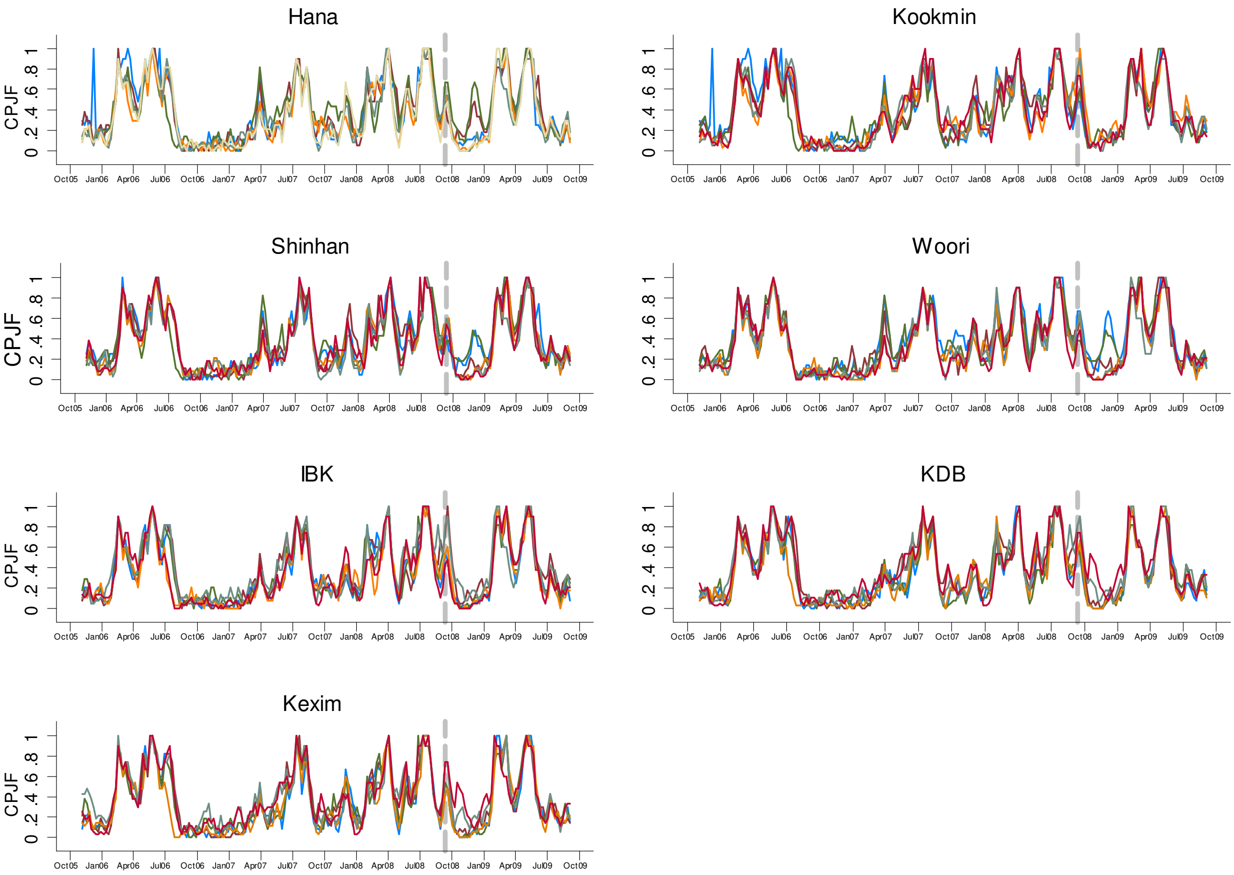
These results indicate that banks within a particular geographical jurisdiction are highly interlinked, with distress in one bank clearly associated with a high conditional probability of joint failure elsewhere in the "local" system. Moreover, the degree of extreme dependence varies from period to period as illustrated by Figures 3 and 4, which present the detailed bilateral interconnections between 7 major South Korean banks and between 3 major U.S. banks, respectively.[12]

[10] In my opinion, the fact that we do not need to impose any structure on the tail or on the distribution, is one of the great advantages of extreme value theory. In other words, just let the tail speak for itself!

[11] In other words, "failure" is used extremely loosely, and at its most basic level, it should be interpreted as "if a bank sneezes, will the system catch a cold".

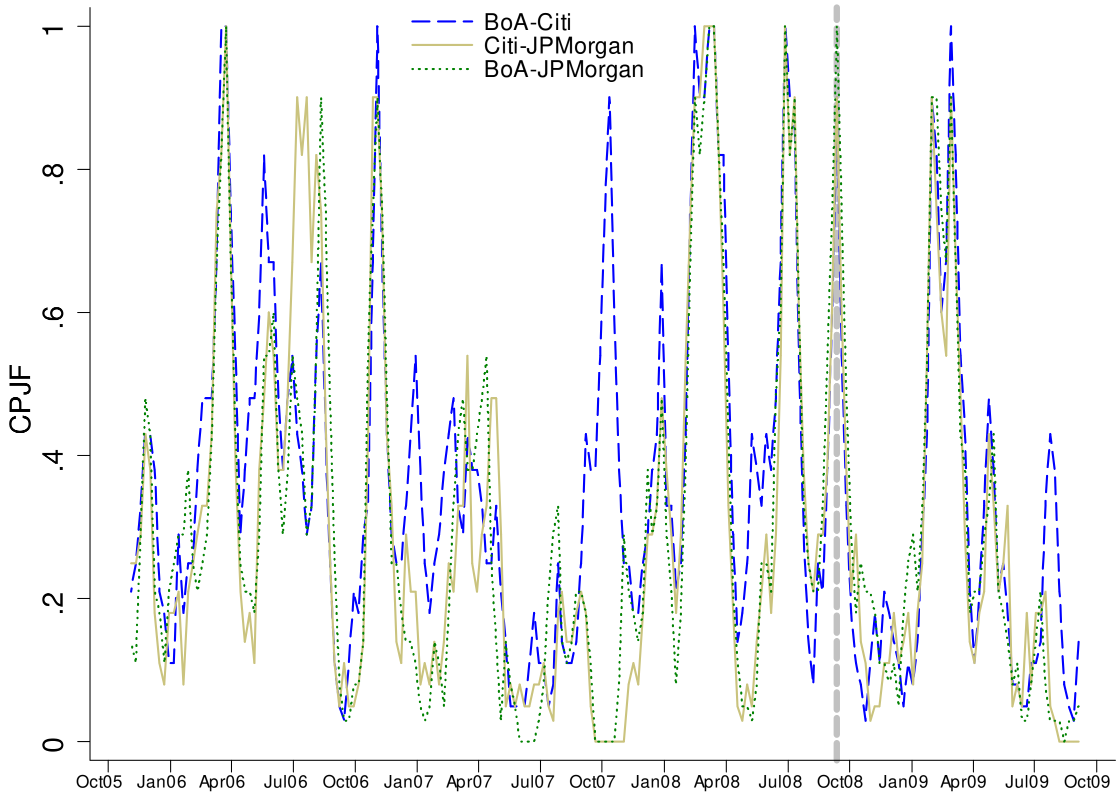
[12] We must keep in mind that the CPJF's as presented herein do not necessarily imply causation; nonetheless, they do provide key insights into the interlinkages and the likelihood of contagion between banks, be it between "local" banks and/or across borders.

Figure 3: Conditional Probability of Joint Failure between 7 Major South Korean Banks. (the dashed vertical gray line indicates when Lehman Brothers filed for bankruptcy).



For South Korean banks, Figure 3 indicates that the most current bout of bilateral distress began as early as March of 2007, following a relatively calm 6-month period; the average CPJF among Korean banks before March 2007 was 0.40, while it was 0.50 after March 2007. The figure also indicates that the bankruptcy of Lehman Brothers did not seem to create any "extra" distress to the bilateral relationships among Korean banks, but clearly more research is needed in this area. As far as U.S. banks, Figure 4 shows a similar pattern as for South Korean Banks; however, bilateral distress began to surface as early as February 2006 for U.S. banks. For the most recent period, we can notice a marked decrease in the CPJFs, which are now lower than they were in late 2005. The last point worth emphasizing is that the bankruptcy of Lehman Brothers did not seem to create any "additional" distress to the bilateral relationships between Bank of America, Citi, and JPMorgan; however, it does appear that the bilateral stress in financial system is what led to Lehman's demise.

Figure 4: Conditional Probability of Joint Failure between 3 Major U.S. Banks (the dashed vertical gray line indicates when Lehman Brothers filed for bankruptcy).

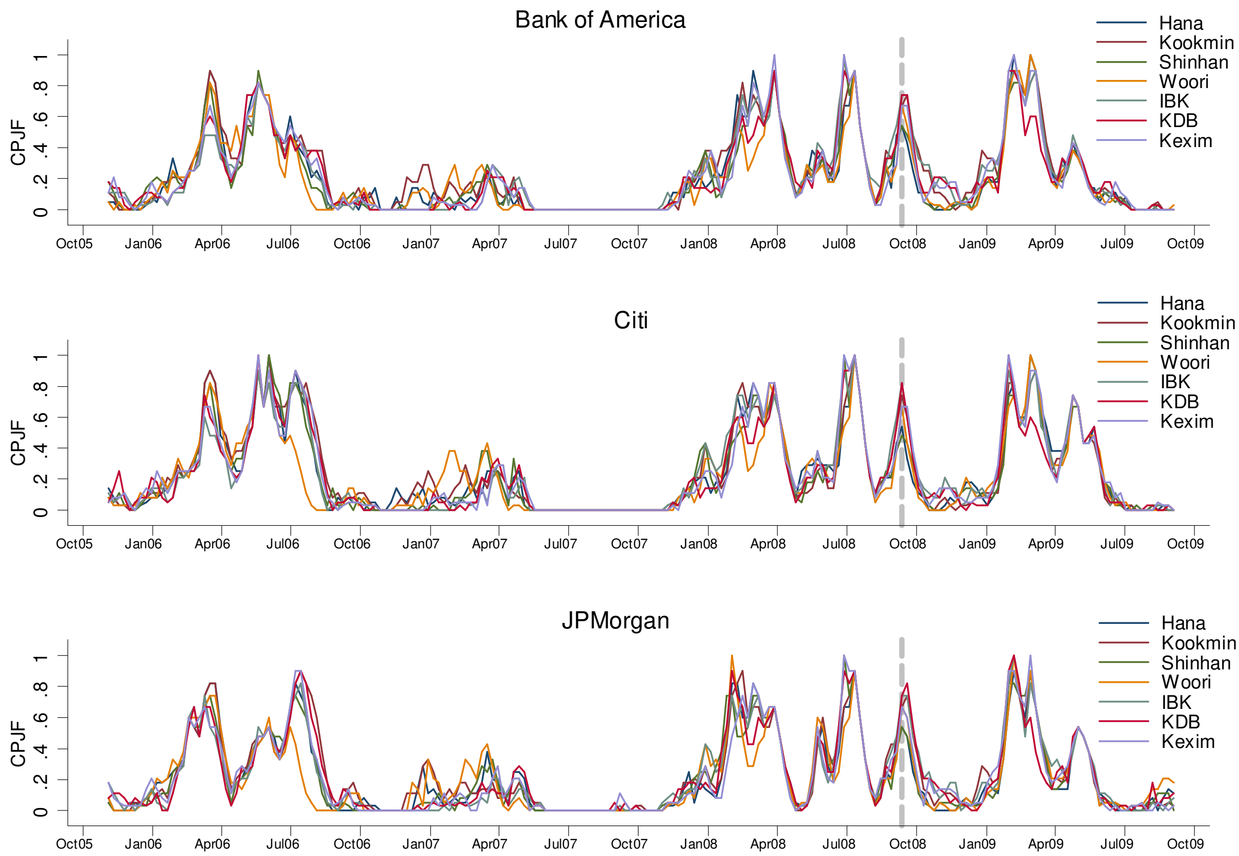


3.2 Global (in)Dependence - Distress Between Specific Banks

In the previous section we saw that bilateral stress of "local" banks can be quite high. However, another aspect of financial stability that is of outmost importance are the contagion spillovers across borders. Therefore, in order to gain insight into cross-border effects, the CPJF's are calculated for 3 major U.S. banks (Bank of America, Citi, and JPMorgan), 7 major European banks (UBS and CreditSuisse from Switzerland; Société Générale and BNP Paribas from France; Deutsche Bank from Germany; ING from the Netherlands; and HSBC from the UK), and 8 major Asian banks (Mizuho from Japan; and Hana, Kookmin, Shinhan, Woori, IBK, KDB, and Kexim from South Korea).

As Figures 5, 6, and 7 underscore, banks around the world are highly interconnected (albeit to a lower degree than within economies - see Table 1); however, the results confirm once again that the degree of bilateral distress varies from period to period. The relationship between Korean and U.S. banks is quite interesting, since there are clearly two periods of high bilateral distress: one period between November 2005 and May 2007 (average $CPJF = 0.21$), and the other period

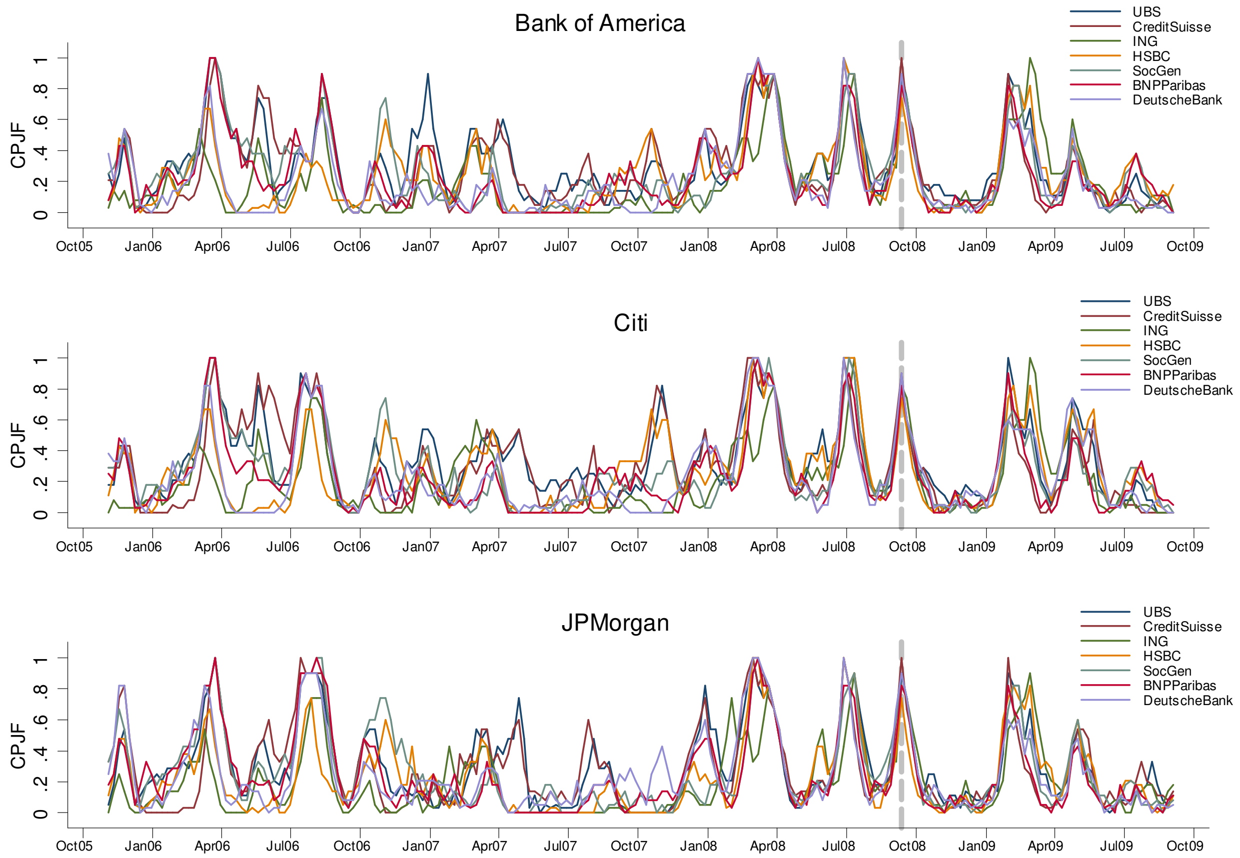
Figure 5: Conditional Probability of Joint Failure between Korean and U.S. Banks (the dashed vertical gray line indicates when Lehman Brothers filed for bankruptcy).



between November 2007 and June 2009 (average $CPJF = 0.30$); with a relatively calm interlude in-between (a similar pattern appears between European and U.S. banks, and between European and Korean banks). As it is by now well known, during the $2005 - 2006$ period, the US economy was hit by various shocks relating to credit markets. More specifically, during the fall of 2005, the booming housing market slowed down abruptly, with median prices nationwide dropping by over 3% from the fourth quarter of 2005 to the first quarter of 2006; and by the summer of 2006, the US home construction index dropped by over 40%, as of mid-August 2006, compared to a year earlier. By the fall of 2007, home sales in the US continued to fall, marking the steepest decline since 1989. By the first quarter of 2007 the Case-Schiller housing price index recorded the first year-over-year decline in house prices since 1991, leading to a collapse of the subprime mortgage industry, to a surge in foreclosure activity (see FDIC, 2007), and rising interest rates threaten to depress prices further as problems in the subprime market spread to the near-prime and prime mortgage markets (New York Times July 25, 2007). This period of distress clearly emerges in

Figures 5, 6, and 7. As previously mentioned, the second period of high distress among banks started in the fall of 2007, reaching its zenith almost a year and a half later when the onset of the current financial crisis was well under way. The relatively calm period in between seems to be related to the perception of market participants that "things cannot get any worse"; after all, it was during the summer of 2007 that the Dow Jones Industrial Average closed above 14,000 for the first time in its history.

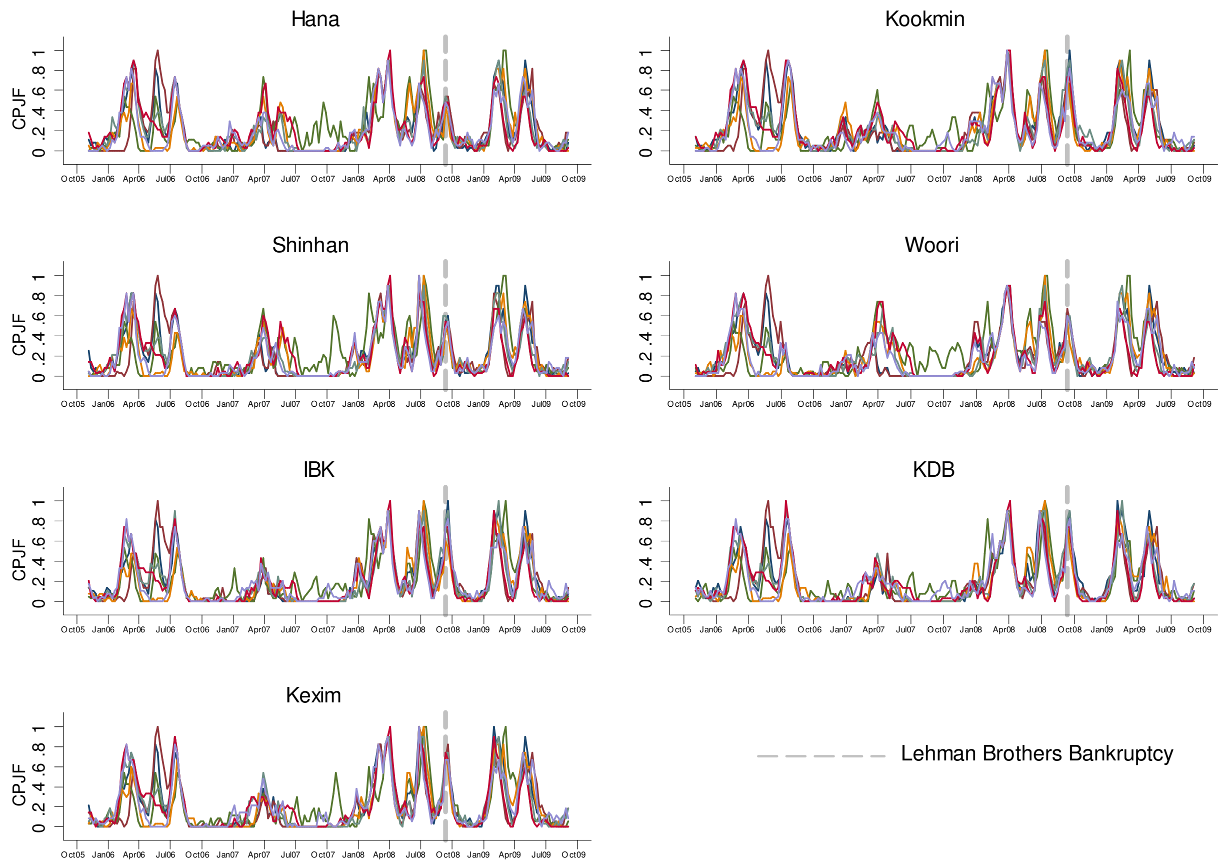
Figure 6: Conditional Probability of Joint Failure between European and U.S. Banks (the dashed vertical gray line indicates when Lehman Brothers filed for bankruptcy).



Links between European and U.S. banks also show a tendency to oscillate period by period, but also to increase as the crisis progressed. In the summer and fall of 2007, which is when subprime mortgage backed securities were discovered in European banks, the most distressed relationships in the summer of 2007 are between JPMorgan-Credit Suisse (average $CPJF = 0.35$) and between JPMorgan-UBS (average $CPJF = 0.31$); while the most distressed relationships in the fall of 2007 are between Citi-Credit Suisse (average $CPJF = 0.44$) and Citi-UBS (average $CPJF = 0.36$).

The aforementioned bilateral distress between European and U.S. banks also seems to have

Figure 7: Conditional Probability of Joint Failure between Korean and European Banks (based on Daily CDS Spreads - in basis points).



been "exported", albeit apparently with a lag, to the relationship between European and Korean banks (see Figure 7); where, by and large, the CPJF increases dramatically during the first quarter of 2008. Nonetheless, there are some notable exceptions like the relationship between ING and Shinhan bank, which experienced high bilateral distress in April 2007 ($CPJF = 0.67$) and in October 2007 ($CPJF = 0.67$). Another notable relationship is between Kexim-Société Générale in March 2007 ($CPJF = 0.54$) and between Kexim-ING in October 2007 ($CPJF = 0.54$).

Table 1, which gives the average conditional probability of joint failure between banks within and across borders, highlights four main points: (1) "risks" vary by geographical region; (2) within border bilateral distress is higher than across borders on average (see numbers in red); (3) regional cross-border contagion is also relatively high, but not as high as within borders (see numbers in blue); and (4) global contagion is present and clearly an issue (see numbers in black). These results indicate that financial stability must be managed inside-out (within borders first), but that international coordination is extremely important.

Table 1: Average CPJF Between Banks Within and Across Regions between November 2007 and September 2009

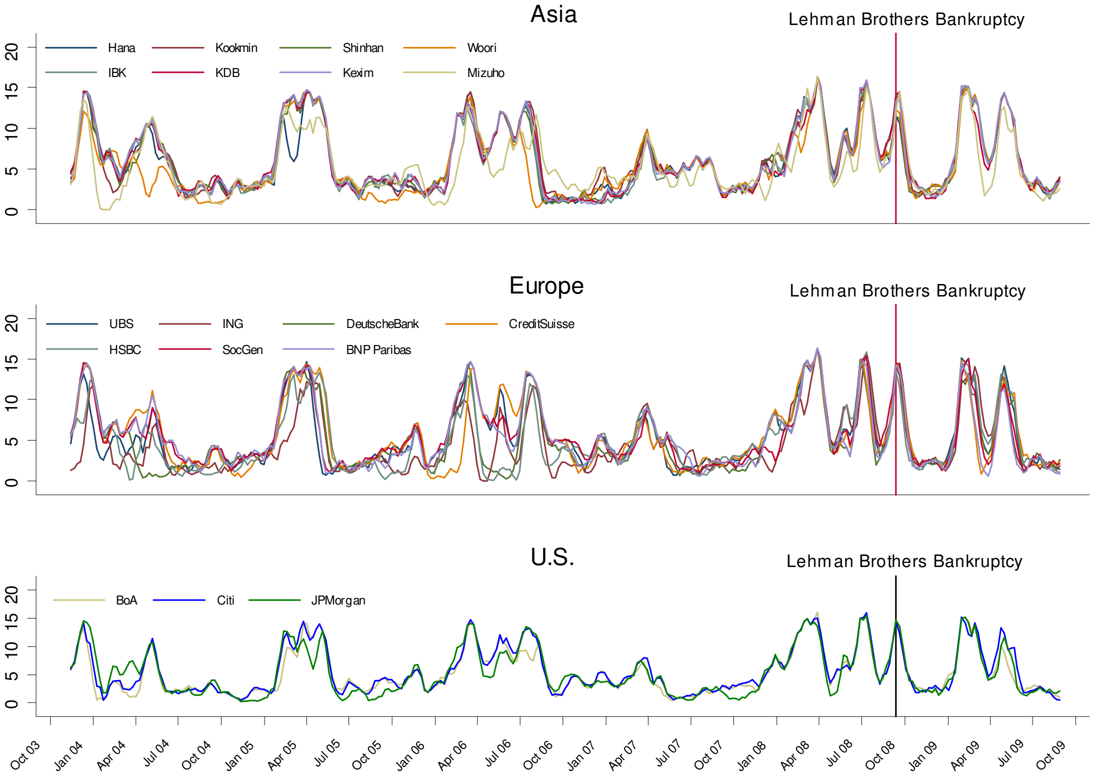
	Asian Banks	Korean Banks	E.U. Banks	U.S. Banks
Asian Banks	0.47	0.48	0.27	0.29
Korean Banks	0.48	**0.51**	0.27	0.30
E.U. Banks	0.27	0.27	0.34	0.29
U.S. Banks	0.29	0.30	0.29	**0.57**

4 Distress to Financial System Linked to a Specific Bank

As explained in section 2.4, the risk-stability index makes it possible to quantify the immediate effect that a "failure" of any risk factor (e.g. bank) can have on an entire financial system, be it economy-wide or world-wide. 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". This index, therefore, allows any economist and/or regulator to pin-point which risk-factor "failure" will have the most adverse effect on a financial system. A risk-stability index (equation 15) 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 any financial system); therefore, the higher the index, the higher the instability of a portfolio.

An immediate result that stands out, especially by looking at Figure 8, is the similarity between this figure and the CPJF graphs. Clearly, the CPJF's and the RSI move in tandem, indicating that as bilateral distress starts to build-up, so does the risk to the financial system (but also, as the financial system starts to experience increased levels of distress, so do the bilateral relationships). The results also show that, on average, U.S. banks tend to cause the most stress to the global financial system (as defined herein), which affect almost 40% of the banks (i.e. over 6 banks are affected by each U.S. bank). U.S. banks are followed by Asian (mainly South Korean banks) and European banks, with an infection rate of 34% and 32% respectively. However, looking at averages masks the fact that risk varies from period to period, but also that financial instability can arise from anywhere, irrespective of geographical location. For example, during the 200 day period ending on the spring of 2006, the RSI indicates that Kookmin, HSBC, Société Générale, JPMorgan, BNP Paribas, and Deutsche Bank each affected over 13 other banks in the system; the RSI also shows that Credit Suisse was the "safest" bank during this period by affecting "only" 8 other banks. However, by the summer-fall of 2008 things were quite different, since it was Citi, UBS, Kexim, and KDB who had infected over 14 banks; moreover, during this period Credit Suisse had become quite risky, affecting over 13 banks (the safest banks during this period were ING and Mizuho, each distressing "only" 9 banks).

Figure 8: Risk Stability Index (daily) Time-Series for 18 Major Banks by Region.



5 Directionality of Contagion and Persistence

Another aspect of financial stability that we economists are particularly interested in, is the directionality of contagion and the persistence of distress. Accordingly, this section aims at uncovering the aforementioned issues by employing, for tractability purposes, 8 periods of 200 non-overlapping days. The results of this particular excercise are presented through the distress dependence matrices (DDM's) found in Tables 4 through 10 (see appendix A). These DDM's show the bilateral conditional probabilities of joint failure of the bank in the column, given that the bank in the row "fails" one period before[13]; moreover, the DDM's show how the directionality of contagion has evolved through time from bank to bank, and from region to region. Therefore, for ease of understanding, depending on one's particular interest, the DDM's can be broken down into four quadrants as follows:

- quadrant 1 = how Korean banks affect other banks in Japan, Europe and the U.S.;
- quadrant 2 = how Korean banks affect each other;

[13] It is worth re-emphasizing that "failure" is used extremely loosly, and at its most basic level, it should be interpreted as "if a bank sneezes, will the system catch a cold".

- quadrant 3 = how Japanese, European, and U.S. banks affect South Korean banks;
- quadrant 4 = how Japanese, European, and U.S. banks affect each other.

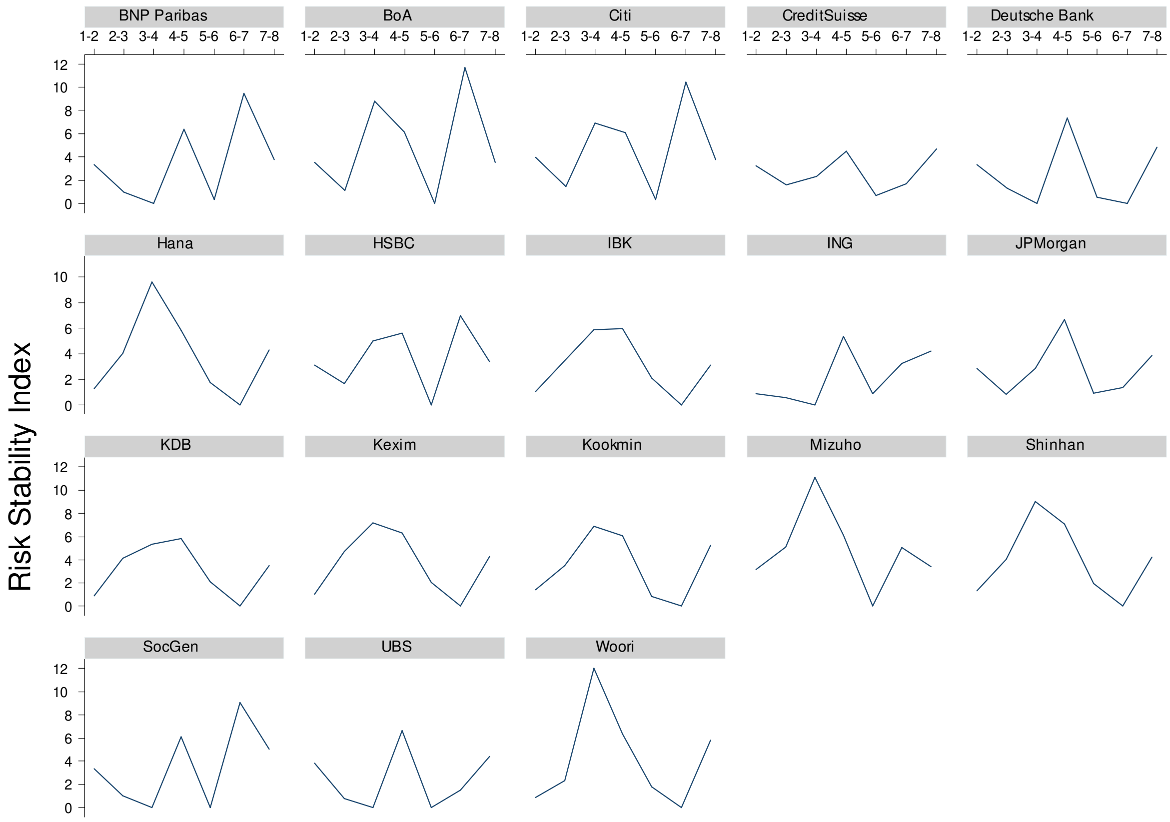
The decomposition of the DDM's into these four quadrants allows us to observe that the degree of contagion within and across-borders varies by period, which is also underscored by Figure 9; this so-called "domino-effect" is best illustrated through Figure 9, which shows the risk-stability index of this exercise.[14] The figure shows how many banks will "fail", given that bank "i" "failed" one period before (the dependence structure, the $L(1,1)$ results, used to construct the RSI are available upon request; however, they can easily be constructed from the distres dependence matrices as follows $L(1,1) = \frac{2}{CPJF+1}$). For example, in section 3 we uncovered that Citi was one of the banks, in this portfolio, that experienced elevated levels of bilateral stress during the summer of 2008 (with an average CPJF of 0.76%). Figure 9 indicates is that in the 3^{rd}, and 4^{th} quarters of 2008 and/or in the 1^{st} quarter of 2009, at least 4 other banks suffered distress due to the fact that Citi experienced distress one period before.

As displayed in Figure 9, the RSI shows that throughout the entire period of analysis (ranging from 2003 until 2009), U.S. banks seem to be the most contagious one period after experiencing distress, on average infecting about 23% of all banks in this portfolio; U.S. banks are followed by Asian and European banks with 21% and 17% respectively. Moreover, we notice from Figure 9 that Bank of America, BNP Paribas, Citi, and Société Générale all show a higher propensity to affect the financial system as time goes by, while CreditSuisse has shown a lower propensity to affect the financial system. Clearly, banks affect a system with a lag; however, what is most interesting, is that they do so at irregular intervals, which implies that the system is constanly under stress, where the source of the stress varies from period to period.

Tables 4 through 10 also allows us to gauge the persistence of distress for bank i in the portfolio; where persistence is quantified by the diagonal of the distress dependence matrices. These diagonals show that, on average, Asian banks tend to experience the most persistence of distress with a 15% conditional probability of joint failure at time t, given that the same Asian bank experienced distress at $t-1$ (South Korean banks experience a 14% CPJF). Asian banks are followed by U.S. banks with a 13% CPJF and by European banks with an 11% CPJF, on average. Individually, the Japanese bank Mizuho tends to experience the most distress persistence ($CPJF = 22\%$), followed by Bank of America and Hana Bank of South Korea, both with a CPJF of 0.20%. Other notables are HSBC ($CPJF = 18\%$) and Woori Bank of South Korea ($CPJF = 17\%$). At the lower end of persistence is the Swiss bank UBS with a CPJF of 4%.

[14] The x-axis of Figure 9 is coded as follows: 1 = Feb 12, 2003 to Nov 18, 2003; 2 = Nov 19, 2003 to Aug 24, 2004; 3 = Aug 25, 2004 to May 31, 2005; 4 = June 1, 2005 to Mar 6, 2006; 5 = Mar 7, 2006 to Dec 12, 2006; 6 = Dec 13, 2006 to Sept 18, 2007; 7 = Sept 19, 2007 to June 24, 2008; 8 = June 25, 2008 to Mar 31, 2009.

Figure 9: Directionality of Contagion (the figure shows the consequences to the banking system conditional on a specific bank "failing" one period before. 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).



6 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, to isolate shocks to one of the variables in the system it is necessary to decompose the residuals in a such a way that they become orthogonal. 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.[15] 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.[16] 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 will employ the risk-stability index time-series (see Figure 8), and the following financial market variables: the short rate (effective federal funds rate), the term spread (difference between the 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 (see Figure 11 in appendix B for a graphical representation of the aforementioned variables). The number of lags in the panel VAR system, which equals 8 weeks, is selected through the Schwarz Information Criteria.

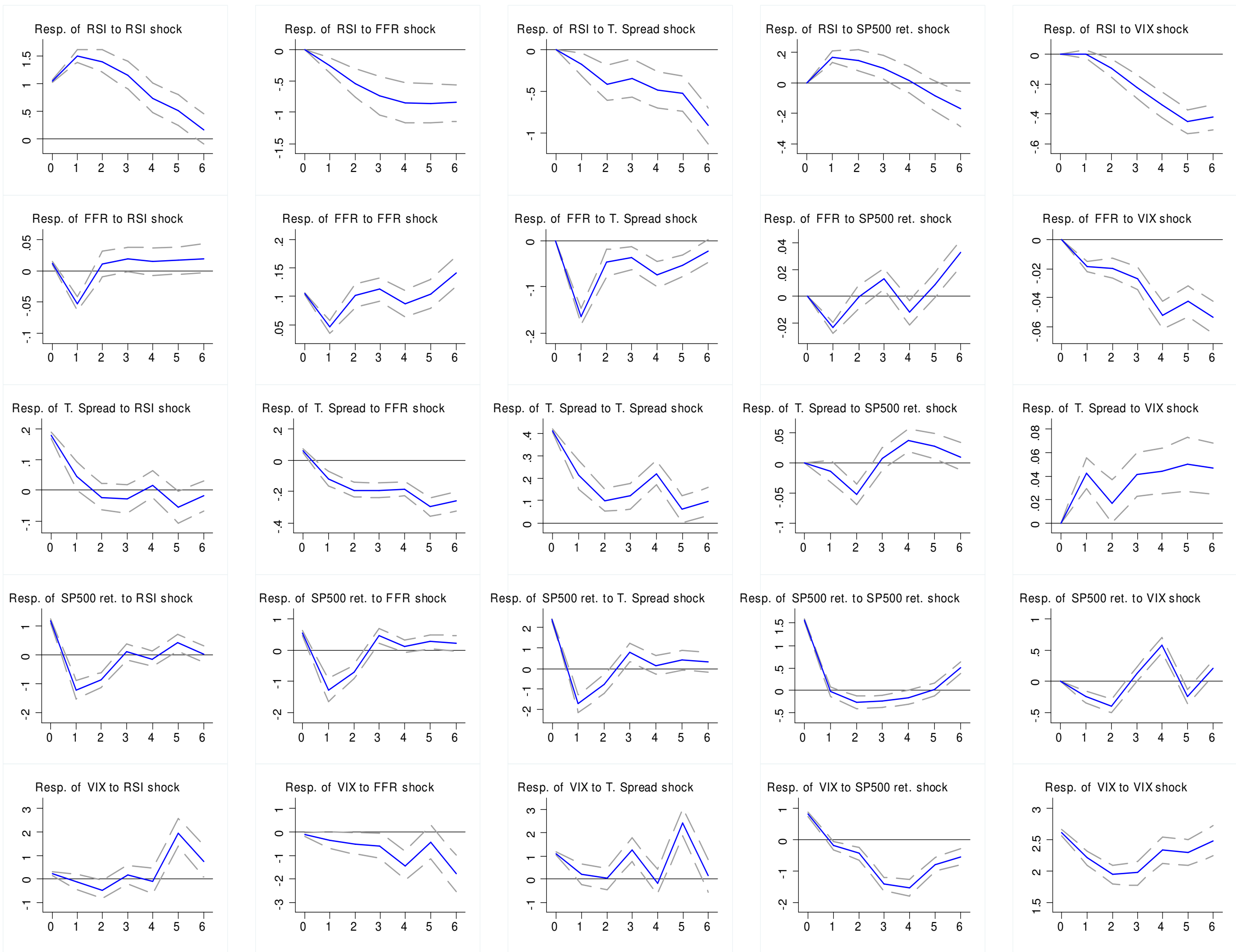
The results found in Figure 10 and Table 11 indicate that the risk-stability index and the returns to the $S\&P500$ are negatively and significantly correlated. This result is intuitive, since the deterioration of the general market (i.e. lower market returns) increases the sensitivity of market participants *vis-à-vis* higher failure risk, as well as their view that the conditional probability of joint failure is higher. The risk-stability index is also negatively and significantly associated with the federal funds rate and the term-spread (defined as the difference between the $10-$year and $3-$month treasury constant maturity rate). This seems to suggest that when monetary policy is "accommodative", most banks move together more closely *vis-à-vis* credit markets. By contrast, when monetary policy is tightened, banks can be affected differently, depending on their liquidity

[15]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).

[16]Formally, if variable x appears earlier in the system than variable y, then x is weakly exogenous with respect to y in the short run.

positions. As is well known, the VAR framework allows for a feedback effect from the banking system to the macro-economy and the general financial market. This feedback effect shows that an increase in the risk-stability index negatively affects interest rates and the returns to the $S\&P500$. Interestingly, the former result suggests that interest rate policy may be affected by financial stability concerns in practice. As a final point, the positive correlation between the risk-stability index and the VIX index is well-matched with market participants' perception that VIX is the "fear index".

Figure 10: Impulse-Responses of a one standard deviation shock for 8-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.



The variance decomposition (Table 2) confirms the above-mentioned results. More specifically, interest rates explain more of the risk-stability index variation (about 30%) than any other variable, especially at longer time horizons. Moreover, the risk-stability index explains about 18% of the variation in the returns on the $S\&P500$; however, the $S\&P500$ returns only marginally explain the variation of the RSI. Last but not least, the RSI does have a significant explanatory power of the VIX, especially at longer horizons.

Table 2: Variance Decomposition - variation in the row variable explained by column variable

	Step-Ahead	RSI	FFR	T.Spread	SP500ret	VIX
RSI	10	0.493	0.227	0.214	0.015	0.049
FFR	10	0.026	0.591	0.258	0.019	0.104
T.Spread	10	0.083	0.446	0.439	0.012	0.018
SP500ret	10	0.184	0.135	0.526	0.120	0.032
VIX	10	0.061	0.182	0.173	0.118	0.464
RSI	20	0.341	0.342	0.253	0.016	0.046
FFR	20	0.090	0.555	0.169	0.064	0.121
T.Spread	20	0.123	0.413	0.429	0.016	0.017
SP500ret	20	0.184	0.137	0.531	0.113	0.033
VIX	20	0.218	0.152	0.209	0.140	0.280
RSI	30	0.272	0.384	0.273	0.025	0.045
FFR	30	0.103	0.571	0.109	0.086	0.129
T.Spread	30	0.101	0.463	0.375	0.026	0.032
SP500ret	30	0.181	0.142	0.529	0.114	0.033
VIX	30	0.163	0.268	0.228	0.124	0.216

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.

7 Conclusion

It is a stylized fact in international (finance) macroeconomics that most financial data are "fat-tailed" (i.e. not normally distributed). This means that extreme co-movements tend to arise more regularly than predicted on the basis of the normal distribution. Accordingly, this paper has proposed an easy and novel methodology for computing systemic risk caused by risk factors in a portfolio or system; moreover, this methodology can be easily applied to *any* risk factor or asset return. This novel approach takes advantage of a multivariate extreme value setup and the concomitant extreme dependence structure to construct the conditional probability of joint failure (CPJF) and a risk-stability index (RSI), which are in turn applied to 18 Asian, European, and U.S. banks. This new risk-stability index offers good insight into (1) the sensitivity of market participants *vis-à-vis* higher failure risk, since it is higher when the conditional probability of joint failure is higher or when the exposure to common risk factors increases; and (2) on the level of a risk-based deposit indemnity plan that safeguards against severe losses in a portfolio or financial (banking) system.

The results obtained in this paper show that extreme dependence varies from period to period, thus supporting the idea that financial stability is a continuum. The results also indicate that banks are highly interlinked both within and across borders; however, as previously mentioned, this interlinkage varies from period to period. The results stemming from the risk-stability index show that, on average, U.S. banks tend to cause the most stress to the global financial system (as defined herein), followed by Asian and European banks. When it comes to contagion or "domino-effects", U.S. banks seem to be the most contagious, followed by Asian banks, and then by European banks. The persistence of distress is also an important variable that must be take into account when analyzing financial stability; accordingly, the results show that Asian banks (mainly South Korean banks) seem to experience the most persistence of distress, followed by U.S. banks, which are in turn followed by European banks.

Interestingly, the (daily time-series of) the risk-stability index does not corroborate the idea that the "failure" of Lehman Brothers caused any *additional* distress to the financial system (as defined herein). However, the results highlighted in this paper clearly indicate that the decision of central banks from around the world not to let *any other* financial institution "fail" was the right decision, since "domino-effects" appear to be long-lived, and severe; thereby impacting not only domestic markets, but also financial systems from around the world. Another aspect that has been much talked about by economists and regulators is that regulation must be aimed at institutions that are "too big to fail". However, while not directly tested, the results herein indicate that "too big to fail" does not seem to be a major factor in explaining instability of a financial system. What does seem to be of more importance is whether financial institutions are "too interconnected to fail"; but this is something that future research will have to uncover.

The panel-data vector autoregression results indicate that the risk-stability index is negatively and significantly associated with the federal funds rate and the term-spread (defined as the difference between the $10-$year and $3-$month treasury constant maturity rate). This suggests that when monetary policy is "accommodative", most banks move together more closely. By contrast, when monetary policy is tightened, banks can be affected differently, depending on their liquidity positions. The VAR results also show that the risk-stability index and the returns to the $S\&P500$ are negatively and significantly correlated. This result is intuitive, since the deterioration of the general market (i.e. lower market returns) increases the sensitivity of market participants *vis-à-vis* higher failure risk, as well as their view that the conditional probability of joint failure is higher. As is well known, the VAR framework allows for a feedback effect from the banking system to the macro-economy and the general financial market. This feedback effect shows that an increase in the risk-stability index negatively affects interest rates and the returns to the $S\&P500$. Interestingly, the former result suggests that interest rate policy may be affected by financial stability concerns in practice. As a final point, the positive correlation between the risk-stability index and the VIX index is well-matched with market participants' perception that VIX is the "fear index".

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, monetary policy, and the real economy. The results herein indicate that the monitoring of financial stability within and between economies should be a counter-cyclical continuous process; and that 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 underscored.

References

Allen, F., Carletti, E., and Babus, A. (2009). Financial Crises: Theory and Evidence. *Annual Review of Financial Economics*, 1(1).

Arrellano, M. and Bover, O. (1995). Another Look at the Instrumental Variable Estimation of Error Component Models. *Journal of Econometrics*, 68.

Aspachs, O., Goodhart, C., Tsomocos, D., and Zicchino, L. (2007). Towards a Measure of Financial Fragility. *Annals of Finance*, 3.

Boyer, B., Gibson, M., and Loretan, M. (1997). Pitfalls in Tests for Changes in Correlation. *International Finance Discussion Paper No 5-97, Board of Governors of the Federal Reserve System.*

Das, S. and Hanouma, P. (2006). Credit Default Swap Spreads. *Journal of Investment Management*, 4(3):93–105.

de Haan, L. and Ferreira, A. (2006). *Extreme Value Theory: An Introduction.* Springer Series in Operations Research and Financial Engineering. Springer, New York, NY, USA.

de Vries, C. (2005). The Simple Economics of Bank Fragility. *Journal of Banking and Finance*, 29:803–825.

deBandt, O. and Hartmann, P. (2000). Systemic Risk: A Survey. *European Central Bank Working Paper Series No.35.*

Diamond, D. and Dybvig, P. (1983). Bank Runs, Deposit Insurance, and Liquidity. *Journal of Political Economy*, 91(5):401–419.

Embrechts, P., de Haan, L., and Huang, X. (2000). Modelling Multivariate Extremes. In Embrechts, P., editor, *Extremes and Integrated Risk Management*, pages 59–67. Risk Books.

Feller, W. (1971). *An Introduction to Probability Theory and its Applications*, volume II. Wiley, New York, 2nd edition.

Forbes, K. and Rigobon, R. (2002). No Contagion, Only Interdependence: Measuring Stock Market Comovements. *The Journal of Finance*, 57(5):2223–2261.

Garita, G. and Zhou, C. (2009). Can Open Capital Markets Help Avoid Currency Crises? *De Nederlansche Bank Working Paper 205.*

Goodhart, C., Sunirand, P., and Tsomocos, D. (2005). A Risk Assessment Model for Banks. *Annals of Finance*, 1:197–224.

Goodhart, C., Sunirand, P., and Tsomocos, D. (2006). A Model to Analyze Financial Fragility. *Economic Theory*, 27:107–142.

Hamilton, J. (1994). *Time Series Analysis*. Princeton University Press.

Hartman, P., Straetmans, S., and de Vries, C. (2004). Asset Market Linkages in Crisis Periods. *Review of Economics and Statistics*, 86:313–326.

Hill, B. (1975). A Simple General Approach to Inference about the Tail of a Distribution. *The Annals of Statistics*, 3:1163–1173.

Holtz-Eakin, D., Newey, W., and Rosen, H. (1988). Estimating Vector Autoregressions with Panel Data. *Econometrica*, 56(6):1371–1395.

Houben, A., Kakes, J., and Schinasi, G. (2004). Toward a Framework for Safeguarding Financial Stability. *IMF Working Paper WP/04/101*.

Huang, X. (1992). *Statistics of Bivariate Extreme Values*. PhD thesis, Erasmus University Rotterdam - Tinbergen Institute.

Hull, J., Predescu, M., and White, A. (2004). The Relationship Between Credit Default Swap Spreads, Bond Yields, and Credit Rating Announcements. *Journal of Banking and Finance*, 28(11):2789–2811.

Hyung, N. and de Vries, C. (2002). Portfolio Diversification Effects and Regular Variation in Financial Data. *Allgemeines Statistiches Archiev*, 86:69–82.

Hyung, N. and de Vries, C. (2005). Portfolio Diversification Effects of Downside Rsk. *Journal of Financial Econometrics*, 3:107–125.

Lehar, A. (2005). Measuring Systemic Risk: A Risk Management Approach. *Journal of Banking and Finance*, 29:2577–2603.

Love, I. and Ziccino, L. (2006). Financial Development and Dynamic Investment Behaviour: Evidence from Panel VAR. *The Quarterly Review of Economics and Finance*, 46:190–210.

Merton, R. (1974). On the Pricing of Corporate Debt: The Risk Structure if Interest Rates. *Journal of Finance*, 29(2):449–470.

Segoviano, M. and Goodhart, C. (2009). Banking Stability Measures. *IMF Working Paper 09/04*.

Weissman, I. (1978). Estimators of Parameters and Large Quantiles Based on k Largest Observations. *Journal of the American Statistical Association*, 73:812–815.

Zhou, C. (2009). Dependence Structure of Risk Factors and Diversification Effects. *De Nederlandsche Bank Working Paper No. 219/2009*.

Appendix A - Descriptive Statistics and Directionality of Contagion Matrices

Table 3: Descriptive Statistics of CDS Spreads (in bps) for 18 Major Banks

	N	**Mean**	**SD**	**Skew.**	**Kurt.**	**Min**	**Max**
Hana	1714	116.47	137.23	2.15	7.35	13.3	863
Kookmin	1715	108.53	125.94	2.20	7.88	12.4	857.4
Shinhan	1710	115.77	136.54	2.15	7.34	13.7	852.9
Woori	1702	129.46	147.80	2.05	6.99	12.3	881.7
IBK	1715	101.73	125.66	2.27	8.09	12.6	848.1
KDB	1715	96.31	118.87	2.40	8.94	12.3	841.4
Kexim	1715	94.89	117.57	2.41	8.95	11.9	832.2
UBS	1715	47.81	70.55	1.98	6.44	4.2	357.2
BoA	1715	54.88	70.19	2.14	7.44	8.1	400.3
Mizuho	1632	45.66	41.33	1.21	3.51	5.8	177.9
Creditsuisse	1715	46.49	49.17	1.76	5.50	9	261.4
ING	1707	40.07	41.40	1.61	4.60	4.4	196.8
HSBC	1715	35.37	39.94	1.76	5.42	5	202.4
Citi	1715	79.78	126.60	2.33	8.05	6.5	638.3
SocGen	1715	33.34	37.22	1.30	3.20	5.8	155.3
JPMorgan	1715	48.74	41.67	1.59	4.85	10.9	227.3
BNP Paribas	1715	26.21	26.76	1.46	4.19	5.4	136.3
Deutsche Bank	1715	40.39	40.28	1.40	3.67	8.9	174.9

Table 4: Distress Dependence Matrix and CPJF of 18 Major Banks based on daily CDS spreads ($Feb12, 2003 - Nov18, 2003 = t-1$ and $Nov19, 2003 - Aug24, 2004 = t$)

	$\mathbf{1}_t$	$\mathbf{2}_t$	$\mathbf{3}_t$	$\mathbf{4}_t$	$\mathbf{5}_t$	$\mathbf{6}_t$	$\mathbf{7}_t$	$\mathbf{8}_t$	$\mathbf{9}_t$	$\mathbf{10}_t$	$\mathbf{11}_t$	$\mathbf{12}_t$	$\mathbf{13}_t$	$\mathbf{14}_t$	$\mathbf{15}_t$	$\mathbf{16}_t$	$\mathbf{17}_t$	$\mathbf{18}_t$
$\mathbf{1}_{t-1}$	0.08	0.11	0.11	0.21	0.08	0.03	0.05	0.00	0.00	0.00	0.00	0.00	0.14	0.00	0.00	0.00	0.00	0.00
$\mathbf{2}_{t-1}$	0.08	0.14	0.07	0.22	0.08	0.08	0.08	0.00	0.00	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{3}_{t-1}$	0.08	0.13	0.05	0.21	0.05	0.03	0.14	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00
$\mathbf{4}_{t-1}$	0.08	0.08	0.03	0.11	0.05	0.03	0.09	0.00	0.00	0.03	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00
$\mathbf{5}_{t-1}$	0.05	0.13	0.03	0.29	0.05	0.05	0.03	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00
$\mathbf{6}_{t-1}$	0.05	0.08	0.11	0.18	0.00	0.03	0.05	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00
$\mathbf{7}_{t-1}$	0.05	0.11	0.08	0.14	0.03	0.05	0.05	0.02	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00
$\mathbf{8}_{t-1}$	0.25	0.23	0.27	0.03	0.33	0.32	0.37	0.00	0.00	0.48	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00
$\mathbf{9}_{t-1}$	0.25	0.22	0.25	0.11	0.25	0.25	0.25	0.00	0.00	0.38	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00
$\mathbf{10}_{t-1}$	0.25	0.14	0.21	0.03	0.33	0.27	0.29	0.03	0.02	0.38	0.05	0.03	0.05	0.00	0.09	0.00	0.00	0.00
$\mathbf{11}_{t-1}$	0.18	0.32	0.21	0.21	0.25	0.20	0.11	0.00	0.00	0.33	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00
$\mathbf{12}_{t-1}$	0.03	0.00	0.00	0.14	0.05	0.03	0.00	0.00	0.00	0.05	0.00	0.00	0.21	0.00	0.00	0.00	0.00	0.00
$\mathbf{13}_{t-1}$	0.29	0.32	0.16	0.12	0.18	0.33	0.29	0.00	0.00	0.28	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00
$\mathbf{14}_{t-1}$	0.23	0.25	0.25	0.08	0.38	0.37	0.33	0.00	0.00	0.48	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00
$\mathbf{15}_{t-1}$	0.25	0.18	0.28	0.03	0.25	0.37	0.33	0.00	0.00	0.43	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00
$\mathbf{16}_{t-1}$	0.25	0.20	0.15	0.14	0.23	0.25	0.21	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{17}_{t-1}$	0.25	0.23	0.33	0.14	0.25	0.25	0.27	0.00	0.00	0.37	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00
$\mathbf{18}_{t-1}$	0.20	0.21	0.25	0.08	0.23	0.23	0.23	0.00	0.00	0.38	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00

Notes: 1=Hana, 2=Kookmin, 3=Shinhan, 4=Woori, 5=IBK, 6=KDB, 7=Kexim, 8=UBS, 9=Bank of America, 10=Mizuho 11=Credit Suisse, 12=ING, 13=HSBC, 14=Citi, 15=SocGen, 16=JPMorgan, 17=BNPparibas, 18=Deutschebank

Table 5: Distress Dependence Matrix and CPJF of 18 Major Banks based on daily CDS spreads ($Nov19, 2003 - Aug24, 2004 = t - 1$ and $Aug25, 2004 - May31, 2005 = t$)

	$\mathbf{1}_t$	$\mathbf{2}_t$	$\mathbf{3}_t$	$\mathbf{4}_t$	$\mathbf{5}_t$	$\mathbf{6}_t$	$\mathbf{7}_t$	$\mathbf{8}_t$	$\mathbf{9}_t$	$\mathbf{10}_t$	$\mathbf{11}_t$	$\mathbf{12}_t$	$\mathbf{13}_t$	$\mathbf{14}_t$	$\mathbf{15}_t$	$\mathbf{16}_t$	$\mathbf{17}_t$	$\mathbf{18}_t$
$\mathbf{1}_{t-1}$	0.33	0.18	0.18	0.23	0.21	0.18	0.25	0.11	0.18	0.35	0.06	0.03	0.11	0.11	0.05	0.12	0.00	0.05
$\mathbf{2}_{t-1}$	0.31	0.11	0.12	0.19	0.11	0.08	0.14	0.14	0.11	0.11	0.06	0.03	0.16	0.11	0.03	0.14	0.00	0.00
$\mathbf{3}_{t-1}$	0.18	0.14	0.20	0.20	0.16	0.15	0.25	0.05	0.20	0.18	0.11	0.03	0.11	0.16	0.08	0.11	0.03	0.00
$\mathbf{4}_{t-1}$	0.05	0.25	0.09	0.10	0.29	0.05	0.20	0.00	0.00	0.03	0.05	0.00	0.05	0.00	0.00	0.05	0.03	0.08
$\mathbf{5}_{t-1}$	0.20	0.18	0.22	0.25	0.25	0.09	0.16	0.00	0.25	0.20	0.00	0.03	0.14	0.27	0.00	0.06	0.00	0.02
$\mathbf{6}_{t-1}$	0.28	0.19	0.20	0.29	0.20	0.15	0.20	0.00	0.23	0.39	0.06	0.05	0.16	0.21	0.03	0.05	0.00	0.00
$\mathbf{7}_{t-1}$	0.18	0.21	0.27	0.39	0.25	0.14	0.18	0.00	0.18	0.54	0.02	0.00	0.25	0.18	0.00	0.11	0.02	0.03
$\mathbf{8}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.00	0.00	0.11	0.16	0.03	0.02	0.03	0.00	0.03	0.03
$\mathbf{9}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.00	0.05	0.11	0.00	0.00	0.11	0.08	0.09	0.00
$\mathbf{10}_{t-1}$	0.35	0.33	0.30	0.39	0.25	0.14	0.28	0.00	0.30	0.43	0.08	0.02	0.21	0.25	0.00	0.08	0.00	0.00
$\mathbf{11}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.00	0.00	0.25	0.11	0.05	0.00	0.26	0.02	0.09	0.21
$\mathbf{12}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.07	0.11	0.03	0.02	0.00	0.00	0.03	0.11
$\mathbf{13}_{t-1}$	0.03	0.08	0.05	0.05	0.05	0.09	0.04	0.03	0.04	0.00	0.05	0.11	0.11	0.11	0.02	0.03	0.09	0.02
$\mathbf{14}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.00	0.00	0.18	0.11	0.00	0.00	0.05	0.14	0.14	0.00
$\mathbf{15}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.05	0.21	0.03	0.00	0.09	0.11	0.11	0.03
$\mathbf{16}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.00	0.00	0.08	0.11	0.05	0.00	0.06	0.04	0.05	0.00
$\mathbf{17}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.15	0.00	0.00	0.08	0.17	0.05	0.00	0.03	0.08	0.08	0.00
$\mathbf{18}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.00	0.00	0.18	0.14	0.00	0.00	0.11	0.06	0.05	0.19

Notes: 1=Hana, 2=Kookmin, 3=Shinhan, 4=Woori, 5=IBK, 6=KDB, 7=Kexim, 8=UBS, 9=Bank of America, 10=Mizuho 11=Credit Suisse, 12=ING, 13=HSBC, 14=Citi, 15=SocGen, 16=JPMorgan, 17=BNPparibas, 18=Deutschebank

Table 6: Distress Dependence Matrix and CPJF of 18 Major Banks based on daily CDS spreads ($Nov19, 2003 - Aug24, 2004 = t - 1$ and $June1, 2005 - March6, 2006 = t$)

	$\mathbf{1}_t$	$\mathbf{2}_t$	$\mathbf{3}_t$	$\mathbf{4}_t$	$\mathbf{5}_t$	$\mathbf{6}_t$	$\mathbf{7}_t$	$\mathbf{8}_t$	$\mathbf{9}_t$	$\mathbf{10}_t$	$\mathbf{11}_t$	$\mathbf{12}_t$	$\mathbf{13}_t$	$\mathbf{14}_t$	$\mathbf{15}_t$	$\mathbf{16}_t$	$\mathbf{17}_t$	$\mathbf{18}_t$
$\mathbf{1}_{t-1}$	0.48	0.47	0.43	0.33	0.32	0.41	0.32	0.37	0.33	0.41	0.21	0.29	0.47	0.60	0.60	0.38	0.43	0.43
$\mathbf{2}_{t-1}$	0.23	0.23	0.23	0.22	0.28	0.23	0.23	0.23	0.14	0.38	0.16	0.12	0.18	0.20	0.29	0.23	0.25	0.25
$\mathbf{3}_{t-1}$	0.35	0.29	0.43	0.24	0.30	0.38	0.25	0.32	0.34	0.38	0.27	0.16	0.32	0.37	0.32	0.35	0.41	0.41
$\mathbf{4}_{t-1}$	0.56	0.54	0.41	0.44	0.45	0.54	0.49	0.48	0.52	0.50	0.52	0.34	0.27	0.47	0.53	0.41	0.54	0.54
$\mathbf{5}_{t-1}$	0.25	0.20	0.25	0.20	0.25	0.27	0.20	0.25	0.19	0.23	0.03	0.23	0.18	0.17	0.22	0.23	0.25	0.25
$\mathbf{6}_{t-1}$	0.10	0.15	0.16	0.18	0.14	0.15	0.16	0.15	0.18	0.29	0.18	0.21	0.29	0.22	0.18	0.23	0.19	0.19
$\mathbf{7}_{t-1}$	0.20	0.25	0.25	0.21	0.30	0.43	0.27	0.22	0.11	0.22	0.12	0.21	0.25	0.17	0.26	0.27	0.38	0.27
$\mathbf{8}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{9}_{t-1}$	0.39	0.37	0.34	0.28	0.35	0.35	0.35	0.39	0.24	0.27	0.20	0.25	0.06	0.27	0.39	0.29	0.39	0.38
$\mathbf{10}_{t-1}$	0.54	0.48	0.52	0.45	0.42	0.41	0.45	0.41	0.41	0.28	0.34	0.21	0.39	0.40	0.46	0.48	0.41	0.48
$\mathbf{11}_{t-1}$	0.06	0.03	0.06	0.05	0.06	0.06	0.03	0.09	0.09	0.08	0.06	0.08	0.09	0.08	0.06	0.06	0.09	0.06
$\mathbf{12}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{13}_{t-1}$	0.19	0.19	0.19	0.13	0.19	0.18	0.16	0.19	0.18	0.10	0.14	0.19	0.21	0.15	0.19	0.16	0.20	0.20
$\mathbf{14}_{t-1}$	0.25	0.23	0.23	0.20	0.32	0.23	0.28	0.23	0.16	0.23	0.19	0.12	0.10	0.23	0.25	0.23	0.32	0.30
$\mathbf{15}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{16}_{t-1}$	0.06	0.08	0.10	0.11	0.09	0.08	0.08	0.11	0.10	0.08	0.08	0.14	0.10	0.03	0.11	0.09	0.11	0.11
$\mathbf{17}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{18}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: 1=Hana, 2=Kookmin, 3=Shinhan, 4=Woori, 5=IBK, 6=KDB, 7=Kexim, 8=UBS, 9=Bank of America, 10=Mizuho 11=Credit Suisse, 12=ING, 13=HSBC, 14=Citi, 15=SocGen, 16=JPMorgan, 17=BNPparibas, 18=Deutschebank

Table 7: Distress Dependence Matrix and CPJF of 18 Major Banks based on daily CDS spreads ($June1, 2005 - March6, 2006 = t - 1$ and $March7, 2006 - Dec12, 2006 = t$)

	$\mathbf{1}_t$	$\mathbf{2}_t$	$\mathbf{3}_t$	$\mathbf{4}_t$	$\mathbf{5}_t$	$\mathbf{6}_t$	$\mathbf{7}_t$	$\mathbf{8}_t$	$\mathbf{9}_t$	$\mathbf{10}_t$	$\mathbf{11}_t$	$\mathbf{12}_t$	$\mathbf{13}_t$	$\mathbf{14}_t$	$\mathbf{15}_t$	$\mathbf{16}_t$	$\mathbf{17}_t$	$\mathbf{18}_t$
$\mathbf{1}_{t-1}$	0.03	0.23	0.00	0.11	0.00	0.00	0.00	0.25	0.11	0.29	0.45	0.23	0.54	0.22	0.50	0.30	0.54	0.20
$\mathbf{2}_{t-1}$	0.03	0.23	0.00	0.12	0.00	0.00	0.00	0.29	0.14	0.30	0.45	0.23	0.54	0.21	0.43	0.25	0.56	0.20
$\mathbf{3}_{t-1}$	0.03	0.21	0.00	0.11	0.00	0.00	0.00	0.74	0.45	0.29	0.43	0.21	0.48	0.21	0.52	0.27	0.48	0.13
$\mathbf{4}_{t-1}$	0.00	0.21	0.00	0.08	0.00	0.00	0.00	0.67	0.11	0.18	0.47	0.28	0.56	0.43	0.47	0.18	0.33	0.17
$\mathbf{5}_{t-1}$	0.05	0.27	0.00	0.11	0.00	0.00	0.00	0.54	0.18	0.25	0.43	0.25	0.52	0.13	0.45	0.25	0.64	0.08
$\mathbf{6}_{t-1}$	0.05	0.23	0.00	0.11	0.00	0.00	0.00	0.52	0.20	0.21	0.43	0.23	0.49	0.17	0.47	0.27	0.54	0.08
$\mathbf{7}_{t-1}$	0.05	0.20	0.00	0.11	0.00	0.00	0.00	0.54	0.16	0.25	0.41	0.23	0.54	0.13	0.47	0.23	0.40	0.14
$\mathbf{8}_{t-1}$	0.03	0.23	0.00	0.11	0.00	0.00	0.00	0.18	0.82	0.30	0.48	0.21	0.54	0.25	0.33	0.25	0.54	0.25
$\mathbf{9}_{t-1}$	0.00	0.25	0.00	0.05	0.00	0.00	0.00	0.43	0.18	0.30	0.25	0.23	0.57	0.25	0.43	0.25	0.54	0.27
$\mathbf{10}_{t-1}$	0.00	0.23	0.00	0.11	0.00	0.00	0.00	0.47	0.34	0.35	0.37	0.19	0.31	0.48	0.34	0.18	0.48	0.25
$\mathbf{11}_{t-1}$	0.09	0.09	0.08	0.12	0.00	0.03	0.05	0.18	0.25	0.19	0.34	0.18	0.23	0.21	0.14	0.11	0.43	0.09
$\mathbf{12}_{t-1}$	0.05	0.33	0.00	0.14	0.00	0.00	0.00	0.25	0.21	0.23	0.31	0.06	0.54	0.23	0.45	0.15	0.38	0.25
$\mathbf{13}_{t-1}$	0.05	0.21	0.00	0.14	0.00	0.00	0.00	0.37	0.30	0.30	0.41	0.21	0.53	0.53	0.48	0.19	0.48	0.14
$\mathbf{14}_{t-1}$	0.03	0.25	0.00	0.11	0.00	0.00	0.00	0.32	0.18	0.29	0.48	0.22	0.52	0.25	0.47	0.22	0.54	0.14
$\mathbf{15}_{t-1}$	0.00	0.23	0.00	0.11	0.00	0.00	0.00	1.00	0.82	0.32	0.45	0.28	0.53	0.11	0.53	0.23	0.52	0.10
$\mathbf{16}_{t-1}$	0.00	0.29	0.00	0.09	0.00	0.00	0.00	1.00	0.65	0.25	0.48	0.25	0.54	0.54	0.43	0.21	0.38	0.15
$\mathbf{17}_{t-1}$	0.00	0.23	0.00	0.11	0.00	0.00	0.00	1.00	0.54	0.32	0.48	0.25	0.48	0.54	0.43	0.23	0.52	0.13
$\mathbf{18}_{t-1}$	0.00	0.23	0.00	0.11	0.00	0.00	0.00	0.67	0.54	0.32	0.47	0.24	0.47	0.54	0.48	0.23	0.54	0.12

Notes: 1=Hana, 2=Kookmin, 3=Shinhan, 4=Woori, 5=IBK, 6=KDB, 7=Kexim, 8=UBS, 9=Bank of America, 10=Mizuho 11=Credit Suisse, 12=ING, 13=HSBC, 14=Citi, 15=SocGen, 16=JPMorgan, 17=BNPparibas, 18=Deutschebank

Table 8: Distress Dependence Matrix and CPJF of 18 Major Banks based on daily CDS spreads ($March8, 2006 - Dec12, 2006 = t - 1$ and $Dec13, 2006 - Sept18, 2007 = t$)

	$\mathbf{1}_t$	$\mathbf{2}_t$	$\mathbf{3}_t$	$\mathbf{4}_t$	$\mathbf{5}_t$	$\mathbf{6}_t$	$\mathbf{7}_t$	$\mathbf{8}_t$	$\mathbf{9}_t$	$\mathbf{10}_t$	$\mathbf{11}_t$	$\mathbf{12}_t$	$\mathbf{13}_t$	$\mathbf{14}_t$	$\mathbf{15}_t$	$\mathbf{16}_t$	$\mathbf{17}_t$	$\mathbf{18}_t$
$\mathbf{1}_{t-1}$	0.21	0.14	0.00	0.27	0.18	0.11	0.11	0.00	0.00	0.00	0.00	0.15	0.00	0.00	0.00	0.00	0.00	0.08
$\mathbf{2}_{t-1}$	0.09	0.09	0.00	0.03	0.09	0.09	0.00	0.00	0.00	0.00	0.00	0.10	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{3}_{t-1}$	0.20	0.05	0.11	0.06	0.10	0.07	0.16	0.00	0.00	0.00	0.00	0.21	0.00	0.00	0.00	0.03	0.00	0.14
$\mathbf{4}_{t-1}$	0.18	0.10	0.08	0.16	0.18	0.12	0.16	0.00	0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{5}_{t-1}$	0.05	0.20	0.04	0.05	0.14	0.11	0.21	0.08	0.00	0.11	0.05	0.06	0.00	0.00	0.02	0.05	0.04	0.11
$\mathbf{6}_{t-1}$	0.03	0.12	0.08	0.05	0.16	0.10	0.19	0.05	0.00	0.05	0.05	0.02	0.04	0.00	0.08	0.11	0.00	0.12
$\mathbf{7}_{t-1}$	0.05	0.09	0.04	0.04	0.08	0.11	0.19	0.05	0.02	0.06	0.04	0.11	0.03	0.02	0.03	0.09	0.04	0.08
$\mathbf{8}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{9}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{10}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{11}_{t-1}$	0.06	0.03	0.05	0.08	0.03	0.05	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{12}_{t-1}$	0.03	0.00	0.03	0.02	0.03	0.00	0.04	0.08	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.03	0.00	0.21
$\mathbf{13}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{14}_{t-1}$	0.00	0.02	0.00	0.04	0.00	0.03	0.02	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{15}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{16}_{t-1}$	0.05	0.04	0.03	0.18	0.05	0.08	0.03	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{17}_{t-1}$	0.02	0.02	0.08	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{18}_{t-1}$	0.05	0.00	0.03	0.08	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.00

Notes: 1=Hana, 2=Kookmin, 3=Shinhan, 4=Woori, 5=IBK, 6=KDB, 7=Kexim, 8=UBS, 9=Bank of America, 10=Mizuho 11=Credit Suisse, 12=ING, 13=HSBC, 14=Citi, 15=SocGen, 16=JPMorgan, 17=BNPparibas, 18=Deutschebank

Table 9: Distress Dependence Matrix and CPJF of 18 Major Banks based on daily CDS spreads ($Dec13, 2006 - Sept18, 2007 = t-1$ and $Sept19, 2007 - June24, 2008 = t$)

	$\mathbf{1}_t$	$\mathbf{2}_t$	$\mathbf{3}_t$	$\mathbf{4}_t$	$\mathbf{5}_t$	$\mathbf{6}_t$	$\mathbf{7}_t$	$\mathbf{8}_t$	$\mathbf{9}_t$	$\mathbf{10}_t$	$\mathbf{11}_t$	$\mathbf{12}_t$	$\mathbf{13}_t$	$\mathbf{14}_t$	$\mathbf{15}_t$	$\mathbf{16}_t$	$\mathbf{17}_t$	$\mathbf{18}_t$
$\mathbf{1}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{2}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{3}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{4}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{5}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{6}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{7}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{8}_{t-1}$	0.05	0.00	0.05	0.05	0.03	0.03	0.03	0.03	0.03	0.16	0.03	0.12	0.03	0.03	0.03	0.03	0.03	0.03
$\mathbf{9}_{t-1}$	0.35	0.37	0.37	0.54	0.25	0.52	0.30	0.25	0.82	0.39	0.67	0.48	0.47	0.90	0.42	0.75	0.37	0.68
$\mathbf{10}_{t-1}$	0.18	0.15	0.18	0.14	0.18	0.18	0.18	0.18	0.16	0.11	0.18	0.00	0.18	0.16	0.14	0.16	0.20	0.16
$\mathbf{11}_{t-1}$	0.08	0.11	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.18	0.00	0.23	0.14	0.00	0.03	0.00	0.05	0.00
$\mathbf{12}_{t-1}$	0.11	0.11	0.11	0.11	0.05	0.11	0.11	0.11	0.11	0.09	0.11	0.08	0.11	0.11	0.10	0.11	0.11	0.11
$\mathbf{13}_{t-1}$	0.25	0.32	0.14	0.32	0.28	0.25	0.20	0.18	0.20	0.46	0.32	0.29	0.25	0.20	0.32	0.25	0.21	0.25
$\mathbf{14}_{t-1}$	0.35	0.38	0.32	0.47	0.18	0.21	0.25	0.79	0.79	0.52	0.43	0.67	0.44	0.14	0.77	0.16	0.18	0.20
$\mathbf{15}_{t-1}$	0.26	0.30	0.38	0.23	0.38	0.48	0.48	0.45	0.48	0.09	0.48	0.27	0.43	0.48	0.30	0.41	0.35	0.41
$\mathbf{16}_{t-1}$	0.04	0.04	0.04	0.05	0.03	0.04	0.04	0.05	0.04	0.05	0.04	0.03	0.04	0.04	0.04	0.04	0.04	0.05
$\mathbf{17}_{t-1}$	0.32	0.43	0.35	0.34	0.48	0.39	0.43	0.29	0.48	0.23	0.43	0.38	0.41	0.37	0.43	0.42	0.39	0.41
$\mathbf{18}_{t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: 1=Hana, 2=Kookmin, 3=Shinhan, 4=Woori, 5=IBK, 6=KDB, 7=Kexim, 8=UBS, 9=Bank of America, 10=Mizuho 11=Credit Suisse, 12=ING, 13=HSBC, 14=Citi, 15=SocGen, 16=JPMorgan, 17=BNPparibas, 18=Deutschebank

Table 10: Distress Dependence Matrix and CPJF of 18 Major Banks based on daily CDS spreads ($Sept19, 2007 - June24, 2008 = t-1$ and $June24, 2008 - March31, 2009 = t$)

	$\mathbf{1}_t$	$\mathbf{2}_t$	$\mathbf{3}_t$	$\mathbf{4}_t$	$\mathbf{5}_t$	$\mathbf{6}_t$	$\mathbf{7}_t$	$\mathbf{8}_t$	$\mathbf{9}_t$	$\mathbf{10}_t$	$\mathbf{11}_t$	$\mathbf{12}_t$	$\mathbf{13}_t$	$\mathbf{14}_t$	$\mathbf{15}_t$	$\mathbf{16}_t$	$\mathbf{17}_t$	$\mathbf{18}_t$
$\mathbf{1}_{t-1}$	0.25	0.21	0.23	0.16	0.32	0.12	0.22	0.05	0.16	0.00	0.05	0.30	0.12	0.54	0.00	0.19	0.00	0.03
$\mathbf{2}_{t-1}$	0.25	0.29	0.36	0.29	0.30	0.11	0.21	0.23	0.25	0.00	0.00	0.18	0.42	0.35	0.00	0.11	0.00	0.00
$\mathbf{3}_{t-1}$	0.18	0.18	0.27	0.25	0.25	0.16	0.27	0.00	0.25	0.00	0.00	0.29	0.04	0.39	0.00	0.08	0.00	0.08
$\mathbf{4}_{t-1}$	0.32	0.43	0.39	0.28	0.30	0.22	0.40	0.11	0.27	0.00	0.20	0.22	0.09	0.33	0.00	0.14	0.03	0.00
$\mathbf{5}_{t-1}$	0.21	0.18	0.25	0.18	0.18	0.12	0.10	0.00	0.18	0.00	0.08	0.20	0.03	0.33	0.00	0.03	0.00	0.00
$\mathbf{6}_{t-1}$	0.25	0.25	0.21	0.19	0.22	0.13	0.20	0.00	0.17	0.00	0.00	0.25	0.00	0.46	0.00	0.03	0.00	0.00
$\mathbf{7}_{t-1}$	0.36	0.25	0.25	0.25	0.23	0.14	0.20	0.00	0.16	0.00	0.00	0.35	0.06	0.37	0.00	0.05	0.00	0.00
$\mathbf{8}_{t-1}$	0.22	0.25	0.22	0.22	0.23	0.11	0.33	0.00	0.16	0.00	0.00	0.35	0.00	0.43	0.00	0.03	0.00	0.00
$\mathbf{9}_{t-1}$	0.22	0.21	0.21	0.11	0.22	0.11	0.14	0.00	0.14	0.00	0.00	0.19	0.06	0.30	0.00	0.05	0.00	0.09
$\mathbf{10}_{t-1}$	0.00	0.21	0.21	0.11	0.21	0.14	0.14	0.00	0.15	0.00	0.00	0.19	0.06	0.30	0.00	0.04	0.00	0.09
$\mathbf{11}_{t-1}$	0.25	0.08	0.18	0.43	0.15	0.11	0.22	0.03	0.25	0.00	0.20	0.30	0.08	0.48	0.03	0.11	0.00	0.03
$\mathbf{12}_{t-1}$	0.10	0.11	0.27	0.18	0.37	0.28	0.12	0.14	0.33	0.00	0.03	0.27	0.16	0.14	0.05	0.20	0.00	0.08
$\mathbf{13}_{t-1}$	0.26	0.00	0.22	0.11	0.14	0.09	0.22	0.00	0.15	0.00	0.00	0.33	0.09	0.49	0.03	0.11	0.00	0.00
$\mathbf{14}_{t-1}$	0.22	0.21	0.21	0.11	0.33	0.11	0.21	0.00	0.16	0.00	0.00	0.29	0.08	0.38	0.00	0.05	0.00	0.09
$\mathbf{15}_{t-1}$	0.25	0.33	0.29	0.21	0.22	0.13	0.22	0.20	0.29	0.00	0.03	0.33	0.08	0.45	0.00	0.12	0.00	0.05
$\mathbf{16}_{t-1}$	0.22	0.05	0.22	0.22	0.22	0.12	0.28	0.00	0.23	0.00	0.00	0.33	0.09	0.41	0.00	0.03	0.00	0.04
$\mathbf{17}_{t-1}$	0.18	0.05	0.14	0.21	0.25	0.16	0.18	0.00	0.22	0.00	0.00	0.25	0.11	0.33	0.03	0.08	0.00	0.06
$\mathbf{18}_{t-1}$	0.26	0.05	0.22	0.21	0.22	0.20	0.22	0.03	0.21	0.00	0.21	0.33	0.06	0.43	0.00	0.08	0.00	0.04

Notes: 1=Hana, 2=Kookmin, 3=Shinhan, 4=Woori, 5=IBK, 6=KDB, 7=Kexim, 8=UBS, 9=Bank of America, 10=Mizuho 11=Credit Suisse, 12=ING, 13=HSBC, 14=Citi, 15=SocGen, 16=JPMorgan, 17=BNPparibas, 18=Deutschebank

Appendix B - VAR Time-Series and VAR Results

Figure 11: Financial Market Factors - Time-series of effective federal funds rate, term spread (difference between 10 year and 3 month treasury constant maturity rate), SP500 (daily) returns, and the VIX (the implied market volatility).

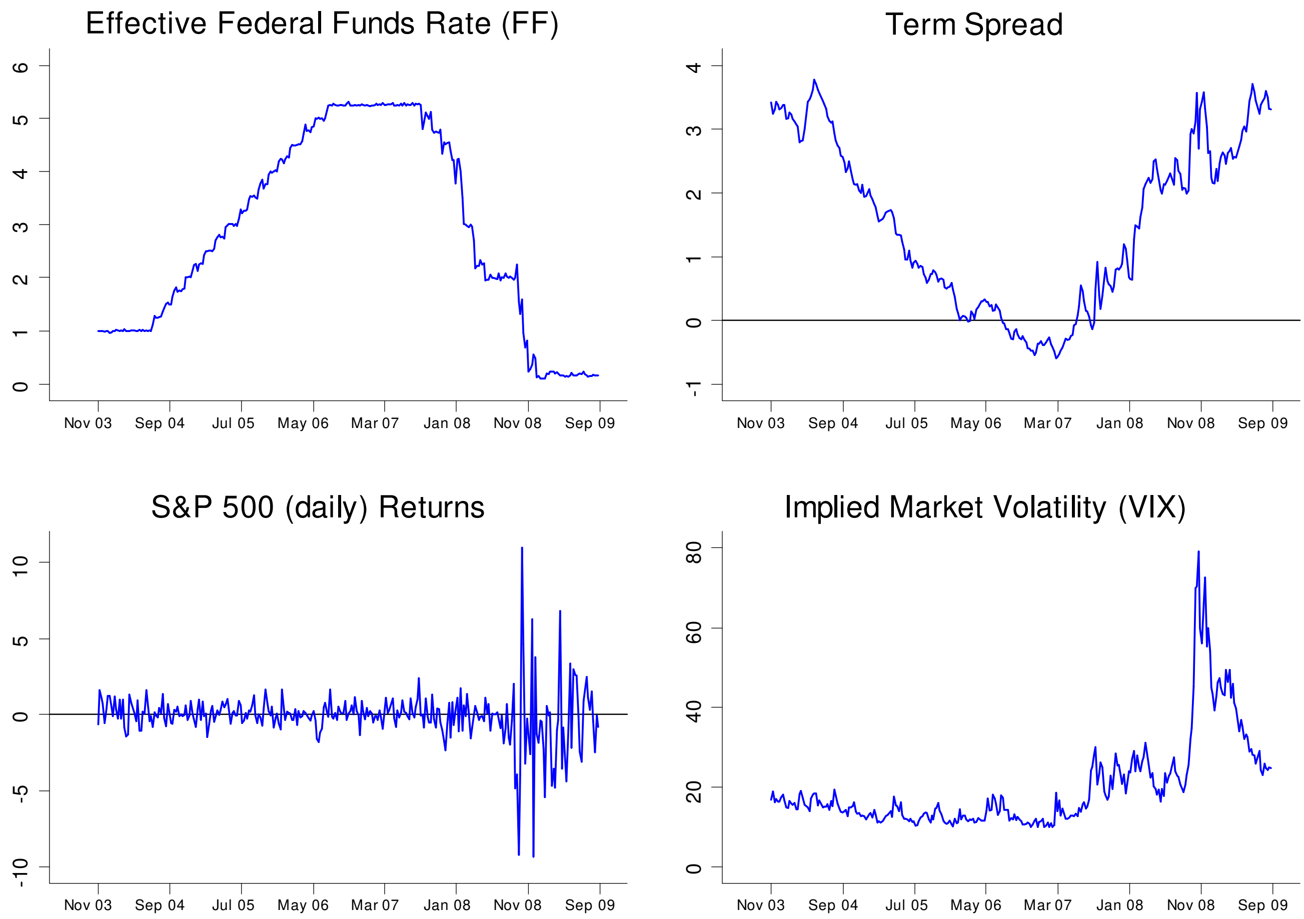


Table 11: Results of Panel VAR with 8-lags (No. of Obs. = 3690; No. of Banks = 18)

	RSI	Fed Funds Rate	Term Spread	SP500ret	VIX
RSI_{t-1}	1.51 (49.60) ***	0.09 (3.89) ***	-0.02 (1.94) *	-0.35 (-4.75) ***	0.09 (1.09)
FFR_{t-1}	-2.36 (-3.82) ***	0.68 (13.01) ***	-1.36 (-5.76) ***	-10.09 (-5.63) ***	-0.37 (-0.20)
$T.Spread_{t-1}$	-1.05 (-5.75) ***	-0.32 (-13.91) ***	0.57 (6.88) ***	-4.12 (-7.79) ***	1.39 (2.48) ***
$SP500ret_{t-1}$	0.11 (7.27) ***	-0.01 (-6.68) ***	-0.02 (-2.29) **	0.03 (0.76)	-0.56 (-12.54) ***
VIX_{t-1}	0.05 (0.007)	-0.07 (-8.29) ***	0.02 (5.05) ***	-0.09 (-4.17) ***	0.85 (34.93) ***
RSI_{t-2}	-0.72 (-17.77) ***	-0.01 (-4.34) ***	0.01 (1.02)	0.07 (0.73)	-0.53 (-4.84) ***
FFR_{t-2}	-0.04 (-0.18)	0.02 (0.79)	-0.41 (-3.97) ***	-5.17 (-7.43) ***	-4.55 (-5.45) ***
$T.Spread_{t-2}$	0.36 (1.60)	0.26 (10.50) ***	-0.44 (-4.13) ***	-1.88 (-2.75) ***	-2.46 (-3.50) ***
$SP500ret_{t-2}$	-0.10 (-6.11) ***	0.01 (0.77)	-0.03 (-4.22) ***	-0.29 (-6.29) ***	-0.16 (-2.84) ***
VIX_{t-2}	-0.03 (-2.59) ***	0.07 (6.34) ***	-0.03 (-6.67) ***	-0.07 (-2.64) ***	-0.05 (-1.77) *
RSI_{t-3}	0.07 (1.87) *	0.02 (0.52)	-0.02 (-1.30)	0.11 (1.11)	0.58 (5.50) ***
FFR_{t-3}	-0.79 (-3.51) ***	0.07 (2.56) **	-0.31 (-3.16) ***	2.52 (3.70) ***	-4.72 (-5.32) ***
$T.Spread_{t-3}$	0.04 (0.19)	-0.07 (-2.43) **	-0.16 (-1.57) *	1.60 (2.33) ***	4.69 (5.86) ***
$SP500ret_{t-3}$	-0.01 (-0.65)	0.03 (1.79) *	0.06 (0.90)	-0.44 (-10.07) ***	-0.81 (-15.07) ***
VIX_{t-3}	-0.02 (-2.02) **	-0.01 (-7.59) ***	0.01 (2.73) ***	0.08 (3.07) ***	0.07 (2.01) **
RSI_{t-4}	-0.03 (-0.78)	0.02 (5.69) ***	0.04 (0.03)	-0.29 (-2.88) ***	-0.01 (-0.17)
FFR_{t-4}	-0.07 (-0.31)	-0.11 (-3.92) ***	-0.05 (-0.50)	-1.88 (-2.79) ***	-0.89 (-1.40)
$T.Spread_{t-4}$	-1.31 (-6.75) ***	0.09 (3.44) ***	0.12 (1.24)	-0.78 (-1.26)	-7.77 (-11.54) ***
$SP500ret_{t-4}$	0.07 (0.55)	-0.01 (-5.37) ***	0.02 (3.06) ***	-0.21 (-4.60) ***	-0.49 (-9.77) ***
VIX_{t-4}	-0.03 (-3.63) ***	0.01 (1.12)	-0.01 (-2.83) ***	0.08 (2.98) ***	-0.05 (-0.16)
RSI_{t-5}	0.18 (-4.44) ***	-0.02 (-7.09) ***	0.04 (2.69) ***	0.47 (4.38) ***	0.02 (0.23)
FFR_{t-5}	-0.81 (-3.29) ***	0.14 (4.17) ***	-0.45 (-4.53) ***	-2.40 (-3.86) ***	2.31 (3.12) ***
$T.Spread_{t-5}$	1.23 (6.38) ***	-0.08 (-3.69) ***	-0.05 (-0.54)	0.34 (0.58)	4.33 (6.62) ***
$SP500ret_{t-5}$	-0.07 (-4.08) ***	0.06 (4.19) ***	-0.01 (-2.34) **	0.06 (1.35)	0.10 (1.91) *
VIX_{t-5}	-0.02 (-1.78) *	0.06 (6.10) ***	-0.04 (-1.09)	-0.35 (-12.46) ***	0.07 (2.77) ***
RSI_{t-6}	-0.20 (-5.40) ***	0.05 (1.56)	-0.01 (-1.14)	-0.22 (-2.36) **	-0.31 (-2.91) ***
FFR_{t-6}	-0.06 (-0.28)	0.08 (3.24) ***	0.19 (2.07) **	2.29 (3.83) ***	0.61 (0.84)
$T.Spread_{t-6}$	-1.67 (-7.44) ***	0.01 (0.64)	-0.16 (-1.56)	-0.96 (-1.33)	-2.65 (-3.73) ***
$SP500ret_{t-6}$	-0.14 (-9.75) ***	0.02 (13.26) ***	-0.02 (-0.40)	0.01 (0.18)	-0.25 (-5.40) ***
VIX_{t-6}	0.06 (5.39) ***	-0.06 (-5.92) ***	-0.02 (-0.42)	0.23 (6.88) ***	-0.12 (-4.17) ***
RSI_{t-7}	0.12 (3.37) ***	0.01 (3.13) ***	-0.03 (-2.80) ***	-0.02 (-0.29)	0.23 (2.48) **
FFR_{t-7}	0.06 (0.26)	0.06 (2.24) **	0.06 (0.66)	-1.63 (-2.58) ***	-1.81 (-2.30) **
$T.Spread_{t-7}$	0.93 (4.14) ***	0.06 (2.71) ***	-0.06 (-0.57)	0.64 (0.84)	-2.60 (-3.82) ***
$SP500ret_{t-7}$	0.01 (0.83)	-0.03 (-1.67) *	0.03 (4.86) ***	0.23 (4.39) ***	-0.09 (-2.09) **
VIX_{t-7}	-0.03 (-2.72) ***	0.05 (5.37) ***	-0.01 (-2.29) **	-0.12 (-4.25) ***	-0.17 (-5.88) ***
RSI_{t-8}	-0.04 (-2.04) **	-0.06 (-3.82) ***	0.02 (3.65) ***	0.01 (0.33)	-0.07 (-1.45)
FFR_{t-8}	2.61 (-5.94) ***	-0.09 (-2.50) **	1.10 (6.61) ***	8.52 (7.01) ***	6.83 (5.31) ***
$T.Spread_{t-8}$	-0.32 (-1.19)	-0.13 (-5.86) ***	-0.38 (-3.57) ***	-4.45 (-5.64) ***	2.42 (2.79) ***
$SP500ret_{t-8}$	-0.06 (-4.03) ***	0.01 (0.85)	0.06 (0.84)	0.02 (0.59)	-0.14 (-2.99) ***
VIX_{t-8}	-0.45 (-0.05)	-0.04 (-4.72) ***	-0.07 (-2.08) **	-0.07 (-3.52) ***	0.08 (3.01) ***

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 SP500. Heteroskedasticity adjusted t-statistics in parentheses;.***, **, * indicate significance at the 1%, 5%, and 10% respectively.