An Inquiry into Banking Portfolios and Financial Stability Surrounding "The Great Recession"

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An Inquiry into Banking Portfolios and Financial Stability Surrounding "The Great Recession"*

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Abstract

By utilizing the extreme dependence structure and the conditional probability of joint failure (CPJF) between banks, this paper characterizes a risk-stability index (RSI) that quantifies (*i*) common distress of banks, (*ii*) distress between specific banks, and (*iii*) distress to a portfolio related to a specific bank. The results show that financial stability is a continuum; that the Korean and U.S. banking systems seem more prone to systemic risk; and that Asian banks experience the most persistence of distress. Furthermore, a panel VAR indicates that "leaning against the wind" reduces the instability of a financial system.

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

Keywords: Conditional probability of joint failure, contagion, dependence structure, distress, multivariate extreme value theory, panel VAR, persistence, risk.

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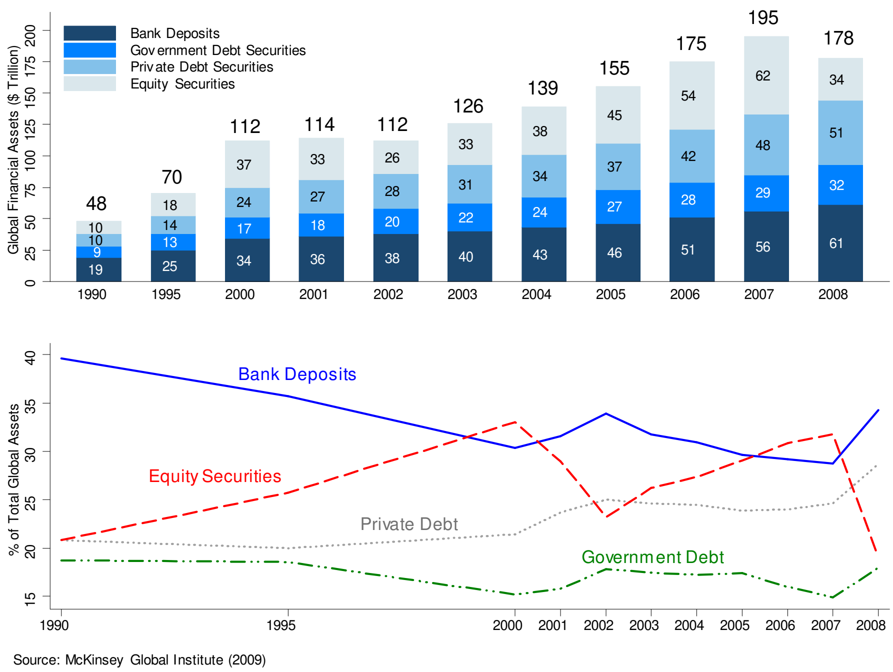
1 Introduction

Figure 1 shows the total value of the world's financial assets (including bank deposits, government and private debt securities, and equity securities), which stood at $195 trillion at the end of 2007, according to the McKinsey Global Institute (2009). This $195 trillion is the total amount of capital intermediated through the world's banks and capital markets, and made available by them to households, business, and governments. Moreover, as the lower panel of Figure 1 shows, banks have been the most important financial intermediaries since 1990, on average intermediating 33% of global financial assets, while capital markets have intermediated 26% of total global assets over the same period, on average. Therefore, given that banks are directly connected (I address this point below) and are among the most important financial intermediaries in an economy, on average, as indicated by Figure 1, then the malfunctioning of such connections can have dire consequences for any financial system, as the current financial crisis has demonstrated.

Figure 1: Global Financial Assets ($ Trillion, using 2008 exchange rates for all years)



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 a 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 to 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.[1]

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 regarding 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,

[1] The interconnectedness within the banking system stems from either a *direct channel* such as interbank lending (see, for example, Allen and Gale, 2000; Dasgupta, 2004), or an *indirect channel* through common exposures via individual diversification effects (see de Vries, 2005).

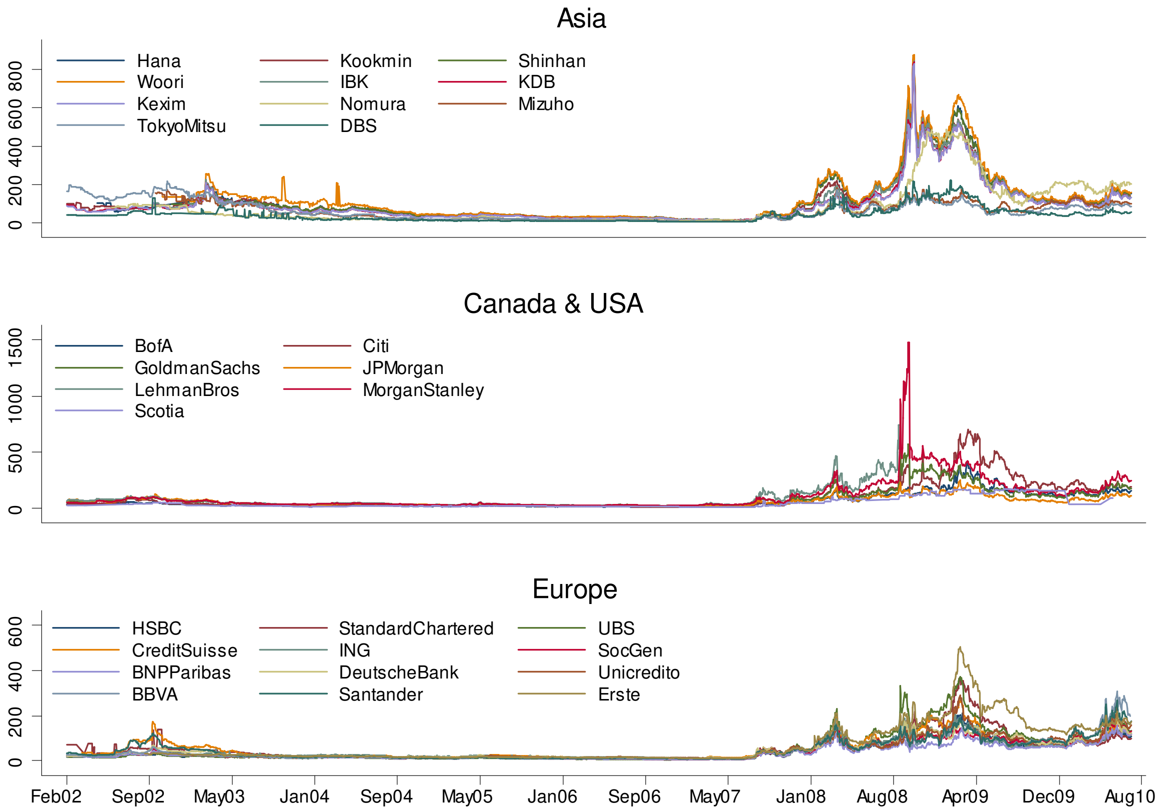
and there is "insufficient" knowledge about the effects and desirability of regulatory measures.

If we 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 a system; however, we do not yet 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 relative to 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 risk factors "fail" due to a common risk exposure (see de Bandt and Hartmann, 2000; Allen et al., 2009 for comprehensive surveys on systemic risk modeling).

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

[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 2: Daily CDS Spreads (in basis points)



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 stay wide of the mark for long, where the direction of the move is by and large a good distress signal (see Figure 2).

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, especially during an economic downturn. 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.

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 regarding 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.[3]

By applying a multivariate extreme value theory ($mEVT$) methodology to a portfolio composed of 30 banks from around the world, I show that extreme dependence, whether it be relationship-specific or system-wide, varies from period to period, thereby lending support to the idea that financial stability is a continuum. The CPJF-based results indicate that banks are highly interlinked especially within geographical borders; corroborating Hartmann et al. (2007), who argued that in a more integrated banking system (e.g. the U.S. or Korea) area-wide systemic risk is higher, and that the lower overall spillover risk in Europe is due to the weak extreme cross-border linkages. The results also 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 results stemming from the risk-stability index show that, on average, Asian banks create slightly more instability to the financial system, followed by U.S., and then by European banks. The panel-data VAR indicates that the RSI 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 monetary policy can help reduce instability in a financial system.

The remainder of the paper evolves as follows: Section 2 will discuss the measures of dependence employed herein. Section 3 provides empirical results for the CPJF, while section 4 provides the results for the risk-stability index. Section 5 looks at the directionality of contagion and the persistence of distress. Section 6 takes advantage of the time-series properties of the Risk-Stability Index, and estimates a panel VAR. Lastly, section 7 concludes.

[3] 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, will eventually die out as the credit spreads become extreme.

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, 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 multivariate measure for the tail dependence (for a formal analysis of univariate EVT, see Embrechts et al., 1997).

2.1 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 in relation to 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

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

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

$$G(x, y) = \lim_{\delta \to 0} \frac{P(X > VaR_x(\delta) * x^{-\frac{1}{\alpha_1}},\ or\ Y > VaR_y(\delta) * y^{-\frac{1}{\alpha_2}})}{\delta} \tag{2}$$

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 (1) as follows:

$$\lim_{\delta \to 0} \frac{P(X > VaR_x(x\delta),\ or\ Y > VaR_y(y\delta))}{\delta} = L(x, y) = L(1, 1) \text{ for } x = y = 1 \tag{3}$$

Through (3) 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 (3) can be modified accordingly. 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:

$$\frac{P(X_1 > VaR_1(x_1\delta),\ or\ X_2 > VaR_2(x_2\delta),\ or, ..., or\ X_d > VaR_d(x_d\delta))}{\delta} = L(x_1, x_2, ..., x_d) \quad (4)$$

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

2.2 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 (2009). 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. Another way of looking at the index is as an estimation of the number of risk factors that would "fail", given that a specific risk factor "fails" (i.e. 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 (4) 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:

$$RSI = \lim_{\delta \to 0} E(\text{number of crises in } X_2 \text{ and } X_3 \mid X_1 \text{ is in crisis}) \quad (5)$$

Denote $\Phi = 1\{X_i > VaR_i(\delta)\}$ as X_i being in crisis, for $i = 1, 2, 3$. Using this to rewrite (5), we obtain:

$$RSI_1 = \lim_{\delta \to 0} E(\Phi_2 + \Phi_3 \mid \Phi_1 = 1) \quad (6)$$

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

$$E(\Phi_2 \mid \Phi_1 = 1) + E(\Phi_3 \mid \Phi_1 = 1) \quad (7)$$

Rewriting (7) in terms of probabilities, and by using equation 13 (see Appendix A) we get:

$$\begin{aligned} RSI_1 &= \lim_{\delta\to 0}\frac{P(\Phi_2=1 \,\&\, \Phi_1=1)}{P(\Phi_1=1)}+\frac{P(\Phi_3=1 \,\&\, \Phi_1=1)}{P(\Phi_1=1)} \\ &= \lim_{\delta\to 0}\frac{2\delta-P(\Phi_2=1 \text{ or } \Phi_1=1)}{\delta}+\frac{2\delta-P(\Phi_3=1 \text{ or } \Phi_1=1)}{\delta} \end{aligned} \tag{8}$$

By using equation (4) in the above expression, it is easy to show that:

$$RSI_1 = 2*(d-1)-\sum_{i\neq j} L_{i,j}(1,1) \tag{9}$$

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.

2.3 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 30 major banks (11 Asian banks, 12 European banks, 6 U.S. banks, and 1 Canadian bank), for which the decision to include these banks was made on the amount of observations. Accordingly, 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. In order to show the evolution of "(in)stability", a 500-day sub-sample moving (weekly) window is used to construct a time-series for both the CPJF and the Risk-Stability Index.

3 Conditional Probability of Joint Failure

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 $k = 45$, which implies a quantile of $\delta = \frac{k}{n} = 9\%$[4] .

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).[5] I measure systemic risk in a bivariate setting through the conditional probability of joint failure (see Appendix and Garita and Zhou 2009). 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 (I will deal with causation and directionality in section 5); 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).

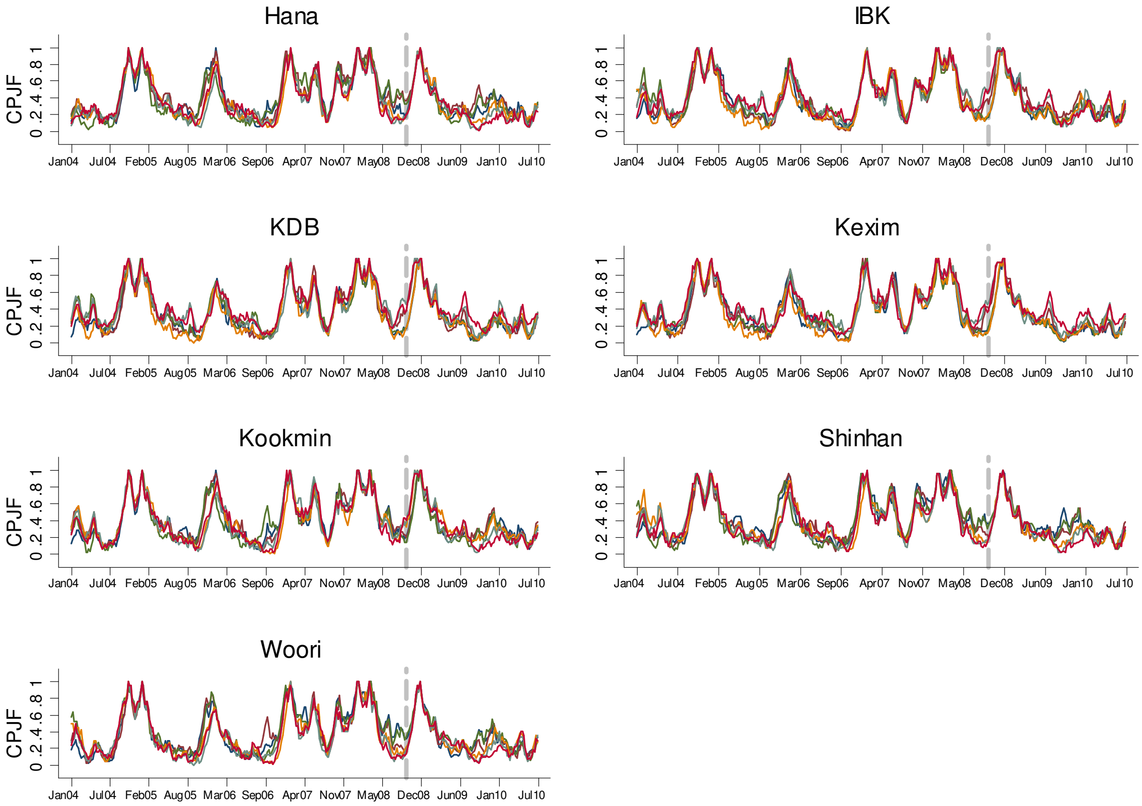
[4] I also performed the analysis with a 200 day sub-sample moving (weekly) window. The quantile for this exercise was $\delta = \frac{20}{200} = 10\%$. Moreover, the results that follow stayed relatively unchanged.

[5] In other words, "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?".

3.1 Common Distress in "Local" Banking Systems

The results found in this subsection indicate that banks within a geographical area 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 (Figure 3) and between 6 major U.S. banks (Figure 4).

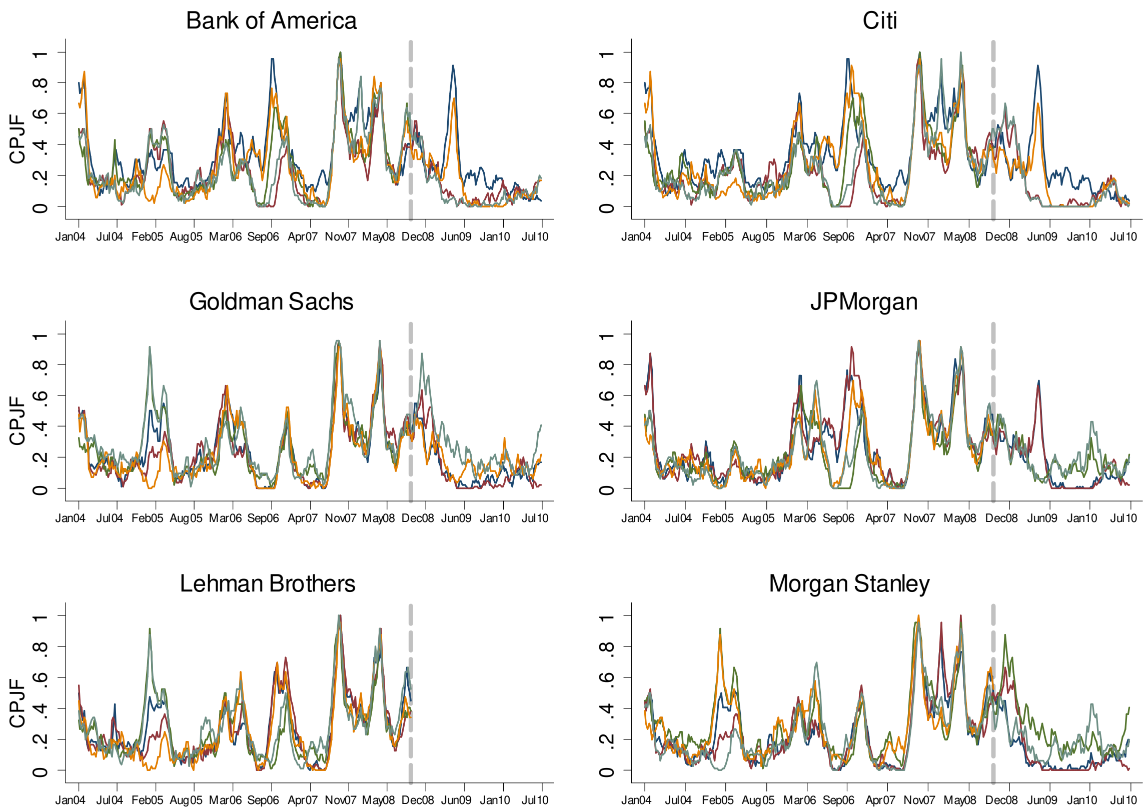
Figure 3: Conditional Probability of Joint Failure between 7 Major South Korean Banks. (the dashed vertical gray line indicates when Lehman Brothers filed for bankruptcy).



For South Korean banks, Figure 3 indicates that these banks have experienced around 5 episodes of "high" bilateral distress between January 2004 and July 2010. The most current bout of bilateral distress began as early as the fourth quarter of 2006, following a relatively calm 6-month period; the average CPJF among Korean banks before September 2006 was 0.46; it was

0.58 between October 2006 and June 2009; and it was 0.33 after June 2009. Figure 4 shows that U.S. banks follow a similar pattern as South Korean Banks; however, U.S. banks (mainly between Goldman Sachs, Lehman Brothers, and Morgan Stanley) were already experiencing high levels of distress as far back as early 2005. The most current episode of high bilateral distress began to surface in earnest as early as April 2007. For U.S. banks, the average CPJF before April 2007 was 0.35; it was 0.41 between April 2007 and December 2009; and it has been 0.22 as of January 2010. 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 U.S. banks, since other banks created just as much, and at times, even more distress than Lehman Brothers.

Figure 4: Conditional Probability of Joint Failure between 6 Major U.S. Banks (the dashed vertical gray line indicates when Lehman Brothers filed for bankruptcy on Sept 15, 2008).

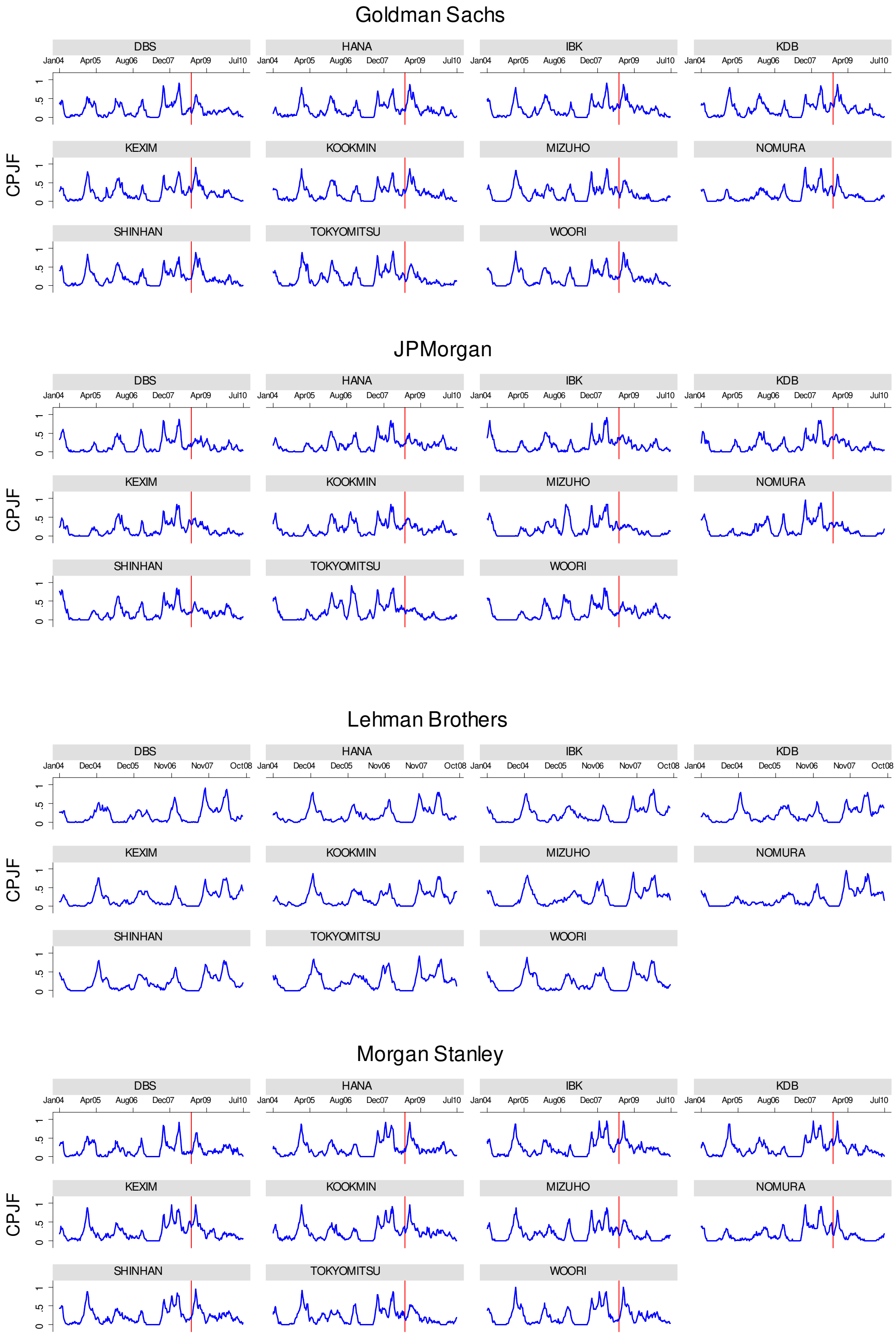


3.2 Global (in)Dependence - Distress Between Specific Banks

In the previous section we saw that bilateral stress of "local" banks can be quite high. However, when comparing across regional borders, is one banking system more at risk than another? What do my indicators say about the relative size of bank contagion risk when comparing economic areas (e.g. the euro area and the United States). Therefore, in order to gain insight into cross-border effects, the CPJF's are now calculated between the 6 U.S. banks, the 12 European banks, and the 11 Asian banks. As Figures 5 to 8 underscore, banks around the world are highly interconnected; furthermore, this interconnection and the degree of bilateral distress varies from varies from period to period. 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

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

Figure 6: Conditional Probability of Joint Failure between Asian and U.S. Banks cont... (the vertical red line indicates when Lehman Brothers filed for bankruptcy.



construction index dropped by over 40%, compared to a year earlier. 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, and rising interest rates that threatened to depress prices further as problems in the subprime market spread to the near-prime and prime mortgage markets. Intriguingly, a relatively calm period followed, which 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. However, by the fall of 2007 home sales in the US continued to fall, marking the steepest decline since 1989, leading to a second period of high distress among banks, reaching its zenith almost a year and a half later when the onset of the current financial crisis was well under way. The aforementioned two periods of distress clearly emerge in Figures 5-6, where the U.S. financial distress influenced the Asian (Korean) banking system through a number of financial channels, namely *(i)* tighter credit availability due to the increased uncertainty and the reduction of available funds in international markets, (ii) the increase in LIBOR, which restricted bank's short-term access to international funds in general and dollars in particular. The most affected relationships on average, during $2007-2008$, were between BOA and Woori ($CPJF = 0.52$), Morgan Stanley and KEXIM ($CPJF = 0.52$).[6]

Links between European and U.S. banks also show a tendency to oscillate from period to period (see Figures 7 and 8). Interestingly, these figures also show two periods of "high" bilateral distress surrounding "the great recession". As we already know, it was during the summer of 2007 when subprime mortgage backed securities were discovered in the balance sheet of European banks, leading to high levels of bilateral distress, which, according to the figures, lasted until the summer of 2008 (just before Lehman Brothers filed for bankruptcy). The results indicate that the average CPJF between European and U.S. banks, between the summer of 2007 and the summer of 2008, was 45%. However, the highest CPJF's during this period were between Morgan Stanley and UBS (average $CPJF = 0.55$), Citi and UBS (average $CPJF = 0.53$), Bank of America and UBS (average $CPJF = 0.52$), and between Bank of America and HSBC (average $CPJF = 0.50$).

[6] See appendix A3 for a graphical representation between Asian and European banks.

Figure 7: Conditional Probability of Joint Failure between European and U.S. Banks (the vertical red line indicates when Lehman Brothers filed for bankruptcy).

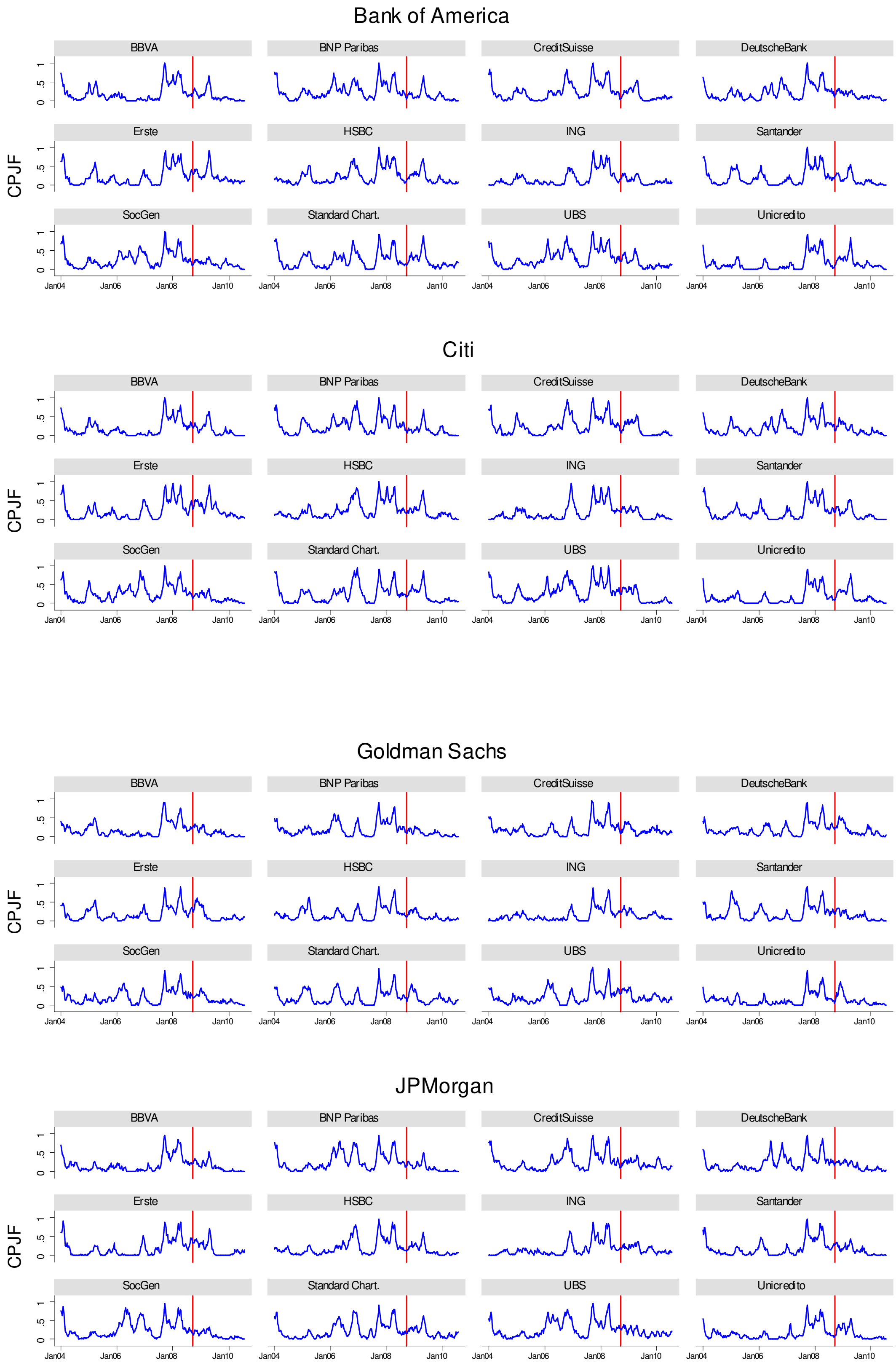
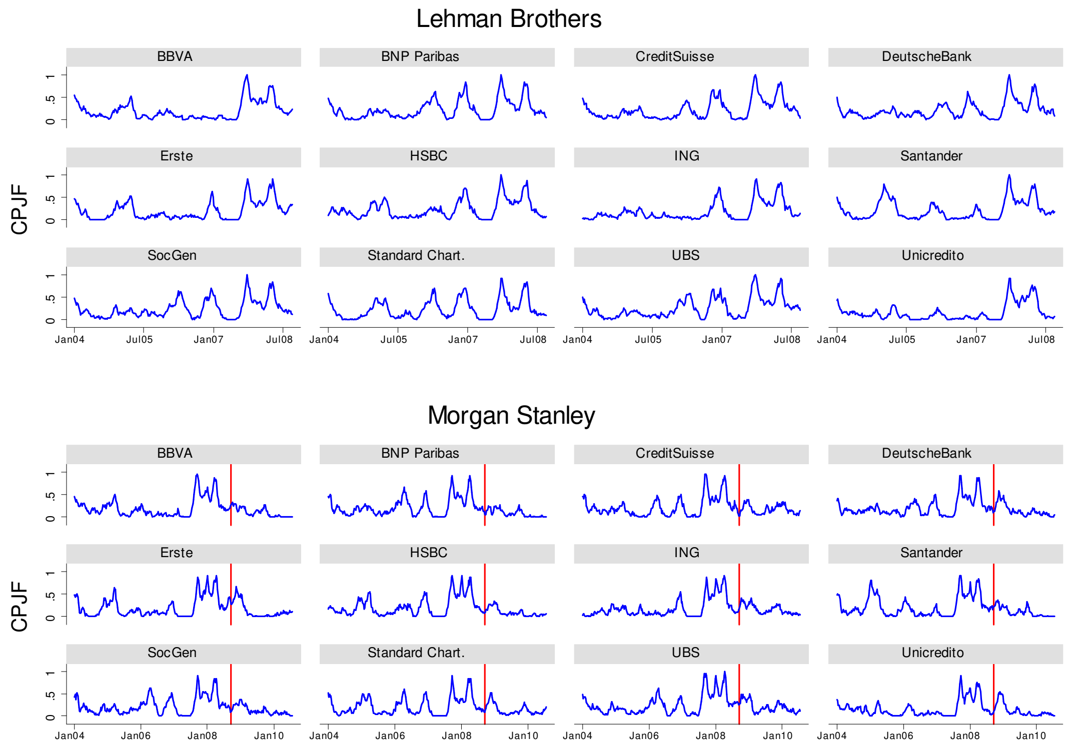


Figure 8: Conditional Probability of Joint Failure between European and U.S. Banks cont... (the vertical red line indicates when Lehman Brothers filed for bankruptcy).



The second period of particular interest (as highlighted by Figures 7 and 8) ranges from January 2006 until the spring of 2007, which can be viewed as a prelude to "the great recession". During this period, the average CPJF was "only" 0.20. However, when we look at individual relationships, we find evidence that the following banks were already quite distressed as early as January 2006: JPMorgan and UBS (average $CPJF = 0.44$), Citi and UBS (average $CPJF = 0.43$), JPMorgan and BNP Paribas (average $CPJF = 0.42$), and Bank of America and UBS (average $CPJF = 0.41$). It is also quite interesting to uncover that Lehman Brothers was not "more" systematically important than other banks; of course, this does not mean that Lehman Brothers was "safe" bank, since its highest CPJF, in this latter period, was with UBS (average $CPJF = 0.31$), and with BNP Paribas (average $CPJF = 0.30$). In the former period, the period between July 2007 and June 2008, Lehman Brothers also experienced high levels of distressed with UBS (average $CPJF = 0.49$).

Table 1: Average CPJF Between Banks Within and Across Regions

Before August 2007					
	Asia Banks	Asia-ex Kor-Banks	Korea Banks	Europe Banks	USA Banks
Asia Banks	0.38	0.34	0.40	0.19	0.16
Asia-ex Kor-Banks	0.34	0.46	0.28	0.19	0.16
Korea Banks	0.40	0.28	0.47	0.19	0.16
Europe Banks	0.19	0.19	0.19	0.24	0.16
USA Banks	0.16	0.16	0.16	0.16	0.34
Between August 2007 and July 2009					
	Asia Banks	Asia-ex Kor-Banks	Korea Banks	Europe Banks	USA Banks
Asia Banks	0.46	0.41	0.49	0.34	0.25
Asia-ex Kor-Banks	0.41	0.52	0.35	0.33	0.34
Korea Banks	0.49	0.35	0.57	0.35	0.36
Europe Banks	0.34	0.33	0.35	0.43	0.36
USA Banks	0.35	0.34	0.36	0.36	0.50
Between July 2009 and July 2010					
	Asia Banks	Asia-ex Kor-Banks	Korea Banks	Europe Banks	USA Banks
Asia Banks	0.21	0.16	0.24	0.07	0.08
Asia-ex Kor-Banks	0.16	0.30	0.08	0.07	0.06
Korea Banks	0.24	0.08	0.33	0.07	0.09
Europe Banks	0.07	0.07	0.07	0.16	0.07
USA Banks	0.08	0.06	0.09	0.07	0.22

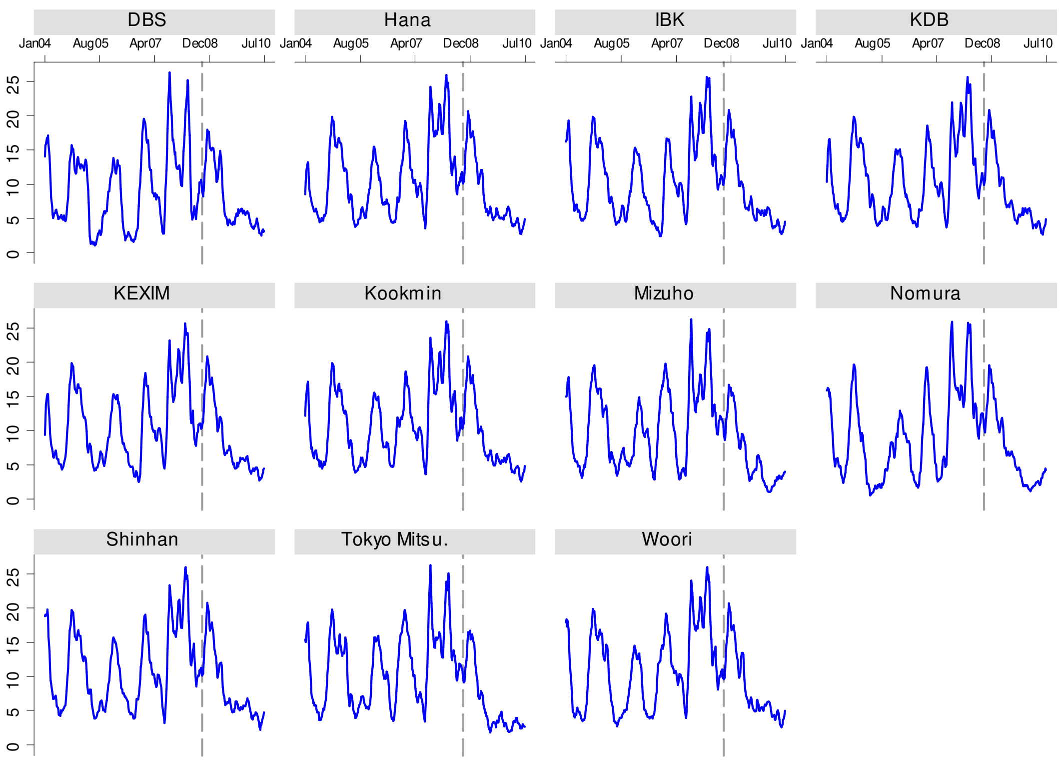
Table 1, which gives the average conditional probability of joint failure between banks within and across borders, highlights four main points: (1) "risks" vary by geographical region; (2) within border bilateral distress is higher than across borders on average, with Korea's banking system being more highly interconnected, followed by the US banking system; (3) regional cross-border contagion is also relatively high, but not as high as within borders; and (4) global contagion is present and clearly an issue. These results, which corroborate the results by Hartmann et al. (2007), indicate that in much more integrated banking systems (e.g. Korea and the United States), economy-wide systemic risk is higher, as banking business is much more interconnected. In other words, the lower spillover risk in Europe is explained by the quite weak extreme cross-border linkages. Moreover, the results also indicate that financial stability must be managed inside-out (within borders first), but that international coordination is extremely important.[7]

[7] The CPJF results also show that regulatory capital requirement rules must be aligned more closely to the underlying risks that individual banks face, since the conditional probability of joint failure varies from period to

4 Distress to Financial System Linked to a Specific Bank

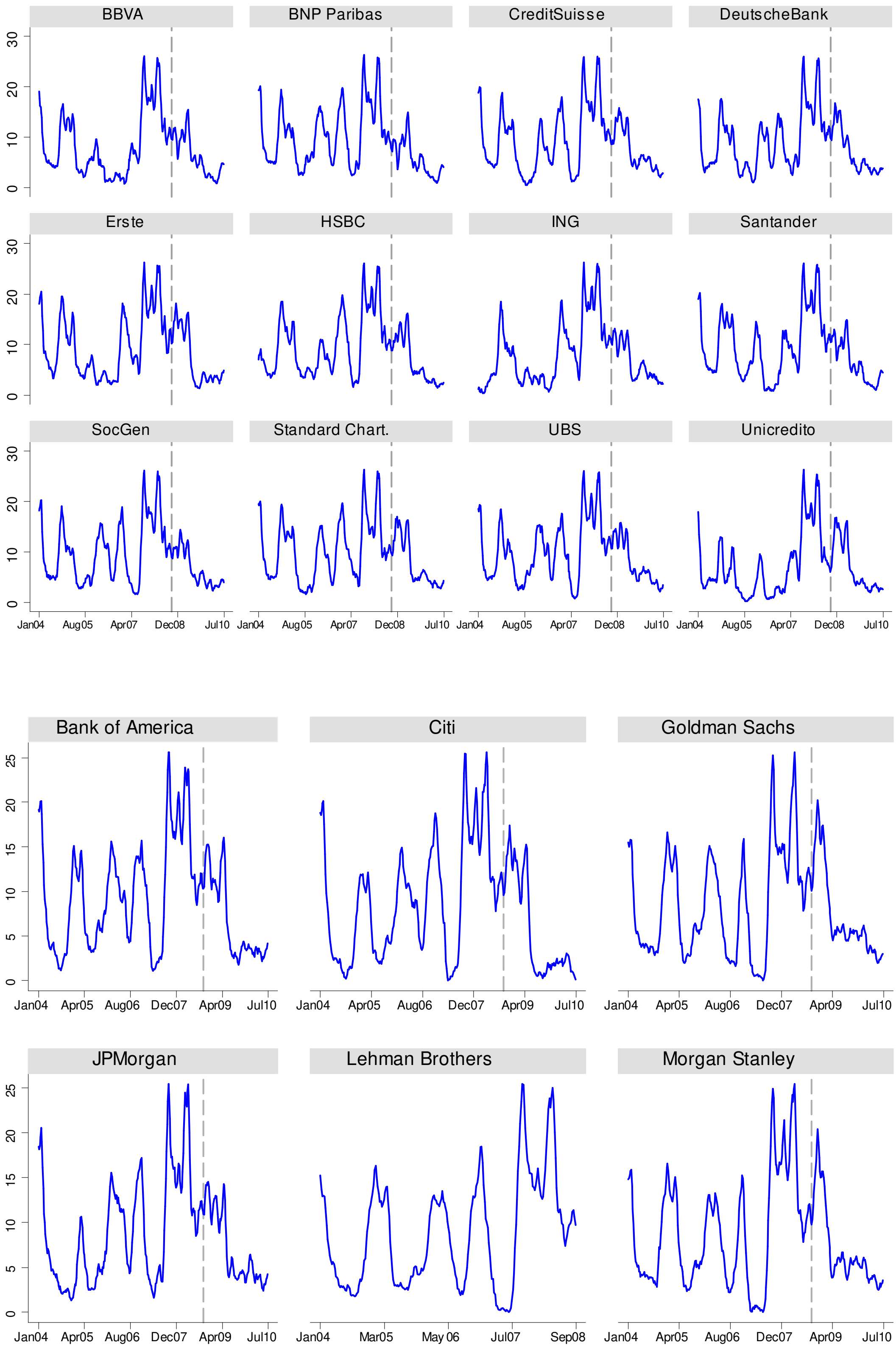
As explained in section 2.4, the risk-stability index makes it possible to quantify the (contemporaneous) effect that a "failure" of any risk factor can have on an entire financial system, be it economy-wide or worldwide. In simple terms, the risk-stability index gives an estimation of the number of risk-factors that would "catch a cold", given that a specific risk-factor "sneezes", by allowing us to pin-point which risk factor failure will most adversely affect a financial system. A risk-stability index (equation 9) 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 or system.

Figure 9: Risk Stability Index Time-Series for 11 Major Asian Banks (the dashed vertical gray line indicates when Lehman Brothers filed for bankruptcy).



period. Therefore, imposing a "one size fits all" approach can actually lead to more instability.

Figure 10: Risk Stability Index Time-Series for 18 Major European and US Banks (the dashed vertical gray line indicates when Lehman Brothers filed for bankruptcy).



An immediate result that stands out is the similarity between the RSI 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, banks tend to affect about 10 other banks, on average, with Asian banks having an infection rate of 33% (Korean banks affect 35% of banks, on average). Asian banks are followed by European and U.S. banks, with an infection rate of 29% each. 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.

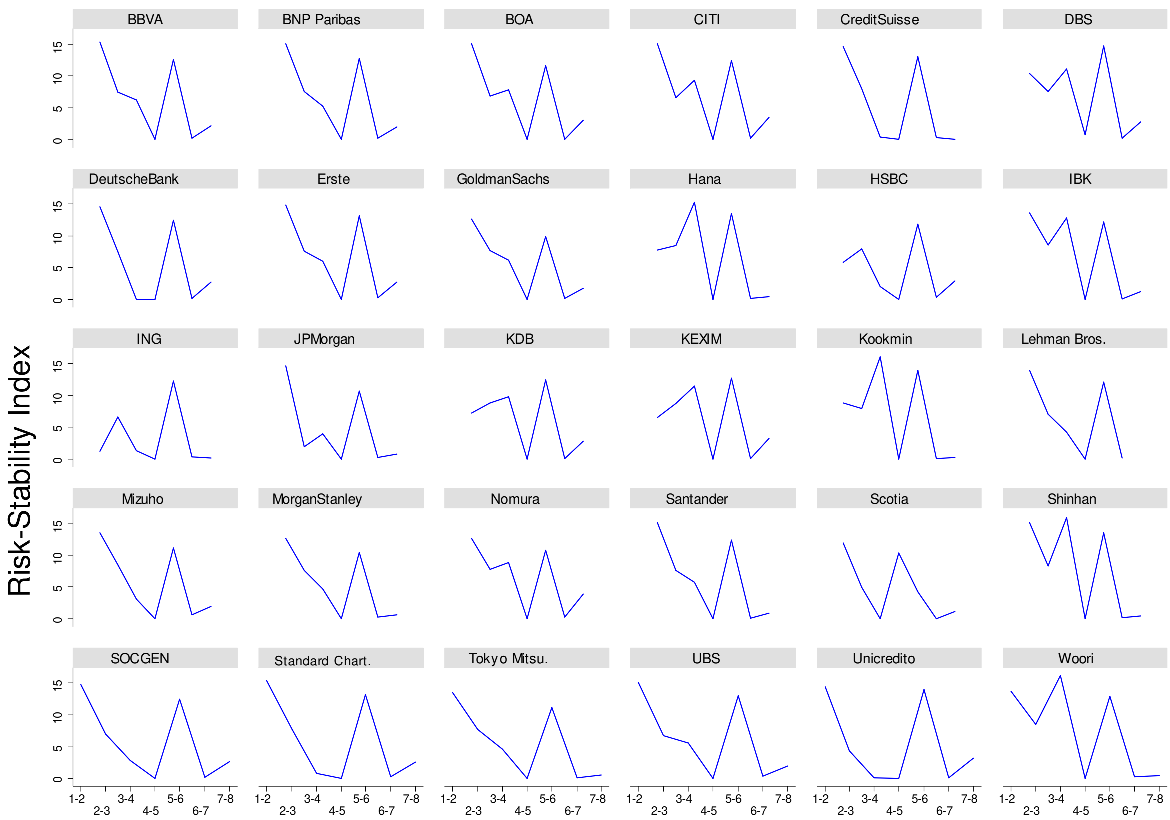
For example, during October 2004, almost all Asian banks were affecting close to 20 other banks, with DBS affecting "only" 15 other banks (see Figure 9). A similar patter can be found for European banks, but with Unicredito being the "less" risky bank (see Figure 10). Interestingly, during this same period, U.S. banks were each affecting less than 5 other banks, and it was not until the beginning of 2005 that most U.S. banks started to systematically impact the financial system (with each bank affecting well over 10 other banks); the exception was JPMorgan, who was only affecting about 2 other banks, and it was not until the spring of 2005 that JPMorgan increased its infection rate to over 10 banks (see bottom panel of Figure 10).

From Figures 9 and 10, we can also discern the height of the financial (banking) crisis. These figures indicate that for most Asian banks, the height of the crisis occurred in April 2008. However, for DBS, Mizuho, and Tokyo Mitsubishi, the height of the crisis was in late 2007 (with Nomura impacting the system with similar fervor during these two periods). Interestingly, European banks show a similar twin-peak pattern as Nomura, with the first peak reaching its zenith (of around 25 banks affected, on average, by each European bank) in September 2007; while the second peak reached similar heights around April 2008. U.S. banks display the same twin-peak pattern as European banks (see Figure 10). Intriguingly, the bottom panel of Figure 10 shows that at the time of its demise, Lehman Brothers was not creating any more instability than any other U.S. bank; it was actually creating slightly less instability than Citi, Goldman Sachs, and JPMorgan.

5 Directionality and Persistence of Distress

Another aspect of particular interest regarding financial stability is the directionality and the persistence of distress. Accordingly, this section aims at uncovering the aforementioned issues by employing, for tractability purposes, 8 periods of 500 days (with a one-year overlap). The results of this particular exercise are presented through Figure 11, which shows how the directionality of contagion to the financial system has evolved through time.[8] In other words, the figure shows how many banks will "fail", given that bank "i" "failed" one period before.

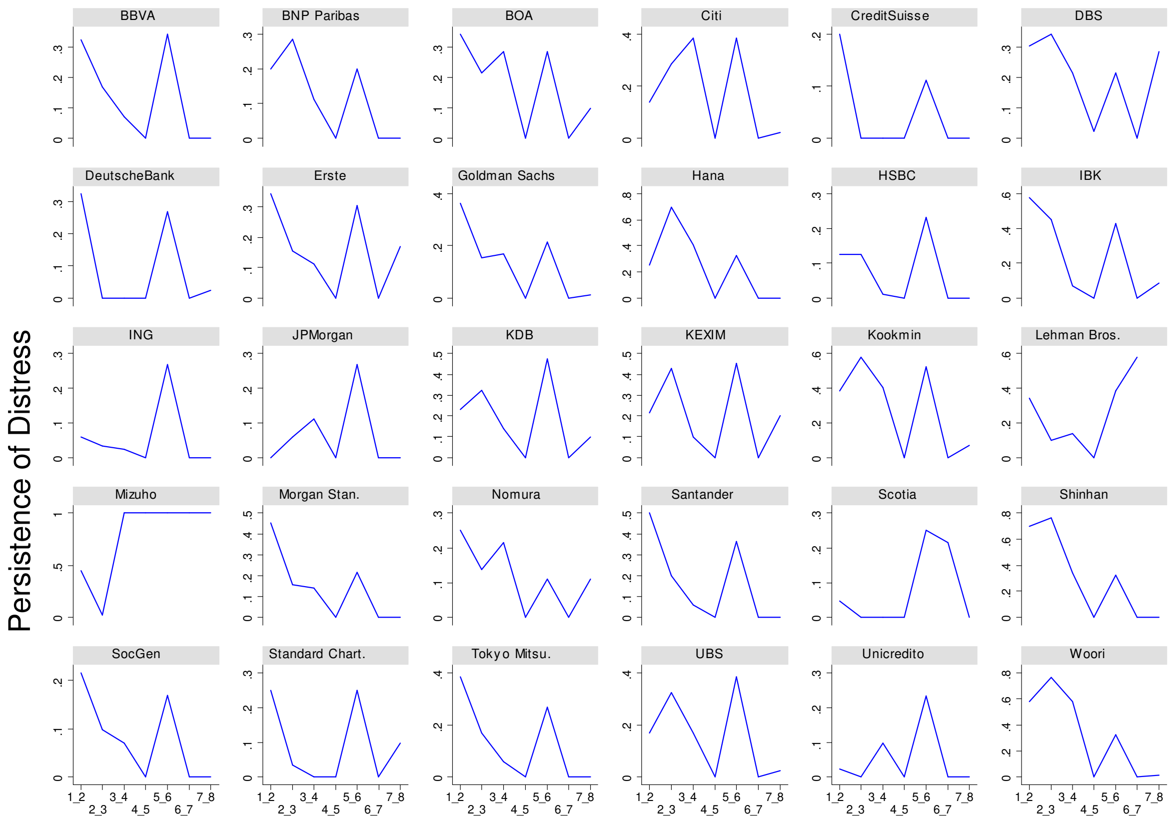
Figure 11: Directionality of Contagion - the figure shows the consequences to the banking system conditional on bank i "failing" one period before (see footnote 8 for period coding). For example, $1-2$ (on the x-axis) shows the repercussion to the system in period 2, given that bank i "fails" in period 1.



[8] The x-axis of Figure 11 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.

For example, in section 3 we uncovered that, during the latter parts of 2007 and early 2008, UBS was one of the banks with elevated levels of bilateral distress (with an average CPJF of 53%). Figure 11 indicates that in 2008 at least 10 other banks suffered distress due to the fact that UBS experienced distress on period before. Figure 11 also shows that the failure of Lehman Brothers did not lead to any major instability of the system, since less than 5 banks suffered due to Lehman Brothers collapsing one period before. Clearly, banks affect a system with a lag; however, what is most interesting, is that they do so at irregular intervals implying that the system is constantly under stress, where the source of the stress varies from period to period.

Figure 12: Persistence of Distress - the figure shows the consequences to bank i, given that it "failed" one period before (see footnote 8 for period coding). For example, $1-2$ (on the x-axis) shows the repercussion to bank i in period 2, given that if "failed" in period 1.



As previously mentioned, another aspect of particular interest regarding financial stability is the persistence of distress for bank i in the portfolio; where persistence is quantified by the diagonal of the distress dependence matrices (available upon request), displayed here as Figure 12. This figure indicates that the Japanese bank Mizuho tends to experience the most distress persistence ($average\ CPJF = 78\%$), followed by Lehman Brothers ($average\ CPJF = 36\%$) from the USA, and then by Woori ($average\ CPJF = 32\%$), Shinhan ($average\ CPJF = 30\%$), and Kookmin ($average\ CPJF = 28\%$), all from South Korea. 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 ($average\ CPJF = 6\%$). In conjunction, the DDM's and Figure 12 also show that within regions, 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 $t-1$ (South Korean banks experience a 25% CPJF). Asian banks are followed by U.S. banks with a 16% CPJF, and then by European banks with an 10% CPJF, on average.

Across regions, Table 2 indicates that Korean banks are the most contagious, with an average CPJF of 20.3%. They are followed by U.S. banks ($average\ CPJF = 17\%$), and then by European banks ($average\ CPJF = 12\%$). On the other hand, the biggest generator of contagious bilateral distress for Asian banks are U.S. banks, with a CPJF of 18%. The abovementioned results indicate that in a much more integrated banking system, such as the one in Korea and the United States, economy-wide systemic risk is higher, as banking business is much more interconnected. In other words, the lower spillover risk in Europe is explained by the quite weak extreme cross-border linkages (see Hartmann et al., 2007).

Table 2: Directionality of Contagion 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

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, 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.[9] 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

[9]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).

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 9-10), and the following financial market variables (from 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 13): an increase of the risk-stability index 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 $S\&P500$. 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.

As is well known, the VAR framework allows for a feedback effect (see row 4 in Figure 13) 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 3) confirms the above-mentioned results. More specifically, the RSI explains about 5.5% if 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.

Figure 13: 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.

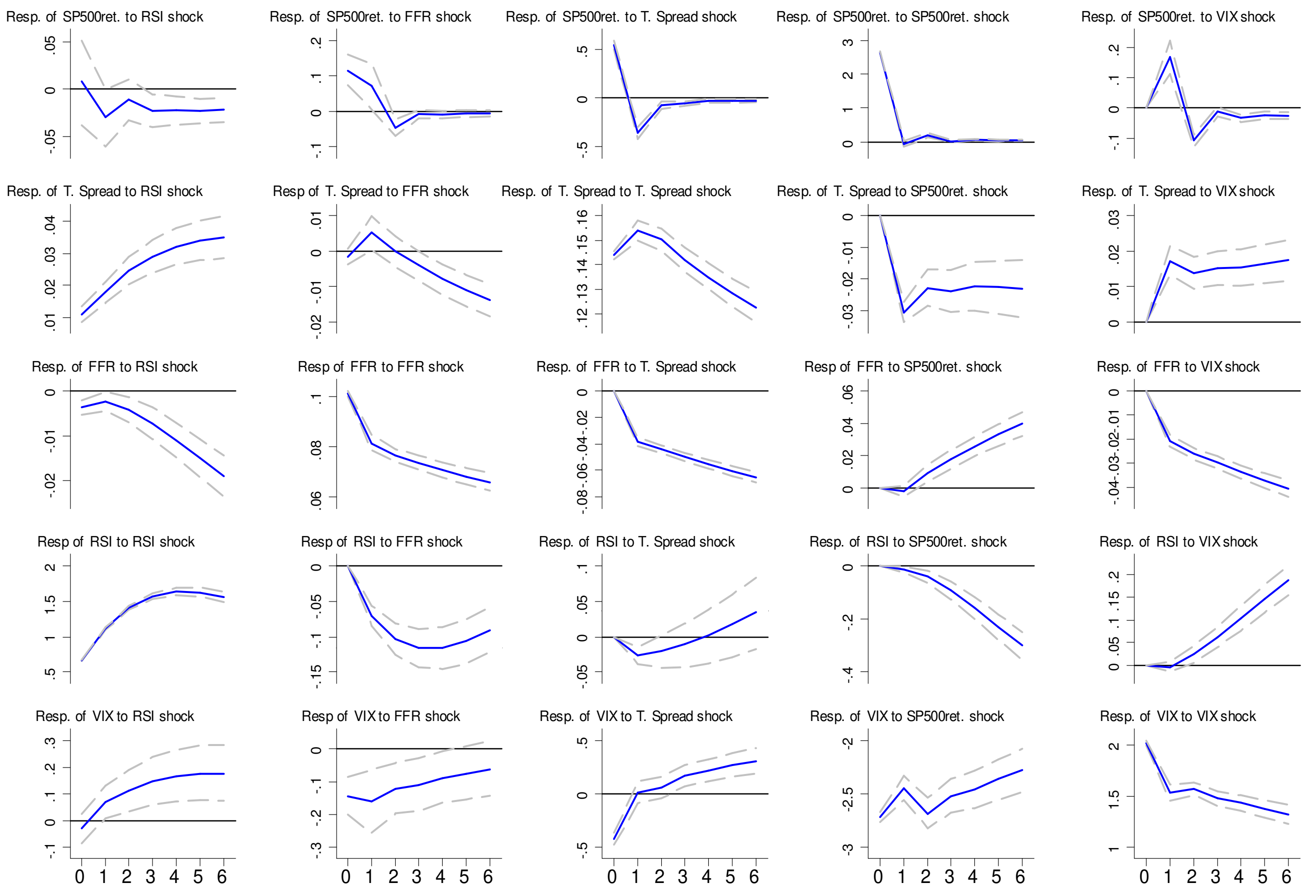


Table 3: Variance Decomposition - variation in the row variable explained by column variable

	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.

7 Conclusion

It is a stylized fact in international (finance) macroeconomics that most financial data are "fat-tailed"; meaning that extreme co-movements tend to arise more regularly than predicted on the basis of the normal distribution. Accordingly, this paper has highlighted an easy 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 30 Asian, European, and U.S. banks. The risk-stability index (RSI) offers good insight into (1) the sensitivity of market participants in relation to 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 bilateral CPJF-based results indicate that banks are highly interlinked especially within geographical borders. These results also show that, on average, Korean banks have a propensity to create and experience higher systemic risk for themselves, followed by U.S. banks, and then by European banks. These last set of results corroborate Hartmann et al. (2007), who argued that in a more integrated banking system (e.g. the United States or Korea) area-wide systemic risk is higher, and that the lower overall spillover risk in Europe is due to the weak extreme cross-border linkages. The persistence of distress is also an important variable that must be taken 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 risk-stability index does not corroborate the idea that the "failure" of Lehman Brothers caused any *additional* distress to the financial system. 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.

Appendix

A1 - 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:

$$CPJF_{i,j}=\lim_{\delta\to 0} P(X_i > VaR_i(\delta) \text{ and } X_j > VaR_j(\delta) | X_i > VaR_i(\delta) \text{ or } X_j > VaR_j(\delta)) \tag{10}$$

which can be rewritten as

$$CPJF_{ij} = E[\kappa|\kappa \geq 1] - 1 \tag{11}$$

where

$$E[\kappa|\kappa \geq 1] = \lim_{\delta\to 0} \frac{P(X_i > VaR_i(\delta)) + P(X_j > VaR_j(\delta))}{1 - P(X_i \leq VaR_i(\delta), X_j \leq VaR_j(\delta))} \tag{12}$$

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 (10) and (12) 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

$$\begin{aligned} CPJF &= \lim_{\delta\to 0} \frac{P(X_1 \text{ } and \text{ } X_2)}{P(X_1 \text{ } or \text{ } X_2)} = \lim_{\delta\to 0} \frac{P(X_1) + P(X_2) - P(X_1 \text{ } or \text{ } X_2)}{P(X_1 \text{ } or \text{ } X_2)} \\ &= \lim_{\delta\to 0} \frac{\delta + \delta - L(1,1) * \delta}{L(1,1) * \delta} \\ &= \frac{2}{L(1,1)} - 1 \end{aligned} \tag{13}$$

A2 - Descriptive Statistics

Table 4: 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

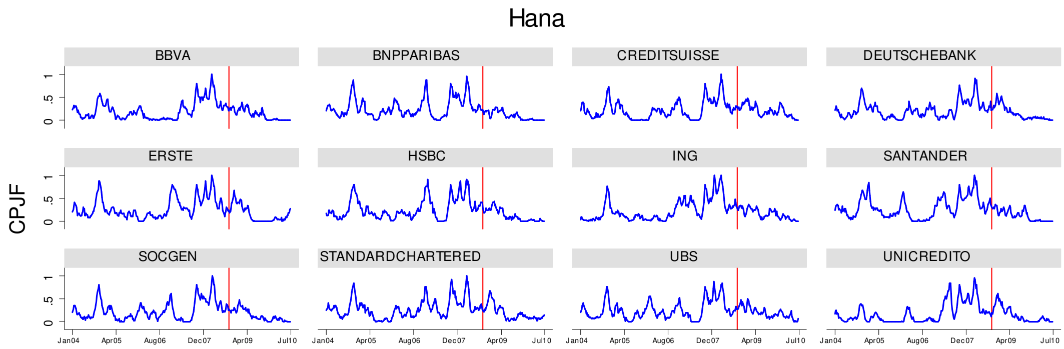
Table 5: CPJF Descriptive Statistics for 30 Major Banks

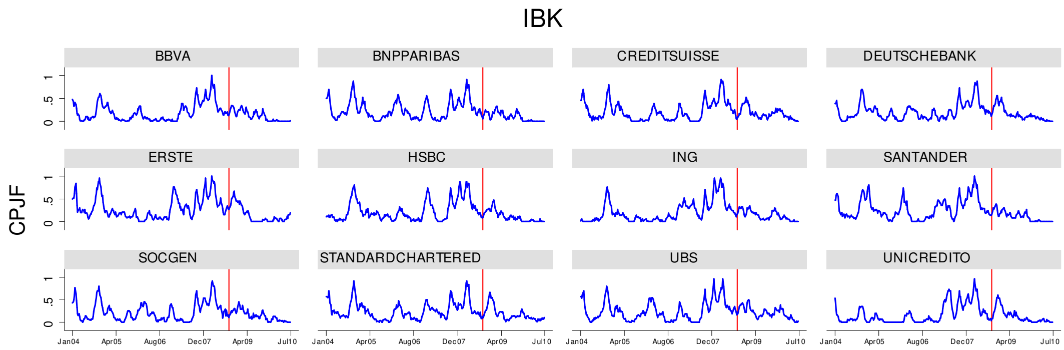
Bank	Mean	SD	Skew.	Kurt.	Min	Max
BBVA	0.21	0.24	1.77	5.85	0.00	1.00
BNP Paribas	0.25	0.25	1.49	4.71	0.00	1.00
Bank of America	0.24	0.24	1.46	4.79	0.00	1.00
Citi	0.24	0.25	1.37	4.41	0.00	1.00
Credit Suisse	0.24	0.24	1.52	5.00	0.00	1.00
DBS	0.24	0.24	1.54	5.24	0.00	1.00
Deutsche Bank	0.23	0.23	1.77	6.08	0.00	1.00
Erste	0.25	0.26	1.34	4.17	0.00	1.00
Goldman Sachs	0.22	0.23	1.68	5.77	0.00	1.00
Hana	0.28	0.26	1.27	3.95	0.00	1.00
HSBC	0.24	0.25	1.51	4.74	0.00	1.00
IBK	0.28	0.26	1.24	3.92	0.00	1.00
ING	0.21	0.24	1.74	5.61	0.00	1.00
JPMorgan	0.23	0.24	1.61	5.27	0.00	1.00
KDB	0.28	0.26	1.27	4.03	0.00	1.00
KEXIM	0.27	0.26	1.27	3.99	0.00	1.00
Kookmin	0.28	0.26	1.21	3.83	0.00	1.00
Lehman Brothers	0.23	0.26	1.43	4.52	0.00	1.00
Mizuho	0.26	0.25	1.32	4.17	0.00	1.00
Morgan Stanley	0.23	0.24	1.58	5.17	0.00	1.00
Nomura	0.23	0.25	1.51	4.81	0.00	1.00
Santander	0.24	0.25	1.48	4.73	0.00	1.00
Scotia	0.14	0.21	2.77	11.21	0.00	1.00
Shinhan	0.28	0.26	1.17	3.69	0.00	1.00
SocGen	0.24	0.24	1.50	4.83	0.00	1.00
Standard Chart.	0.26	0.25	1.38	4.42	0.00	1.00
Tokyo Mitsu.	0.26	0.25	1.26	4.02	0.00	1.00
UBS	0.26	0.25	1.36	4.42	0.00	1.00
Unicredito	0.19	0.24	1.86	6.08	0.00	1.00
Woori	0.28	0.26	1.11	3.54	0.00	1.00
Total	0.24	0.25	1.46	4.65	0.00	1.00

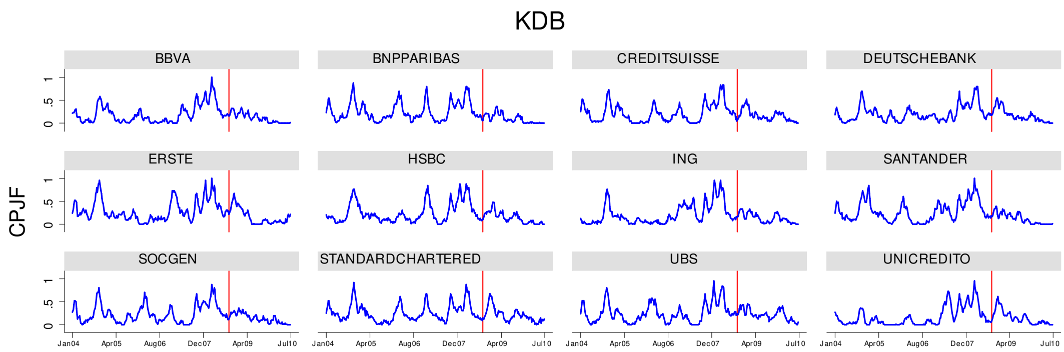
Table 6: RSI Descriptive Statistics for 30 Major Banks

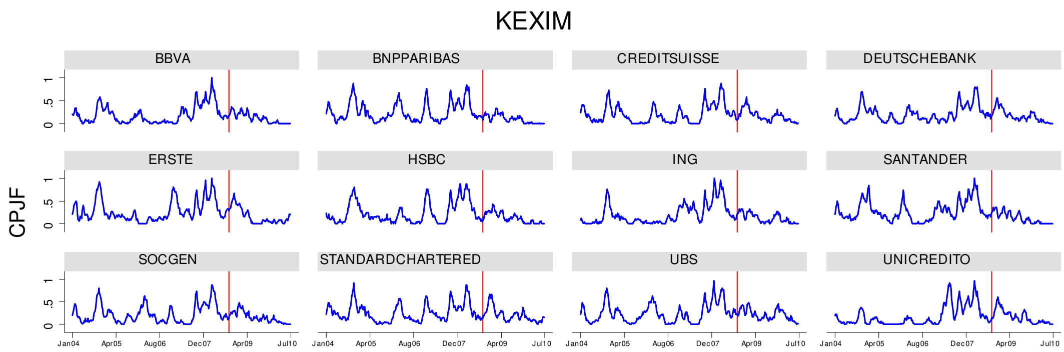
Bank	Mean	SD	Skew.	Kurt.	Min	Max
BBVA	7.92	5.85	1.02	3.42	0.78	26.09
BNP Paribas	9.23	5.66	0.79	2.98	0.96	26.29
Bank of America	8.96	5.84	0.62	2.56	1.09	25.62
Citi	9.04	6.13	0.55	2.34	1.24	25.78
Credit Suisse	8.99	5.81	0.71	2.94	0.56	25.96
DBS	9.07	5.41	0.63	2.77	1.07	26.29
Deutsche Bank	8.67	5.39	0.90	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

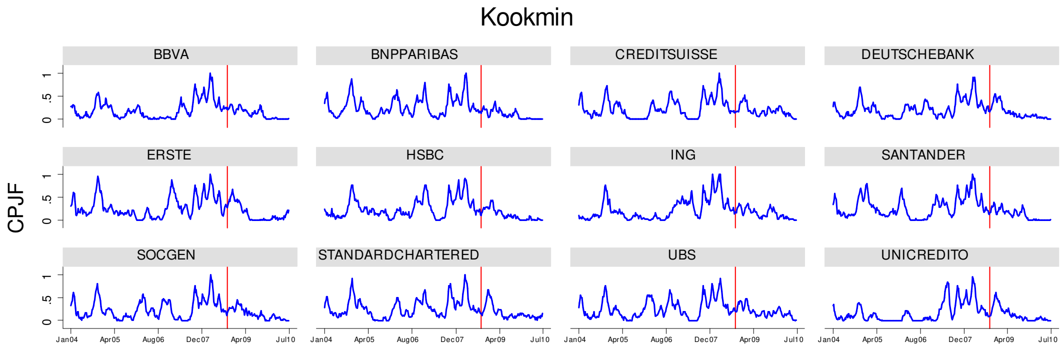
A3 - CPJF Between Asian and European Banks







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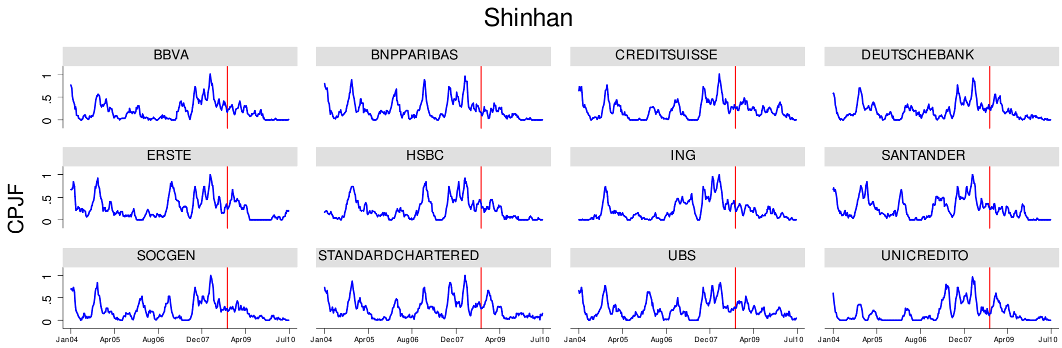
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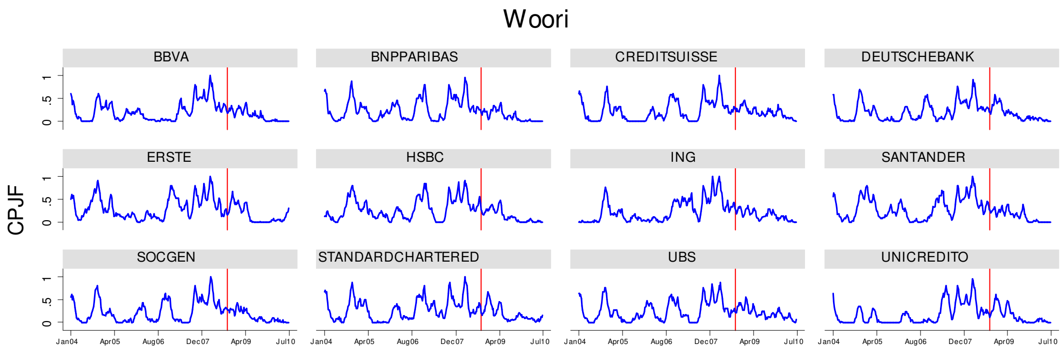
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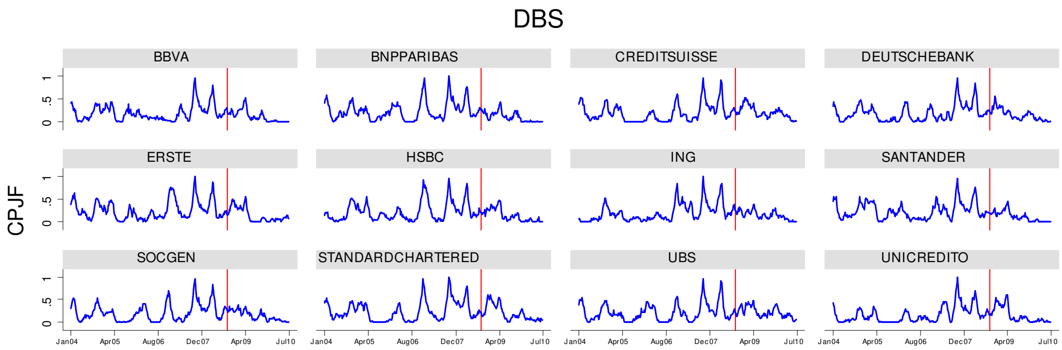
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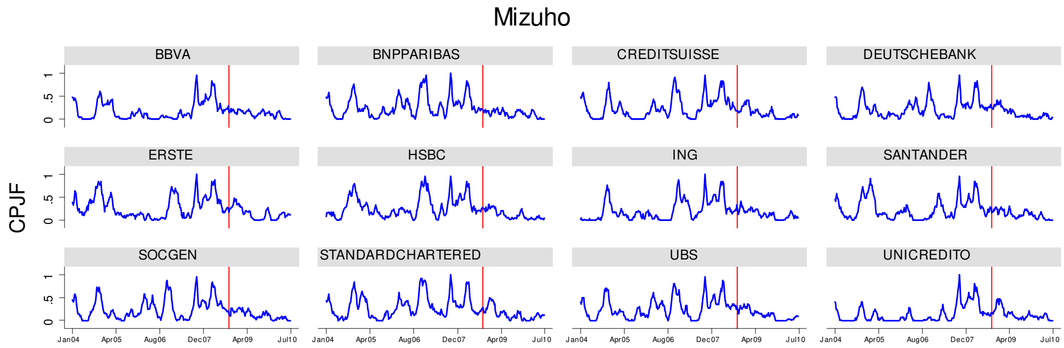
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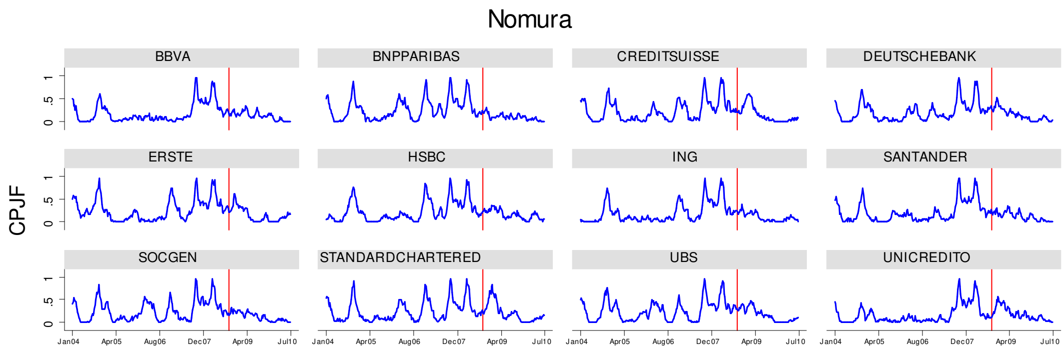
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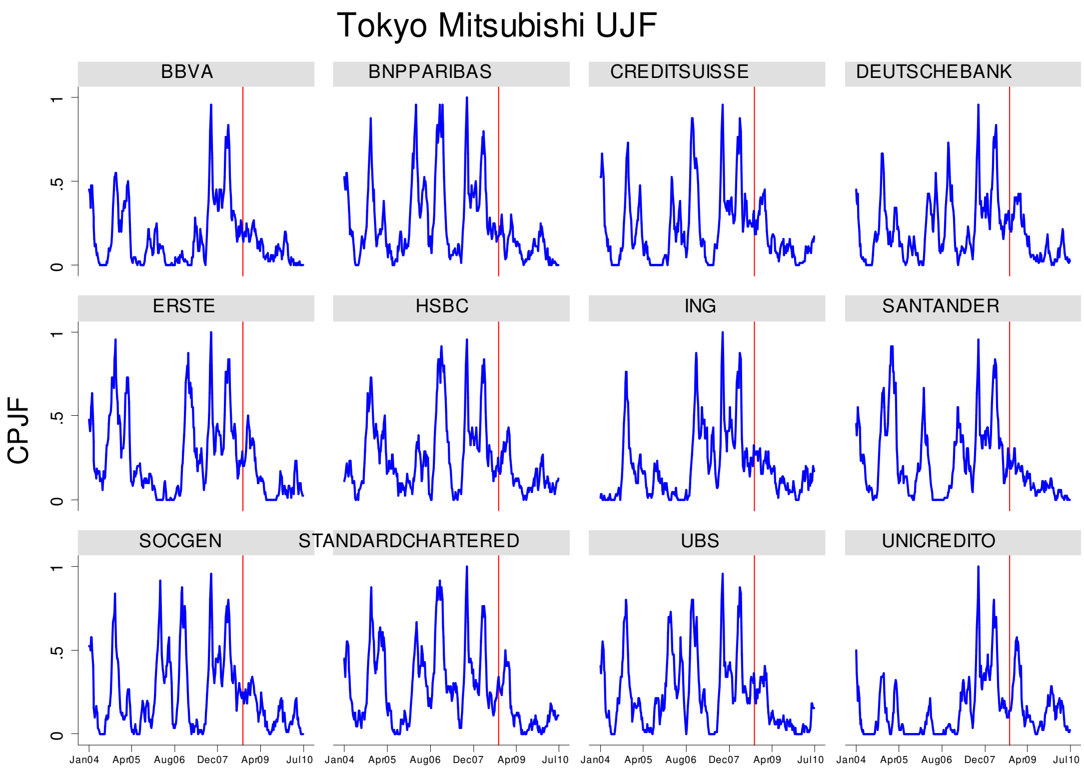
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