MEASURING SYSTEMIC RISK AND FINANCIAL LINKAGES IN THE THAI BANKING SYSTEM

Rungporn Roengpitya* and Phurichai Rungcharoenkitkul**

26 February 2010

Abstract

This paper addresses the measurement issues of systemic risk in the Thai banking sector. The concept of conditional value-at-risk (CoVaR), due to Adrian and Brunnermeier (2008), was used to quantify the level of systemic risk and financial linkages among six major Thai commercial banks over the period of 1996Q2-2009Q1. Intuitively, CoVaR measures the degree of 'risk externalities' that a single institution imposes on the system. We found that there was additional risk imposed onto the overall system by individual banks, both during the Asian crisis time and in subsequent periods. There is some evidence that larger banks contribute more to this systemic risk, as measured by the concept of "ΔCoVaR," but size is far from being a dominant factor. We further apply the concept of CoVaR to measure the financial linkage between any two banks and investigate the changing nature of the linkages over time as well as other bank characteristics that drive such inter-bank relationships. These measures of risk externalities serve as a useful additional toolbox to the regulators, and themselves have novel regulatory implications.

*Supervision Group and **Monetary Policy Group, Bank of Thailand. Contact rungporr@bot.or.th or phurichr@bot.or.th. The authors are grateful to the executives of the Supervision and Monetary Policy Groups, Bank of Thailand, for their guidance and valuable suggestions. We also very much appreciate the support and encouragement from our colleagues who made this research project possible. Views express in this research are our own.

INTRODUCTION

This paper attempts to estimate the level of systemic risk and financial linkages in the Thai financial system, with the focus on the banking industry. Assessing the level of systemic risk and financial linkages has received a great deal of attention following the recent U.S. financial crisis. The main point surrounding the issue of systemic risk is the danger of one bank being in distress amplifying the fear and panic in the financial system during stress time, leading to the failure of other institutions and consequently to the financial crisis. Therefore, assessing the level of contribution to such risk and the financial linkage can serve as an additional tool for bank supervisors to employ in determining the more tailor-made level and policy regarding bank regulation, especially the banks that are considered "too-big-to-fail."

The existing literatures regarding systemic risk and financial linkage estimations mostly use the credit default swap (CDS) data. Although this type of estimation reflects well the default dependence between institutions, it can only capture one type of risk which is credit risk, let alone the fact that the CDS data in emerging market economies may be scarce.[1] Recently, Adrian and Brunnermeier (2008) proposed a new methodology in estimating both systemic risk and financial linkages, using publicly available data from the stock market. This estimation method has an advantage over the employment of CDS data in a sense that, under the assumption of the market efficiency, the stock market price should reflect all types of risk of an institution combined. Using the stock market data, they found that financial institutions in the U.S. whose relative sizes as well as levels of leverage, maturity mismatch and market to book value are large contributed more to systemic risk. In addition, investment banks and insurance companies seemed to make the system more risky when compared to commercial banks.

Using this concept, we attempt to quantify the level of systemic risk as well as financial linkages in the Thai banking system, using the stock market data from the years 1996-2009, covering the Asian crisis period to capture systemic risk during the stressed time. We found that Thai banks

---

[1] For more details about the systemic risk estimation using CDS data, see Chan-Lau, et al. (2009a) for network simulation model, Chan-Lau, et al. (2009b) for co-risk analysis, Giesecke and Kim (2009) for default intensity model and Chan-Lau, et al. (2009b) as well as Segoviano and Goodhart (2009) for the time varying multivariate density, distress dependence, and tail risk types of models.

did impose additional risk onto the banking system during the Asian crisis time and banks with large relative size contributed more to the system risk.

This paper is divided into four main parts. Section 1 discusses briefly on the sources of systemic risk as well as existing literatures regarding the systemic risk estimations. Then, Section 2 presents our systemic risk estimation and analysis for the Thai banking industry. The estimations as well as analyses on the financial linkages are in Section 3. Section 4 outlines the summary of policy implications from our findings. The paper ends with our concluding remarks.

1. SOURCES OF SYSTEMIC RISK AND EXISTING SYSTEMIC RISK QUANTIFICATION METHODS

In light of the recent financial crisis, regulators are now focusing more attention on constructing a framework that will enhance further financial stability. According to the Bank of International Settlements (BIS), this framework consists of two types of analyses—cross-sectional and cross-time (BIS 79th Annual Report). The source of instability across time, which arises from the behavior of agents in response to the business cycle, will be address in the next section regarding the "procyclicality" of the financial system. The cross-sectional analysis of financial instability regards the issues of financial linkages between institutions and, more importantly, the identification of the sources of systemic risk. The sources of systemic risk can be classified into three types: (i) from *instruments* such as loans, bonds, equities and derivative instruments; (ii) from *markets* such as bilateral over-the-counter (OTC) trading in the markets; and (iii) from *institutions* such as banks, securities dealers, insurance companies, etc. Our study will focus the attention on the last source of risk—institutions, although systemic risk caused by institution linkages closely ties to the instruments these institutions employ and markets they trade.[2]

Numerous literatures have addressed the importance and identified possible causes and consequences of financial linkages and systemic risk. Generally, there are a few ways one can define

---

[2] As noted in Chapter 1 of Brunnermeier, et al. (2009), banks and other financial intermediaries involve in trade among themselves than corporates do via interbank and derivative markets as well as brokerage services.

the term "systemic risk" in the banking industry.[3] In this paper, we defined the term "systemic risk" as the probability that, if one institution is in distress, it can possibly trigger other institutions to also be in distress, which can consequently lead to bank run and the collapse of the financial system when a certain number of institutions are affected. In order to understand the cause, the following sections outline a few types of theoretical models and insights that help shed some light onto the existence of systemic risk.

1.1 BANKS' ATTEMPT TO REDUCE AGGREGATE RISK LEADS TO MORE SYSTEMIC RISK

The main idea of this theory relies on the observation that there are aggregate risks which cannot be diversified away embedded within the financial system itself and the attempt by banks to pass on these risks leads to an increase in systemic risk. In the past, banking crises usually happened in conjunction with macroeconomic shocks, namely interest rate and exchange rate risks, which by nature is the aggregate risk and consequently is not diversifiable (Hellwig 1995, 1997, 1998). The only way the banking industry will be able to reduce this is to limit its exposure to aggregate risk or to pass the risk onto the third party, mainly depositors (Hellwig (1995) and Staub (1998)). However, this mechanism of passing on the risk to depositors is inefficient since depositors can withdraw money at any time, regardless of the macroeconomic environment and therefore the shocks. This non-contingent nature of deposit contracts pushes banks to try other means possible to limit the exposure to these aggregate shocks.

Since shifting the risks to depositors is inefficient, banks try to reduce this macroeconomic risk in other ways. For example, banks may try to limit the interest rate risk by using derivative contracts, such as swaps, to transfer the risk to the third party. However, these derivative instruments carry additional counterparty risk, creating the default-dependent contracts. The contracts that are highly relevant to these types of hidden risk are OTC derivatives and money market transactions,

[3] Kaufman and Scott (2003) summarized three possible definitions of "systemic risk" in the banking industry. First, it is "an event having effects on the entire banking, financial, or economic system, rather than just one or a few institutions." (Bartholomew and Whalen (1995)). Second, systemic risk is the "risk of a chain reaction of falling interconnected dominos." (Kaufman (1995)). The third definition of systemic risk focuses on the similarities in third-party risk exposures among the institutions involved.

which are off-balance-sheet items (Staub (1998)). Hence, the reduced interest rate risk comes back to banks in the form of counterparty or default risk (Hellwig (1997) and Staub (1998)). As a bank enters these contracts with the third party that also has similar contracts with other banks, the interconnection between financial institutions is established and thus systemic risk increases when one counterparty defaults. Therefore, an attempt to mitigate aggregate shocks does lead banks to be exposed to more systemic risk.

1.2 THE CAPITAL STRUCTURE OF BANKS MAY LEAD TO THE "COLLECTIVE RISK SHIFTING" WHICH INCREASES SYSTEMIC RISK

In corporate finance, capital structure can substantially affect the risk taking behavior. Under the debt-financing capital structure and the limited liability condition, the owner of the firm has an incentive to take more risk since, in the event of bankruptcy, all debts are forgiven after all the assets have been liquidated and the debt holder redemption has been executed as best as possible (Milgrom and Roberts 1992). The implication of this theory is particularly strong for banks, which are highly-leveraged institutions. Acharya (2001) examined this risk shifting incentive in the banking industry. In his theoretical model, he demonstrated that banks shifted the risk in such a way that they invested into correlated assets and therefore took too much risk after having taken into account the interest of depositors and the social cost coming from the financial distress. Therefore, the interconnection between banks in his model stems from the correlation of bank assets. Moreover, Acharya also showed that, if there were strong negative effects[4] from a bank's failure upon one or more banks, banks would be induced to invest in the same industry, so as to survive or fail together—the strategy which he called *collective risk taking*. The consequence of this strategy is that banks will hold assets that will be even more highly correlated which leads to a higher probability of the joint bank failure.

[4] Acharya (2001) called this negative effects "negative externalities," on which its magnitude depends on the size of the failing bank, the uniqueness of the failing bank, as well as the case where the surviving banks do not benefit from taking over the facilities of the failing bank.

Therefore, Acharya's model demonstrates that systemic risk in the banking industry is a part of an incentive problem[5] regarding the collective risk taking strategy of banks.

1.3 COORDINATION PROBLEM, DOMINO EFFECT AND LIQUIDITY SHORTAGE

Another realm of literatures reasons that systemic risk simply is a problem of coordination and this is usually the version of the systemic risk explanation one is accustomed to. The spread of bank failure through the interconnection of institutions may come from the coordination failure during the confidence and liquidity crises. In theory, if the credit market is perfect, then an illiquid but solvent bank will be able to raise fund at any time because of its solvency status. However, in practice this is not the case. When the coordination between banks fails during liquidity shortage, a solvent bank will not be able to raise funds as it wishes. In the recent crisis, for example, Bear Sterns's capital was adequate throughout the period of mid March 2008 but its liquidity level went from more than \$18.1 billion on March 10th to less than \$2 billion on March 13th.[6] Therefore, when banks refuse to lend to other banks (even if that bank is solvent) during confidence and liquidity crises, the interbank and short-term repo markets freeze and consequently trigger series of liquidity shortage and panic in the financial system.[7] Although this coordination problem has been in existence with banking crises in the past, the severity of this problem escalated particularly during this recent crisis. The lesson learned from Bear Sterns is that, when there is a crisis of confidence among counterparties, fellow banks or financial institutions can be unwilling to make even secure funding available to those who are in serious need of liquidity, leading to market freeze and consequently the

---

[5] Another related incentive issue that leads to systemic risk deals with the liquidity management. Rochet and Tirole (1996) studied the interbank market and liquidity management. They found that the misalignment of incentives between bank managers and depositors led to banks taking more risky projects and the problem was made worse when the projects were subjected to random liquidity shocks. Although this incentive misalignment can be alleviated using the interbank market where lending banks monitor the risk taking behavior of borrowing banks, if not monitored properly, the default of one institution can trigger series of defaults in other institutions because short-term liquidity management in interbank markets leads to a large amount of uncollateralized exposures.

[6] SEC Chairman Christopher Cox's letter to Basel Committee in support of New Guidance on Liquidity Management. http://www.sec.gov/news/press/2008/2008-48.htm.

[7] In Chapter 2 of Brunnermeier, et al. (2009), the authors reasoned that confidence crisis does not have to originate from the counterparty default risk but may arise from an asset price spiral that deteriorates the asset value of financial institutions' balance sheets as well as the loss spiral that was reinforced by margin/haircut effects.

spread of liquidity crisis to other institutions. Therefore, the systemic risk caused by liquidity shortage in the financial system has been made more severe in this latest financial crisis.[8]

1.4 EXISTING LITERATURES ON SYSTEMIC RISK QUANTIFICATION

Most of the existing systemic risk literatures employed interbank exposure data or credit default swap (CDS) data. Chan-Lau, et al. (2009a) used the cross-country interbank exposure data for their network simulation model. Their findings provided means to quantify the domino distress matrix as well as potential capital losses. Other literatures such as the default intensity model by Giesecke and Kim (2009), the co-risk analysis by Chan-Lau, et al. (2009b) and the time-varying multivariate density, distress dependence and tail risk approaches by Chan-Lau, et al. (2009b) and Segoviano and Goodhart (2009) quantified the probability of sequential bank failures and measured the system risk and financial linkages through distress or failure dependent matrices.

Even though these models provide an important assessment on the relationship among financial institutions via credit risk channels, they may have left out the inter-institution connections through other types of risk such as market, operation or liquidity. In addition, the CDS data may become scarce in emerging market settings like Thailand where the capital market is still developing. Therefore, the method employed by us followed the techniques used by Adrian and Brunnermeier (2008), who used the stock market data to estimate the systemic risk. The details of our estimations will be presented in the next section.

2. SYSTEMIC RISK AS EXTERNALITIES

The health of the banking system as a whole is a composite of each individual bank's financial viability, which in turn may depend on a number of factors, both idiosyncratic and aggregate in nature. For instance, credit/liquidity risks taken on by each bank are the source of idiosyncratic differences among banks, while the stage of business cycle or the existence of bubbles in the credit market is a macro environment that impinges on the banking system as a whole. One has an option of

[8] For more on the studies regarding solvency and liquidity, Diamond and Dybvig (1983) Bank Run Model provided a theoretical analysis of how panic to withdraw could have led to bank failure. Freixas and Rochet (1997) examined the reasons why solvent banks could not raise liquidity in practice.

analyzing the risk to the banking system in terms of a reduced-form function of the aggregate factors only. In this macro perspective, one is implicitly assuming that the idiosyncratic factors are but independent shocks that obscure the underlying contents of the analysis, which is derived primarily from macro environment. For example, in the narratives of the recent subprime crisis in the U.S., many economists and commentators focus on the housing bubble and incentive issues on the part of mortgage borrowers and lenders that led to eventual collapse of house prices and financial market more generally. The threat to the U.S. banking system as a whole can then be seen as a consequence of this aggregate shock.

From the point of view of the regulators, the macro perspective represents only a partial analysis at best and offers little advice on how to make the banking system more resilient to these macro shocks. It is evident that, in the modern banking system, banks operate in an increasingly intricate network, such that one idiosyncratic shock has an increasing potential to transmit across the network and pass on impact to other institutions and the system as a whole. It is precisely these inter-linkages between banks and implications for the banking system that together define the notion of *systemic risk*. A systemic risk has 2 central properties: (1) it is conceived at the individual bank's level, and is conceptually microeconomic in nature, and (2) its size is measured with respect to the impact on the system. In short, a systemic risk is a micro risk that has large macro implications.

Given such definition, a systemic risk is conceptually similar to the notion of externalities. A bank that is more systemically important (i.e. whose systemic risk is larger), can be thought of as generating externalities on other banks. The total welfare costs of a bank failure is potentially well beyond those accrued to the shareholders of the bank concerned, but is crucially dependent on the bank's systemic importance. The size of these externalities may be a subject of disagreements, but their existence was never in doubt.[9]

An important objective of bank regulation is to internalize these externalities, and *ex ante* minimize the potential welfare cost. Policy implications are clear in principles: those banks that are

---

[9] The arguments presented by the Federal Reserve Chairman to the U.S. Senate, as he sought approvals for bailout funds, were largely defended on the grounds that significant externalities exist. In his March 2009 testimony to the Senate Budget Committee, for example, Chairman Ben Bernanke said "We know that failure of major financial firms in a financial crisis can be disastrous for the economy. We really had no choice…".

more systemically important (i.e. impart more externalities) should be more tightly regulated and monitored. Apart from the obvious benefit of helping regulators focus limited resources on 'banks that matter', this regulatory design has the essential benefit of providing the incentives for the banks to internalize the externalities they generate. In forming their business strategies, banks would now need to set the private benefits of becoming 'too big to fail' or 'too systemic to fail' against the resultant cost of more regulation. Provided that the degree of regulation is correctly scaled to address the externalities, the ex ante social welfare can be improved from the baseline case of one-size-fits-all regulation.

While risk-dependent regulation may be conceptually appealing, there remain many technical issues that complicate the implementation in practice. A particularly critical question is, how should one go about measuring the systemic risk? The most straightforward method would be to investigate details of inter-linkages between banks at the balance sheet level, and unveil the network of interdependencies among banks from the ground up. This 'accounting' method has an obvious appeal, despite (or indeed because of) the meticulous due diligence work required. Nonetheless, its success ultimately relies on the acumen on the part of regulators to quickly interpret the implications for inter-linkages between banks in light of changing macro conditions. The recent subprime crisis and the subsequent fallout in the U.S. banking sector may have proven this requirement to be too demanding. Meanwhile an alternative measure of risk spillovers from one bank to another is in relative short supply.

2.1 MEASURING SYSTEMIC RISK: CONDITIONAL VALUE AT RISK (COVAR)

Adrian and Brunnermeier (2009) propose a reduced-form statistical measure of systemic risk that is relatively easy to compute and interpret in real time. The starting point is to define the notion of risk associated with a given bank *i* at time *t* by A_t^i, the market value of the bank's total asset. By definition, $A_t^i = M_t^i L_t^i$, where M_t^i is the bank's market capitalization (obtained from the stock market) and L_t^i is the bank's asset-to-equity ratio (the leverage ratio). We are interested in the risk in terms of changes in the asset values of bank *i* as perceived by the market, hence we define

$$X_t^i = \frac{A_t^i - A_{t-1}^i}{A_{t-1}^i} \tag{1}$$

Similarly the 'asset return' associated with the system is given by

$$X_t^{sys} = \frac{A_t^{sys} - A_{t-1}^{sys}}{A_{t-1}^{sys}} \tag{2}$$

where $A_t^{sys} = \sum_i A_t^i$.

Now that asset returns are available, value-at-risk (VaR) of both the bank's and the system's market returns can now be defined. The typical definition of VaR is the threshold value below which the historical market returns do not fall by more than some pre-specified frequency or level of confidence. Specifically, VaR with level of confidence *q* is defined by

$$\Pr(X_t^i < VaR_q^i) = q \tag{3}$$

The key insight of Adrian and Brunnermeier (2009) is that, one can compute VaR of the banking system either as an unconditional standard VaR,

$$\Pr(X_t^{sys} < VaR_q^{sys}) = q \tag{4}$$

or a VaR conditional on the event that a specific bank has come under stress (i.e. the bank's market returns reaches its VaR level), which may be dubbed conditional VaR (CoVaR).

$$\Pr(X_t^{sys} < CoVaR_q^i \mid X_t^i = VaR_q^i) = q \tag{5}$$

CoVaR is precisely a measure of risk spillover in our preceding discussion. When bank *i* contributes a lot to systemic risk, $CoVaR_q^i$ would be very low, possibly a large negative number indicating a higher potential loss to the system with probability *q*. In other words, when a systemically important bank is under stress, the VaR of the banking system as a whole tends to be significantly lower as well. The difference between CoVaR and the unconditional VaR of the system (ΔCoVaR) captures the externality that the underlying bank imposes on the banking system:

$$\Delta CoVaR_q^i = CoVaR_q^i - VaR_q^{sys} \tag{6}$$

As we have discussed, a policy that aims to internalize externalities should aim to regulate those banks with higher ΔCoVaR more tightly than others.

2.2 REVIEW OF ESTIMATION PROCEDURE

As the preceding definition makes clear, measuring VaR and CoVaR amounts to estimating the underlying probability distribution of returns. In general, this distribution could be estimated through various means, e.g. bootstrapped from the historical return distribution, or estimated as a parameterized fit to the historical sample. Following Adrian and Brunnermeier (2009), we adopt the latter approach and estimate VaR and CoVaR via quantile regression. This method has the well-known virtue that it makes no assumption about the functional form of the underlying assumption (in particular, normality is not required). In addition, it allows us to easily introduce macro state variables which help avoid the omitted variable bias arising from failure to differentiate between systemic risk and macro risk.

The specification for bank *i*'s asset return is given by

$$X_t^i = \alpha^i + \beta^i M_{t-1} + \varepsilon_t^i \tag{7}$$

where M_{t-1} is a vector of exogenous observed macro variables, and $\beta^i M_{t-1}$ may be interpreted as the expected part of asset return. Replacing superscript *i* with *sys* and we obtain the specification for the system's return. The parameters α^i and β^i are estimated by quantile regression, and the fitted values are the measures of VaRs.

$$VaR_t^i = \hat{\alpha}^i + \hat{\beta}^i M_{t-1} \tag{8}$$

$$VaR_t^{sys} = \hat{\alpha}^{sys} + \hat{\beta}^{sys} M_{t-1} \tag{9}$$

Throughout our analysis, we focus on the 1st-quantile which corresponds to the 1% VaR. Given these equations, $\hat{\beta}^i M_{t-1}$ now has the additional interpretation of the expected size of the tail, thus M_{t-1} is informative both in terms of first and second moments of returns.

If one expands the information set at time *t* to include X_t^i as well as M_{t-1}, then the specification for the system's asset return can be written in augmented form as:

$$X_t^i = \alpha^{(sys|i)} + \beta_{t-1}^{(sys|i)} M_{t-1} + \gamma^{(sys|i)} X_t^i + \varepsilon_t^{(sys|i)} \tag{10}$$

whose fitted values evaluated at $X_t^i = CoVaR_t^i$ corresponds to the definition of CoVaR

$$CoVaR_t^i = \alpha^{(sys|i)} + \beta_{t-1}^{(sys|i)} M_{t-1} + \gamma^{(sys|i)} VaR_t^i . \tag{11}$$

It is worth noting that the current methodology has features that help circumvent a popular criticism of VaR, namely that the return distribution is non-normal and hence the tail risk of is ill-described by VaR. To the extent that the non-normality is due to the time-varying nature of expected returns, this is no more than a standard warning against misspecification problem (e.g. omitted variables in M_{t-1}^i) rather than a criticism of VaR concept itself. On the other hand, even if the returns follow some fat-tailed non-normal distribution, estimates of VaR via quantile regression still possess all the finite sample and asymptotic properties obtained under normality or indeed any distribution (see Bassett and Koenker (1978)).

2.3 ESTIMATION

Our interests lie in measuring systemic risk in the Thai financial sector. The Thai financial industry, as listed in stock market, is made up of 23 commercial banks, 43 financial companies, and 24 insurance companies. The banking sector dominates the entire financial industry by far, and there is a significant degree of concentration even within the banking sector itself. We therefore choose to focus on a relatively few number of banks with the benefit of having a longer time series data that include the stress period of 1997, which is of essential value given that our objective is to study risk spillover under stress conditions.[10]

2.3.1 DATA

The data set includes weekly equity prices of 6 major commercial banks in Thailand, covering the period of May 1996 to March 2009. Leverage data are obtained from the quarterly balance sheets of these banks, and are converted into weekly series by linear interpolation. Market valuations of total assets are then derived in weekly frequency and thus weekly returns X_t^i and X_t^{sys} can be computed accordingly. Due to several mergers, recapitalizations and other structural changes over the sample, these weekly returns can exhibit unusual volatility that is unrelated to the market perception

[10] Many firms in the financial industry are set up long after 1997 crisis, and have limited time-series data.

of the banks' asset values. To correct for these, we 'clean' the weekly returns data by censoring weekly returns that are above or below the 3 standard deviations (computed within the sample). These thresholds remain sufficiently large to account for tail and stress events (for instance, 3 standard deviations of system's returns are equivalent to 20% weekly return or loss). The macro state variables M_{t-1} include 8 variables: 4 lags of SET index weekly returns, and 4 lags of the 30-day historical volatility of SET index weekly returns. In principles, one could include in M_{t-1} macroeconomic variables (such as GDP, Industrial Production, CPI), or market variables (such as policy rates, yield spread, sovereign CDS spread). However, we are led by both anecdotal observation and extensive data analysis to believe that for Thai stock data, simple time-series factors are more than adequate in capturing expected returns. Once we condition for these factors, other fundamental variables add negligibly little to the explanatory power of asset returns.

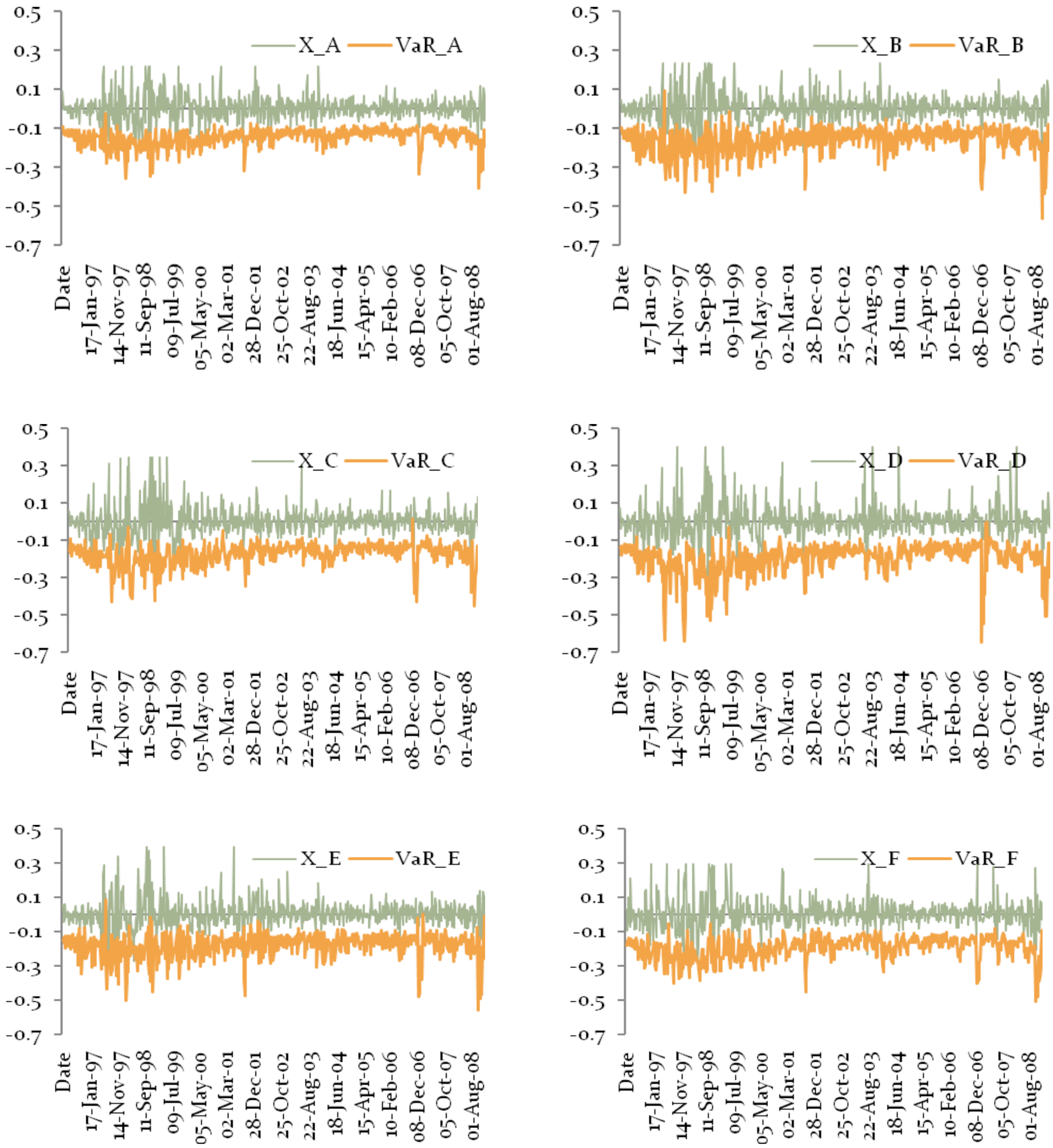
2.3.2 RESULTS

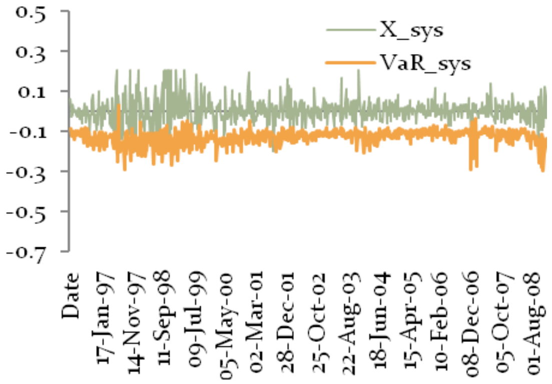
We shall maintain the anonymity of the 6 chosen banks throughout the analysis, and will henceforth refer to them as banks A, B, C, D, E and F (arranged in no particular order).

The first set of plots shows the weekly asset returns for each of the 6 banks and the system, together with their corresponding standard VaRs. The first observation is that these individual returns exhibit different structural volatilities. It is apparent for instance that Bank D faces more volatile weekly returns than does Bank A in general. This observation is confirmed by the fact that VaR for Bank D is broadly lower than that of Bank A, and is also more volatile. As we have stressed however, these unconditional VaRs alone are not sufficient in drawing policy implications. Banks with relatively low volatility in their own returns may well be the ones that contribute more to the risk of the overall system.

The second observation is that VaRs are positively correlated, which is an evidence of a common underlying trend in VaRs. Over the periods surrounding the 1997 crisis, VaRs of all banks were relatively lower, but in subsequent periods, all VaRs trended up together in recognition of the economic recovery. In the post-1997-crisis era, VaRs have generally been driven by the overall conditions in the stock market, including the recent risk aversion episode during the subprime crisis. Nonetheless, each bank responds differently to the common shocks, and some are more resilient than others.

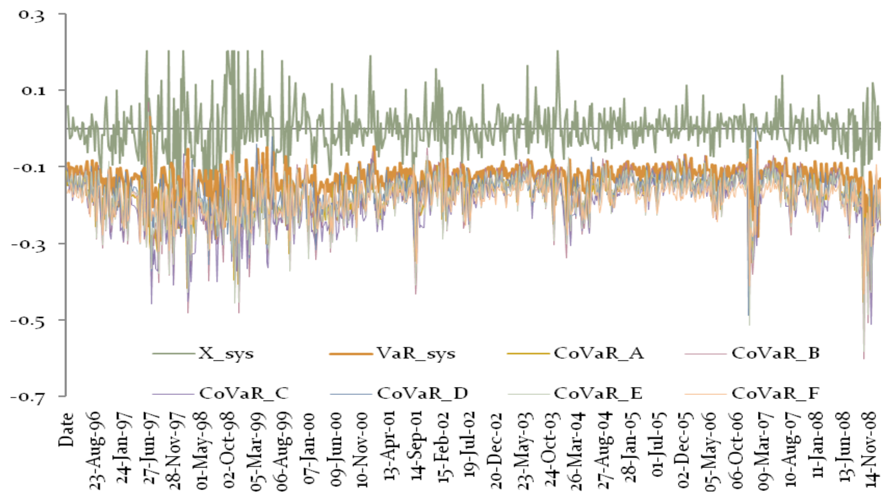
Figure 1: Weekly Asset Returns and VaRs For Each of the Six Banks and the System





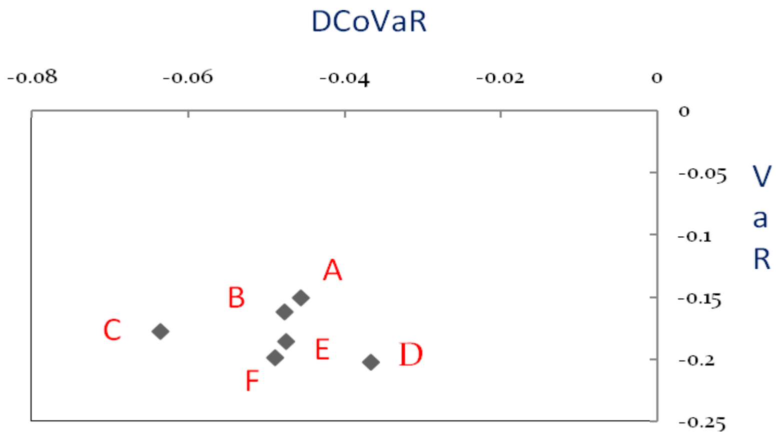
We next calculate the CoVaR corresponding to each bank, which is plotted below. Clearly, conditional on any individual bank being under stress (i.e. its return is at the individual VaR level), the system's VaR tends to be lower than otherwise. The impact on system's VaR appears to vary from one bank to another, suggesting that ΔCoVaR^i are significantly different across banks.

Figure 2: CoVaR Estimation



The next figure scatter-plots the full-sample averages of VaRs against the average delta CoVaRs. Admittedly since there are only 6 banks in our cross-sectional sample, we may not be able to draw strong inferences from the apparent lack of a positive relationship. Even so, it should be noted that Bank C, which contributes most to the systemic risk (i.e. the one with most negative delta CoVaR), is only ranked 4th in terms of unconditional VaR. On the contrary, Bank D which has the most negative unconditional VaR and is therefore unilaterally the riskiest, is at the same time imposing the least risk to the system.

Figure 3: Delta CoVaR Estimation



The result suggests that significant externalities may indeed exist, and the notion of systemic risk deserves due attention by the regulator. It is possible that a bank is seemingly operating prudently and is subject to a limited level of risk itself, yet at the same time is indispensable for the financial viability of the system.

Could sizes explain the systemic importance? While size may have played a part in our sample, there is more to the story than size itself. The correlation between the delta CoVaR ranking and the size ranking is positive but only around 0.26; thus there may be more to the story than 'too large to fail.' In particular, financial linkages among banks may also be important. The recent crisis in the U.S. may give the false impression that these linkages are significant only in a well-developed and sophisticated financial market. In fact, in Thailand or in other developing countries, commercial banks participate actively in the money market to manage their liquidity and interact with the monetary operation of the central bank. In addition, financial linkages could also exist in the credit markets, if not via the financial market. The next section turns to investigating the degree of these linkages.

3. MEASURING AND ANALYZING FINANCIAL LINKAGES IN THE THAI BANKING SYSTEM

The method introduced by Adrian and Brunnermeier (2008) can be used to estimate the financial linkages between financial institutions also. Basically, the equations used to estimate the

ΔCoVaR in the previous section can be modified to estimate how banks are related to each other. Basically, one can apply this concept to estimate how the value-at-risk (VaR) of an institution is affected if another institution were to be in distress. Therefore, we first calculate for "CoVaR(A|B)" which is the "CoVaR" of Institution A conditional on Institution B being in trouble. The net effect of the Institution A's VaR increase from Institution B when compared to Institution A's own VaR is called the "ΔCoVaR(A|B)." The concept of can also be viewed as *externalities* not captured when one considers only the VaR of an institution. This is because ΔCoVaR(A|B) represents the excess amount of Institution A's VaR, apart from the stand-alone VaR of Institution A, caused by Institution B. This measurement reflects negative externalities when one only considers the VaR of Institution A alone.

This estimation of "ΔCoVaR(A|B)" can also be used as a relative measurement tool when it comes to determining which financial institution causes more disturbances to an institution than others. For example, if |ΔCoVaR(A|B)|>|ΔCoVaR(A|C)|, then one can make a good inference that, since Institution B's impact is more than Institution C's impact on Institution A, then Institution A should be more financially-linked to Institution B than C in the crisis time.

3.1 OUR METHODOLOGY AND THE RESULTS OF FINANCIAL LINKAGE ESTIMATIONS FOR THE THAI BANKING INDUSTRY

In our study, we employed the same dataset used in the estimation of systemic risk in the previous section. The linkages of six Thai commercial banks were estimated using the weekly stock market data between the 1996Q2-2009Q1 period. To obtain the financial linkage estimations, we followed the following four steps:

1. Estimating the CoVaR(A|B) which is the value-at-risk of Institution A conditional on the value-at-risk of Institution B by performing the following quantile regression (which is a modification of Equation (10)):

$$X_t^A = \alpha^{(A|B)} + \beta_t^{(A|B)} M_t + \gamma^{(A|B)} X_t^i + \varepsilon_t^{(A|B)} \tag{12}$$

where M_t is the group of independent variables that predict well the normalized change in total asset value in the Thai stock market, namely the SET weekly return variable (four lags included in total, t-1, t-2, t-3 and t-4) and the SET 30-day volatility variable (four lags also) used in the estimation of systemic risk in the previous section. X_t^A is the change in the market value of total financial assets of Institution A as defined also in the previous section.

2. Calculating for the CoVaR(A|B) by means of fitted values of equation (12):

$$CoVaR_t^{(A|B)} = \alpha^{(A|B)} + \beta_t^{(A|B)} M_t + \gamma^{(A|B)} VaR_t^B \qquad (13)$$

where VaR_t^B is the estimated value-at-risk of Institution B obtained in a similar fashion as in the systemic risk section.

3. Calculating the ΔCoVaR(A|B) by the following equation:

$$\Delta CoVaR_t^{(A|B)} = CoVaR_t^{(A|B)} - VaR_t^A \qquad (14)$$

4. Assessing the level of financial linkage by means of measuring the change in an institution's VaR if another institution were to be at its 99-percent VaR (highest level of VaR at the 99-percent quantile) using the following formula:

$$\text{Percent change of } \Delta CoVaR_t^{(A|B)} = \frac{CoVaR_t^{(A|B)} - VaR_t^A}{VaR_t^A} \qquad (15)$$

where *t* is the time period where VaR(B) registered the value at the 99-percent quantile. That is, we define an institution being in distress when its VaR value reached the 99-percent quantile of its VaR distribution over the specified time period. This measurement reflects an additional VaR of Institution A if Institution B were to be in distress as a percentage increase with respect to Institution A's standalone VaR at that time period.

Using the method outlined above, we obtain the following statistics for our CoVaR(A|B) estimations for all of the commercial banks in our sample. The tables below present the average for all the CoVaR(A|B), ΔCoVaR(A|B) and the percent change of ΔCoVaR(A|B) both across the whole time period in the study and segmented into pre-Asian crisis (1996Q2-1999Q4) and post-crisis periods

(2000Q1-2009Q1).[11] The plot of CoVaR(A|B), ΔCoVaR(A|B) and VaR(A) for each institution in our study is presented in the appendix.

Table 1: Average CoVaR(A|B) For All Commercial Banks in the Study

Average (1996Q2-2009Q1)	Bank A	Bank B	Bank C	Bank D	Bank E	Bank F
Bank A		-0.23308	-0.20825	-0.18568	-0.18976	-0.20271
Bank B	-0.19476		-0.22792	-0.18696	-0.20711	-0.19134
Bank C	-0.22372	-0.22693		-0.18547	-0.20644	-0.22308
Bank D	-0.27343	-0.28194	-0.30953		-0.23903	-0.2365
Bank E	-0.24779	-0.26988	-0.25197	-0.21708		-0.2562
Bank F	-0.23252	-0.25264	-0.23981	-0.22667	-0.22888	

Average (1996Q2-1999Q4)	Bank A	Bank B	Bank C	Bank D	Bank E	Bank F
Bank A		-0.28301	-0.2615	-0.22107	-0.23223	-0.2394
Bank B	-0.22762		-0.28509	-0.22229	-0.24851	-0.22248
Bank C	-0.27576	-0.27543		-0.21216	-0.23406	-0.26728
Bank D	-0.32377	-0.32463	-0.36712		-0.27348	-0.26948
Bank E	-0.31249	-0.33838	-0.31415	-0.25246		-0.30454
Bank F	-0.28851	-0.30497	-0.29722	-0.25526	-0.26776	

Average (2000Q1-2009Q1)	Bank A	Bank B	Bank C	Bank D	Bank E	Bank F
Bank A		-0.21319	-0.18704	-0.17159	-0.17285	-0.18809
Bank B	-0.18168		-0.20515	-0.17289	-0.19062	-0.17893
Bank C	-0.20299	-0.20761		-0.17484	-0.19544	-0.20547
Bank D	-0.25338	-0.26494	-0.28659		-0.2253	-0.22336
Bank E	-0.22202	-0.24259	-0.2272	-0.20299		-0.23694
Bank F	-0.21022	-0.23179	-0.21695	-0.21529	-0.21338	

Table 2: Average ΔCoVaR(A|B) For All Commercial Banks in the Study

Average (1996Q2-2009Q1)	Bank A	Bank B	Bank C	Bank D	Bank E	Bank F
Bank A		-0.08239	-0.05756	-0.035	-0.0390786	-0.05202
Bank B	-0.01862		-0.05178	-0.01082	-0.0309652	-0.01519
Bank C	-0.04554	-0.04875		-0.0073	-0.0282654	-0.0449
Bank D	-0.07052	-0.07903	-0.10662		-0.0361152	-0.03359
Bank E	-0.05463	-0.07672	-0.05881	-0.02392		-0.06304
Bank F	-0.01656	-0.03668	-0.02385	-0.01071	-0.0129156	

Average (1996Q2-1999Q4)	Bank A	Bank B	Bank C	Bank D	Bank E	Bank F
Bank A		-0.10654	-0.08503	-0.0446	-0.0557643	-0.06293
Bank B	-0.02811		-0.08558	-0.02277	-0.0489933	-0.02297
Bank C	-0.06854	-0.06821		-0.00495	-0.0268427	-0.06007
Bank D	-0.07856	-0.07941	-0.1219		-0.0282621	-0.02426
Bank E	-0.09019	-0.11609	-0.09185	-0.03016		-0.08225
Bank F	-0.03487	-0.05133	-0.04358	-0.00162	-0.0141257	

[11] The number represented in each cell is the additional VaR on average of institutions located in the rows carried when institutions resided in the columns were at different levels of their weekly VaR.

Average (2000Q1-2009Q1)	Bank A	Bank B	Bank C	Bank D	Bank E	Bank F
Bank A		-0.07277	-0.04662	-0.03117	-0.032432	-0.04768
Bank B	-0.01484		-0.03832	-0.00605	-0.0237839	-0.0121
Bank C	-0.03638	-0.041		-0.00823	-0.0288322	-0.03886
Bank D	-0.06732	-0.07888	-0.10053		-0.0392434	-0.0373
Bank E	-0.04047	-0.06104	-0.04565	-0.02144		-0.05539
Bank F	-0.00927	-0.03084	-0.016	-0.01433	-0.0124335	

Table 3: Average Percent ΔCoVaR(A|B) For All Commercial Banks in the Study

Average (1996Q2-2009Q1)	Bank A	Bank B	Bank C	Bank D	Bank E	Bank F
Bank A		54.68	38.20	23.23	25.93	29.54
Bank B	10.57		29.40	6.14	17.58	8.63
Bank C	25.56	27.36		4.10	15.86	25.20
Bank D	34.76	38.95	52.54		17.80	16.55
Bank E	28.28	39.72	30.45	12.39		29.19
Bank F	7.67	16.98	11.04	4.96	5.98	

Average (1996Q2-1999Q4)	Bank A	Bank B	Bank C	Bank D	Bank E	Bank F
Bank A		60.37	48.19	25.28	31.60	35.66
Bank B	14.09		42.89	11.41	24.56	11.51
Bank C	33.08	32.92		2.39	12.95	28.99
Bank D	32.04	32.38	49.71		11.53	9.89
Bank E	40.57	52.22	41.32	13.57		32.43
Bank F	13.75	20.24	20.24	0.64	5.57	

Average (2000Q1-2009Q1)	Bank A	Bank B	Bank C	Bank D	Bank E	Bank F
Bank A		51.83	33.20	22.20	23.10	33.96
Bank B	8.90		22.97	3.63	14.26	7.25
Bank C	21.83	24.61		4.94	17.31	23.32
Bank D	36.18	42.39	54.03		21.09	20.05
Bank E	22.29	33.62	25.15	11.81		27.56
Bank F	4.61	15.35	15.35	7.13	6.19	

The next table exhibits our percent change in ΔCoVaR(A|B) estimation when an institutions resided in the columns are at their 99-percent VaR levels. Note that each institution did not necessarily have their 99-percent level on the same date and therefore the numbers presented could be from different dates, depending on when an institution would be at its distress level.[12]

[12] For Bank A and B, the 99%-distress date were November 14, 2008. For Bank C, such date fell on February 27, 1998 and February 20, 1998 for Bank D. For Banks E and F, the dates were December 18, 1998 and September 12, 1997 respectively.

Table 4: CoVaR(A|B), ΔCoVaR(A|B) and Percent ΔCoVaR(A|B) at the 99-percent Distress Level

Actual CoVaR	Bank A	Bank B	Bank C	Bank D	Bank E	Bank F
Bank A		-0.52021	-0.60574	-0.31093	-0.51070	-0.32864
Bank B	-0.37950		-0.57910	-0.31694	-0.56573	-0.32726
Bank C	-0.51615	-0.49276		-0.23738	-0.38231	-0.39916
Bank D	-0.72314	-0.63689	-0.85555		-0.59414	-0.31394
Bank E	-0.70875	-0.75199	-0.77930	-0.37685		-0.45708
Bank F	-0.58554	-0.56132	-0.64288	-0.26921	-0.50591	

Actual ΔCoVaR	Bank A	Bank B	Bank C	Bank D	Bank E	Bank F
Bank A		-0.17355	-0.25779	-0.08020	-0.14741	-0.05269
Bank B	-0.00193		-0.20645	-0.14281	-0.15895	0.03627
Bank C	-0.20026	-0.17686		0.01024	-0.03955	-0.15496
Bank D	-0.21472	-0.12848	-0.21331		-0.12213	-0.04342
Bank E	-0.19035	-0.23359	-0.23232	-0.13710		-0.08385
Bank F	-0.03486	-0.01065	-0.35664	-0.18484	-0.14929	

Percent ΔCoVaR	Bank A	Bank B	Bank C	Bank D	Bank E	Bank F
Bank A		50.06	74.09	34.76	40.58	19.10
Bank B	0.51		55.40	82.02	39.07	0.00
Bank C	63.39	55.99		0.00	11.54	63.45
Bank D	42.23	25.27	33.21		25.87	16.05
Bank E	36.72	45.06	42.47	57.18		22.47
Bank F	6.33	1.93	124.60	219.08	41.86	

3.2 ANALYSIS OF FINANCIAL LINKAGE ESTIMATIONS

The analysis of the estimation done in the previous section is performed on two different levels. The first is to perform the general analysis on the financial linkage estimation itself based upon the results from Tables 1-4 and upon the simple asset correlation calculation. The second part of the analysis involves employing panel data regression techniques to identify important bank-level characteristics that may help explain the similarities and differences in the degree of financial linkages for each commercial bank in our study.

3.2.1 GENERAL ANALYSIS AT A GLANCE

In our sample, Bank A, B, C and E should be considered as large commercial banks while Bank D and F are of medium size. From Table 3 which presents the average percentage increase in an institution's VaR coming from other institutions' VaRs, we see that, in general, commercial banks were in general less financially-linked going from the pre-crisis to post-crisis, except for Bank D whose VaR seemed to have become more sensitive to the level of VaR from other institutions. One possible explanation for this change in the relationship between Thai commercial banks over time is that the stock market data during the post-crisis period is more abundant than the pre-crisis period. This is because there are more banks listed in the stock market after 2000 when compared to the period between the years 1996-1999. Therefore, if a bank conducts a business with another bank not listed in the stock market for the whole time period of our study (and consequently was excluded from our estimation and analysis), and if that bank is in business with this unlisted institution to diversify risk (and hence has less asset co-movement), then the listed bank's relationship with other listed banks can be less intense since the effects of the asset movement and therefore the VaR estimation are partly transferred to the banks not included in our study.

Another interesting point coming out from the financial linkage average analysis is that, for all commercial banks, the degree of relationship between an institution and its few most important counterparties remained quite stable over time (pre-crisis vs. post-crisis). For example, Bank A's VaR impacted Bank C, Bank D, and Bank E much more than Bank A and Bank F—the trend that persisted throughout both the pre and post-crisis and, consequently, the whole period average. We therefore can conclude, in part, that although the strength of the financial linkage had changed over time, the important counterparties to a bank were somewhat time-invariant.

Also, from Table 4 which represents the financial linkage estimation during distress time of each financial institution, what policy makers and banks themselves need to be aware of is the case like the effects of Bank C and D had on Bank F. When Bank C was at its 99-percent distress level, it increased Bank F's VaR by 124.6 percent while when Bank D was in distress, it raised Bank F's VaR by 219.6 percent. Bank F needed very much to be aware of this potential risky linkage it had with these two banks in order to assess how it would be affected should these banks be in distress in order to create possible action plans to mitigate the risk transfer between banks.

When one considers the possible hypothesis that size does matter, one should expect to see that large commercial banks are more financially-linked to one another and the medium-sized ones should relate among themselves. This conjecture was not obvious from our estimation. Upon consulting further with the data, we found that the above hypothesis was mostly true when one looked at the movement of the change in market-valued total financial assets but such association failed to hold when an institution VaR was calculated. Table 5 below presents the bi-lateral correlation between financial institutions for the change in total financial assets (X_t) and institutions' VaRs.

Table 5: Correlation of Financial Assets and VaR For Different Time Periods

Correlation Xt (1996-2009)	Bank A	Bank B	Bank C	Bank D	Bank E	Bank F
Bank A						
Bank B	0.806395					
Bank C	0.625343	0.627122				
Bank D	0.523237	0.529784	0.596425			
Bank E	0.671305	0.732816	0.629398	0.540085		
Bank F	0.619138	0.646472	0.579778	0.61835	0.598367	

Correlation VaR (1996-2009)	Bank A	Bank B	Bank C	Bank D	Bank E	Bank F
Bank A						
Bank B	0.853473					
Bank C	0.51773	0.390639				
Bank D	0.518565	0.583994	0.597349			
Bank E	0.826658	0.734694	0.700627	0.57626		
Bank F	0.531711	0.465297	0.621618	0.410152	0.721072	

Correlation Xt (1996-1999)	Bank A	Bank B	Bank C	Bank D	Bank E	Bank F
Bank A						
Bank B	0.815887					
Bank C	0.605859	0.59784				
Bank D	0.599169	0.594566	0.692168			
Bank E	0.690322	0.74665	0.676445	0.701755		
Bank F	0.62406	0.63718	0.599385	0.746909	0.644553	

Correlation VaR (1996-1999)	Bank A	Bank B	Bank C	Bank D	Bank E	Bank F
Bank A						
Bank B	0.847642					
Bank C	0.43657	0.346565				
Bank D	0.434698	0.428748	0.528065			
Bank E	0.824776	0.76449	0.643538	0.495983		
Bank F	0.338565	0.359044	0.435704	0.149082	0.586381	

Correlation Xt (2000-2009)	Bank A	Bank B	Bank C	Bank D	Bank E	Bank F
Bank A						
Bank B	0.796037					
Bank C	0.666817	0.682308				
Bank D	0.446994	0.462944	0.494528			
Bank E	0.650395	0.721162	0.570999	0.377812		
Bank F	0.614338	0.660664	0.551971	0.481466	0.649486	

Correlation VaR (2000-2009)	Bank A	Bank B	Bank C	Bank D	Bank E	Bank F
Bank A						
Bank B	0.842315					
Bank C	0.484029	0.337796				
Bank D	0.48687	0.647657	0.571662			
Bank E	0.810457	0.688728	0.704532	0.58217		
Bank F	0.565448	0.465272	0.676617	0.483758	0.76924	

From the table above, the yellow highlight represents the hypothesis that large financial banks should be more linked within the same group. For most large commercial banks, the claim was true when one considered the asset correlation X_t and the claim also became more obvious for the time period between 2000-2009. However, when looking at the correlation of estimated institution VaR, such relationship no longer held. For example, during the years 2000-2009, Bank A's change in total financial assets was highly correlated most with Bank B, C and E—its peer banks (measured by asset size). Nevertheless, its VaR was correlated with Bank F more than Bank C. The lesson to be drawn from this is that the behavior of an institution's change in total financial assets does not have to be the same as the behavior of its VaR. This is because, when VaR was estimated, the quantile regression fitted the estimation around the 99th quantile of the negative change in an institution's asset value and therefore does not guarantee the same correlation relationship going from X_t to VaR.

Consequently, size may not be the only factor contributing to the differences in the degree of financial linkages for each commercial bank in our study. Therefore, we investigated further on the plausible factors that may shed light onto how financial institutions are connected to each other. The results and analysis on the panel data regression is presented in the next section.

3.2.2 PANEL DATA REGRESSION USING BANK-LEVEL BALANCE SHEET DATA

In this section, we considered performing fixed-effect panel data regressions using bank balance-sheet data during the years 1996Q2-2009Q1 and see whether the degree of financial linkages of an institution, as measured by ΔCoVaR(A|B), can be explained by bank balance-sheet characteristics.

Since our balance-sheet data is monthly while our ΔCoVaR(A|B) estimation is weekly, we calculated the simple average of ΔCoVaR(A|B) to get a monthly frequency on the estimation. The fixed-effect panel data regression is executed for each institution. For example, the regression for Bank A (hereby called *impacted bank or institution*) is as follows

$$\Delta CoVaR(A\,|\,i)_t = \alpha + v_i + \beta Z_{it} + \varepsilon_{it}\,, \tag{16}$$

where i represents all commercial banks which are not Institution A (hereby called *peer banks*) , ΔCoVaR(A|i) is the average monthly ΔCoVaR(A|i) coming from peer institution i and v_i is the binary variable for each institution i. Z_{it} is the peer bank characteristics in consideration—total loans, interbank assets, interbank deposits, interbank loans, common equity, retained earnings, and liabilities on demand. Even though total assets are generally used to control for bank size, here we used total loans to control for size instead, as it is highly correlated with total assets and can also reflect the main business of commercial banks—lending. The interbank-related variables, notably interbank assets, interbank deposits and interbank loans, should explain well the degree of financial linkages between banks.[13] Common equity and retained earnings reflect the solvency and crisis-absorption ability of banks, while liability on demand is a proxy for a bank's liquidity position. The correlations between all the independent variables used in the regressions are in the appendix. The fixed-effect regression results are as follows.

Table 6: Fixed-Effect Regression Results for Banks A-F

Balance-sheet variables (in thousand baht)	Regressions of ΔCoVaR of the Following Banks:					
	Bank A (in x10(-10) unit)	Bank B (in x10(-10) unit)	Bank C (in x10(-10) unit)	Bank D (in x10(-10) unit)	Bank E (in x10(-10) unit)	Bank F (in x10(-10) unit)
Total loans	-0.442 (0.131)***	-0.192 (0.125)	-0.543 (0.160)***	-0.179 (0.120)	-0.768 (0.162)***	-0.330 (0.137)**
Interbank assets	-0.017 (0.162)	0.117 (0.165)	0.470 (0.261)*	-0.063 (0.154)	-0.126 (0.205)	0.038 (0.178)
Interbank deposits	-13.8 (1.38)***	-13.2 (1.45)***	-10.6 (1.53)***	-4.01 (1.44)***	-19.5 (1.68)***	-8.53 (1.53)***
Interbank loans	1.07 (0.923)	0.805 (0.908)	-0.466 (1.02)	1.90 (1.01)*	3.01 (1.18)**	-0.252 (1.02)
Common equity	1.53 (0.675)**	0.942 (0.496)*	1.37 (0.524)***	-0.0007 (0.465)	1.43 (0.598)**	1.28 (0.556)**
Retained earnings	3.30 (1.16)***	1.49 (1.02)	2.72 (1.15)**	2.38 (1.00)**	3.91 (1.20)***	2.13 (1.12)*
Liabilities on demand	0.642 (4.67)	5.43 (5.51)	-2.56 (4.86)	-5.96 (5.00)	12.2 (7.80)	0.217 (5.47)
Adjusted R-square	0.4233	0.3428	0.3418	0.5454	0.4122	0.1666
No. of observations	690	690	690	690	690	690

From the table, it can be seen that total loans of peer banks seem to be an important driving factor that increases an impacted institution's ΔCoVaR in general. For example, the average level of total loans of Bank E's peer institutions is 617 billion baht. If the peer institution were to increase the loans by 5%, or 30.85 billion baht, it would have made ΔCoVaR of Bank E more negative by

[13] *Interbank assets* represent the outstanding interbank items on the asset side of the balance sheet. It includes the deposits of a bank at other banks and the amount of interbank loan outstanding that a bank lends to other banks. *Interbank deposits* and *interbank loans* are items on the liabilities side of the balance sheet. *Interbank deposits* are the amount of deposits at a bank by other banks while *interbank loans* are the outstanding loans that a bank borrowed from other banks.

-0.002369 units (from the average ΔCoVaR level of -0.0556398 units) or making the average ΔCoVaR of Bank E even more negative by about 4.26%. The results that an increase in the loan size of peer banks contributes to more negative ΔCoVaR of an impacted bank are also consistent across most impacted institutions, although the degrees of impact may differ. If one wants to interpret total loans as a measurement for the size effect, then it seems that the bigger the size of a peer bank, the more negative contribution it makes to an institution ΔCoVaR.

Another surprisingly important factor that affects ΔCoVaR of an institution is the interbank deposits which are the deposits that other peer banks have at an impacted bank. The effect of this factor is unanimous across impacted banks—the more deposits of other peer banks an impacted bank have, the more negative externalities it imposes onto an impacted bank's ΔCoVaR. For example, the average size of interbank deposits of the peer banks of Bank A is 11.7 billion baht. A 5% increase in interbank deposits (or by 0.585 billion baht) by Bank A's peer banks will add to Bank A's average ΔCoVaR by around 1.51% (i.e. increasing the externalities by 1.51%). This negative effect of an increase in interbank deposits on an impacted bank's ΔCoVaR is also consistent across impacted institutions. One possible explanation regarding this effect will be that an institution possessing a high level of interbank deposits by other banks may be more liquidity-risky during the downturn time if the peer banks require immediate withdrawals of their deposits at an impacted bank, since the interbank deposits tend to be of large amount and quite concentrated by depositors when compared to regular retail depositors. Also, note that the size of the coefficients is larger (i.e. more negative) for impacted banks whose size are large, as Banks A, B, C, and E are classified as large banks.

The coefficients of both common equity and retained earnings variables are positive, which indicate that if the peer banks are solvent and possess the ability to absorb shocks (through their superior availability of funds), then they should help decrease the risk of an impacted bank. For example, the average common equity of the peers of Bank E is 61.5 billion baht. If this increases by 5% (or about 3.075 billion baht), then the average ΔCoVaR of Bank E should decrease (i.e. become less negative) by 0.004397 units, or about 7.90% of the average ΔCoVaR of Bank E. It is intuitive to think that if peer banks are well-capitalized, then the negative effect that will be passed on to an impacted bank should be lessened.

Finally, it is worth noting that the ΔCoVaR of each impacted bank is sensitive not only to different the balance-sheet variables but also to different degrees. For instance, Bank B may have been driven by only the levels of interbank deposits and common equity of its peer banks while Bank E is sensitive to the amount of total loans, interbank deposits, interbank assets, common equity and retained earnings of its peer banks. Moreover, a 5-percent increase in total loans of the peer institutions of Bank E makes ΔCoVaR more negative by 4.26% while a 5-percent increase in the common equity of peers makes ΔCoVaR less negative by 7.90%, indicating different impacts on ΔCoVaR (in absolute value). This analysis confirms the claim by Adrian and Brunnermeier (2008) that the symmetric nature of CoVaR(A|B) does not have to hold. That is CoVaR(A|B) does not have to equal CoVaR(B|A).

3.2.3 ANALYSIS OF FINANCIAL LINKAGES THROUGH INTERBANK DATA

Another possible channel of financial linkages is through activities conducted through interbank markets. In this case, we considered some classes of interbank activities of the six banks in our study, notably currency swaps (both buy-sell and sell-buy contracts) during the years 2004Q1-2009Q1, where the date specified in each transaction is the contract-originated date. We did not include interest rate swap and interbank lending data due to their limited activities and did not consider the outright forward contracts, as they are usually executed on the spot and therefore carry no counterparty risk that can potentially affect the VaR of a bank.

The granularity of our data is by-transaction and therefore needs to be combined to somewhat match with our ΔCoVaR(A|B) estimations. First, for each month, we totaled the amount of interbank contracts Bank A did with *all counterparties* and then calculated the percentage of the amount of each contracts originated by Bank A to the total amount of interbank contracts Bank A did with *all counterparties* in that month. We then summed the percentage calculated by counterparties in our study (for example, for Bank A, we grouped the contracts by counterparties such as Bank B, C, D, etc.) within each month. Finally, we merged the monthly average CoVaR(A|B) and ΔCoVaR(A|B) data with the percentage of currency swaps calculated previously. Then, for each year and counterparty, we took the mean of this monthly data and calculated the correlation between

CoVaR(A|B) or ΔCoVaR(A|B) and the percentage of currency swaps for each year. The results are as follows:

Table 7: Correlations Between CoVaR(A|B) or ΔCoVaR(A|B) and Percentage of Swaps

Bank A		
correlation w/ CoVaR	Sell-Buy CCY Swaps	Buy-Sell CCY Swaps
2004	-0.7018	-0.7852
2005	0.0384	-0.7653
2006	-0.4231	-0.3186
2007	-0.9517	0.3407
2008	-0.5331	-0.7603
2009	-0.9639	-0.5472
correlation w/ ΔCoVaR	Sell-Buy CCY Swaps	Buy-Sell CCY Swaps
2004	-0.7720	-0.7089
2005	-0.0004	-0.7259
2006	-0.4962	-0.3284
2007	-0.9573	0.1223
2008	-0.6718	-0.8029
2009	-0.9349	-0.5472
Bank B		
correlation w/ CoVaR	Sell-Buy CCY Swaps	Buy-Sell CCY Swaps
2004	-0.7993	0.6055
2005	-0.7958	-0.1124
2006	0.2166	0.7856
2007	0.2945	-0.0726
2008	0.5247	-0.6571
2009	0.0889	-0.9183
correlation w/ ΔCoVaR	Sell-Buy CCY Swaps	Buy-Sell CCY Swaps
2004	-0.8256	0.494
2005	-0.6233	-0.1835
2006	-0.0994	0.8558
2007	0.0101	0.1535
2008	0.5849	-0.8056
2009	0.1263	-0.887
Bank C		
correlation w/ CoVaR	Sell-Buy CCY Swaps	Buy-Sell CCY Swaps
2004	0.9177	-0.2106
2005	0.9772	-0.4334
2006	-0.5965	0.0033
2007	-0.2743	-0.1531
2008	-0.4230	-0.7532
2009	-0.8875	-0.5297
correlation w/ ΔCoVaR	Sell-Buy CCY Swaps	Buy-Sell CCY Swaps
2004	0.9214	0.2217
2005	0.9296	-0.3479
2006	-0.4994	-0.6096
2007	-0.8434	-0.4699
2008	-0.3763	-0.8924
2009	-0.7832	-0.5976
Bank D		
correlation w/ CoVaR	Sell-Buy CCY Swaps	Buy-Sell CCY Swaps
2004	-0.0059	-0.4657
2005	0.1511	-0.1242
2006	0.6771	0.663
2007	-0.5093	0.1728
2008	-0.0394	-0.3634
2009	0.0387	0.4520

Bank D		
correlation w/ ΔCoVaR	Sell-Buy CCY Swaps	Buy-Sell CCY Swaps
2004	0.6384	0.1392
2005	0.1832	-0.0271
2006	0.6593	0.1915
2007	-0.0631	0.7829
2008	0.4127	0.3697
2009	0.2756	0.7708

Bank E		
correlation w/ CoVaR	Sell-Buy CCY Swaps	Buy-Sell CCY Swaps
2004	0.4085	0.3403
2005	0.5621	0.6130
2006	-0.6664	-0.6999
2007	0.2483	-0.5645
2008	-0.4625	-0.7587
2009	-0.1189	-0.6526
correlation w/ ΔCoVaR	Sell-Buy CCY Swaps	Buy-Sell CCY Swaps
2004	0.8675	-0.0609
2005	0.2811	0.6569
2006	-0.4378	0.0950
2007	-0.5079	-0.2061
2008	-0.5939	-0.7386
2009	-0.2285	-0.6711

Bank F		
correlation w/ CoVaR	Sell-Buy CCY Swaps	Buy-Sell CCY Swaps
2004	0.5386	0.2046
2005	0.5586	0.2832
2006	-0.2470	-0.3517
2007	-0.3819	-0.2008
2008	0.1771	0.4096
2009	-0.4158	-0.1974
correlation w/ ΔCoVaR	Sell-Buy CCY Swaps	Buy-Sell CCY Swaps
2004	0.6544	-0.0354
2005	0.4815	0.1192
2006	-0.3347	-0.5765
2007	-0.0970	-0.1233
2008	-0.6760	0.5573
2009	-0.3361	-0.1485

From Table 7, it can be seen that interbank activities, namely swaps in this case, can be used to explain an increase in a bank's VaR only partly and to different degrees. For example, for Bank A, the correlation between the amount of sell-buy swap activities and ΔCoVaR is negative for all years, meaning that major counterparties of Bank A (as measured by the percentage of amount of swaps executed) may have contributed more to Bank A's risk, in addition to its own VaR. This can be interpreted as Bank A being financially linked more to its interbank counterparties and inter-institution risk can be transmitted through this interbank channel. However, the major counterparties in the sell-buy swaps of Bank D seemed to help decrease ΔCoVaR of Bank D and therefore the interbank swap activities may not be the main source contributing to an increase in ΔCoVaR of Bank D, meaning that the financial linkage and risk transmission of Bank D to other banks may be from other channels. Therefore, how banks are financially linked may be contributed partly from their interbank activities but there must be other sources of the interbank relationship.

Finally, it is worth noting that the financial linkage calculation via the ΔCoVaR(A|B) concept should be done at a specific bank level, as each bank is linked to other peer banks in different fashions. Therefore, such financial linkage calculation should also be performed by banks themselves so that they are well-aware of whether and how they are connected to their peer banks, especially when they can employ their internal data to better determine the causes of such financial linkages.

4. REGULATORY POLICY IMPLICATIONS REGARDING THE SYSTEMIC RISK QUANTIFICATION

The results presented in Section 3 represent just how much more bank supervisors will have to deal with in mitigating systemic risk in the future. In this respect, the ΔCoVaR results provide an additional tool for policy makers to assess the degree of negative externalities and financial linkages but it may be insufficient to employ only this tool to identify the systemic risk potential. Therefore, to discuss in greater details on what is left to be done, this section is divided into two parts. The first section attends to the forward-looking policy options currently being considered by central bankers. Then the second part puts forward remaining challenges facing supervisors and policy makers with regards to the systemic risk issue.

4.1 FORWARD-LOOKING POLICY OPTIONS

Since the issue of systemic risk has become a topic which receives much attention, especially during the aftermath of this recent crisis, there are many policy options being discussed. This section provides analyses on four main categories of policy tools which are being reflected on at the forefront of systemic risk policy discussion.

First, there are discussions regarding how to craft supervisory policies so that they match the specific characteristics of the regulated entities that can potentially create systemic risk. This characteristic determination is still far from being definitive—from its asset size to leverage ratio to the degree of complexity and potentially to its contribution to systemic risk. On top of identifying these institution factors, there is also an issue of what should be the appropriate implementation tools—from charging more regulatory capital to taxation to possibly purchasing insurance. In their paper, Adrian and Brunnermeier (2008) proposed that institutions should be required to hold capital not only to cover their VaR but also their ΔCoVaR, while central bankers should be aware of bank characteristics that could potentially produce a large ΔCoVaR in the future. While Brunnermeier, et al. (2009) proposed the ceiling of loan-to-value ratios for mortgage exposures (which was actually implemented by the Bank of Thailand on high-value real estate loans back in 2003), Kashyap, et al. (2008) suggested the idea of an institution having a 'capital insurance,' meaning that banks should buy capital insurance policies that would pay in case the whole financial system was to be under distress. On the level of complexity and size of financial institutions, Chairman Bernanke, on his speech at the Council for Foreign Relations on March 10th, 2009, emphasized the importance of large banks being "capable of monitoring and managing their risk in a timely manner" and thus any entity whose failure would most lead to system distress should be monitored more closely on their risk taking strategies as well as be subjected to higher capital and liquidity standards.

Second is the topic involved the possibility of an institution failure due to heightened counterparty risk. Since the failure of one or more entities can possibly lead to the system meltdown if the default exposures and institutions are large enough, there has been a proposal to impose limits on inter-institution financial exposures (Schwarcz (2008)). The idea behind it is that putting a ceiling on such exposures can promote risk diversification, thereby limiting the loss of a contractual counterparty and also the likelihood of counterparty default. This idea, however, is not the favorite of Chairman Bernanke, as he believed that large financial institutions will seek to protect themselves from such risk, especially when lending to hedge funds, and regulators should therefore concentrate on the institution's stress testing methodology.[14] Also, since the failure of a major bank to meet its payment obligations can possibly spread fear of sequential defaults, there is a proposal for central banks to guarantee payment of transfers made by banks in order to minimize the possible payment and trade failures associated with counterparty contracts. However, this comes at a cost in a sense

[14] Remarks by Chairman Ben Bernanke at the New York University Law School on April 11, 2007. http://www.federalreserve.gov/boardDocs/speeches/2007/20070411/default.htm.

that banks can therefore lose an incentive to monitor their counterparties (Kaufman and Scott (2003)). This is another issue central bankers will need to think about when it comes to drafting payment-related policies.

Third, much talk has been about the disclosure of information and transparency. This is because the lack of information on the true nature and risk of complex derivatives is one of the leading causes of this recent financial crisis. A market for derivatives can wipe out the information associated with bank debt and consequently reduce welfare (Morrison (2005)). In addition, derivatives traded over-the-counter should be encouraged to trade in an organized exchange market to promote the standardization of future contracts so that the relevant economic parties will have much clearer information (Eichengreen (2008), Kregel (2008)). Also, during the distress time, if depositors and other peer banks can still differentiate the economically solvent from insolvent banks in a timely manner, the possibility of solvent independent banks being driven into insolvency rarely happens, as evident from the fact that almost all failed banks during the Great Depression were small unit banks (Kaufman and Scott (2003)). Kupiec and Nickerson (2001) suggested that transparency should help enhance the efficiency of implementing the capital adequacy ratio requirement. In fact, the disclosure of information is addressed in Pillar III of the current Basel II Framework, which is already in effect since June 2009 for banks using the standardized approach (SA) for their regulatory capital calculation and will be in effect in June 2010 for the banks employing the internal rating-based methodology.

Finally, there is an issue about panic prevention. There are two folds to this story. First, to prevent the panic of depositors that can lead to bank run, one of the policy tools used widely is to establish the deposit insurance institution (Schwarcz (2008)). The current debate regarding this policy option is about how banks should pay the premium to this institution—based on size, the level of risk, etc. Also, there is a discussion regarding the trade-off between the blanket guarantee and the moral hazard. The blanket guarantee will give depositors the comfort but may lead to excessive risk taking by bank management because they do not have to be responsible for paying back depositors at any time and consequently imposing a large social cost. Because of this same analysis, Kaufman and Scott (2000) suggested that there should be no deposit-insurance coverage of interbank transactions, as it is crucial for banks to have incentives to protect themselves from the risk associated with such transactions. Second, to prevent liquidity shortage that can potentially trigger liquidity crisis among banks, the central bank also carries a role of the lender of last resort. The central bank can facilitate the liquidity in two ways—by providing liquidity to prevent financial entities from defaulting (thereby alleviating institution-based shortage) and by providing liquidity to capital markets (and lessening the system-wide shortage). However, when considering these policy options, one needs to be aware that it might potentially lead to the same moral hazard problem by banks and cost to tax payers (Macey and O'Hara (2003)). To minimize the moral hazard cost, banks can be provided with liquidity under the agreement that the central bank possesses the right to intervene while the cost to tax payers can also be taken care of by imposing risk premiums to financial market participants (Schwarcz (2008)).

4.2 REMAINING CHALLENGES TO BANK SUPERVISORS

This section discusses briefly the remaining challenges for bank supervisors in crafting related policies to cope with financial linkage and systemic risk. Insofar, there are two key policy implications we wish to elaborate here.

First, there is a debate regarding the systemic risk measurement and detection. As mentioned previously in Section 1, some econometric quantification methods have been proposed to assess the level of financial linkages and systemic risk in the financial market. While most models rely on the credit default swap (CDS) data to assess the co-movement of probability of defaults among institutions, the ΔCoVaR measures rely on the estimation of the value-at-risk (VaR) through the change in normalized total assets. However, these econometric tools will not provide policy makers with the absolutely complete picture on the issue, not to mention that the applications of these tools and the analysis should be tailor-made to match the specific characteristics and environment of each country's financial system. Therefore, bank supervisors will need to be aware of the limitations and the explanatory power of each quantification method and use these models to help identify the underlying factors that can possibly increase the level of systemic risk identified by such models. In addition, they should keep in mind that this quantification of linkages and risk must be used in combination of other policies, such as monitoring the risk level of banks along with bank management as a stand-alone entity. They also must make certain that these institutions are aware of not only their risk but also how they are related to other institutions as well as how they will be affected if the system is to be under distress. This forward-looking view therefore should be employed by both the supervisors and bank management alike.

Finally, there still is a complication when it comes to considering the trade-off between systemic risk prevention and minimizing the moral hazard.[15] This is a classic case of the mission to strike the right balance between stability and efficiency in the system facing all bank supervisors. The policy options mentioned in Section 5.1 are examples of these trade-offs—from deposit insurance coverage to payment system guarantee to alleviating liquidity shortage. In addition, since the crisis this time involved major non-bank entities in the U.S., there is also another trade-off debate on whether and how non-bank institutions should be supervised, since the risk produced by these entities can potentially spread to the banking sector. After all, the main reason why banks need supervising in the first place is because, without regulation, the externalities caused by systemic risk will not be prevented or internalized, since the motivation of market participants is to protect themselves and not the system as a whole and hence no institution will have an incentive to limit risk taking in order to reduce the contagion effect for other entities (President's Working Group on Financial Markets (1999)), while this view can possibly be true for non-bank entities as well (Kupiec and Nickerson (2001)). Therefore, bank supervisors will need to carefully consider all the possible alternatives before issuing policies so that they can internalize all the negative externalities in the system and balance well between stability and efficiency and consequently minimize the social cost.

CONCLUSION

Although systemic risk has been an issue in banking supervision throughout history, it has become even more important after the recent financial crisis because the severity and nature of it have changed course from new financial engineering innovations and the now-crucial financial linkages. It may be true that systemic risk may never be completely and costlessly eliminated from the system (Kupiec

[15] Speech of Chairman Yutaka Yamaguchi of the Committee on the Global Financial System at the Third Conference on Risk Measurement and Systemic Risk.

and Nickerson (2001)), especially when financial intermediation constantly evolves at an unimaginable speed, as pointed out by Chairman Yutaka Yamaguchi of the Committee on the Global Financial System. Also, banks need to be aware of the financial linkages between themselves so that they are fully aware about how they will be affected should their peer banks be in distress. As for bank supervisors and policy makers, they will first need to be aware of the system risk present in the system, as well as the sources of such risk, and then craft the policies and also possible early warning indicators so as to mitigate this risk with the least social cost. Finally, supervisors must keep the guard up at all times, even during the time when there seems to be only a small chance of severe financial distress happening.

REFERENCES

Acharya, Viral V. (2001) "A Theory of Systemic Risk and Design of Prudential Bank Regulation." *Working Paper Series.* Stern School of Business, New York University.

Adrian, Tobias and Markus Brunnermeier. (2008) "CoVaR." *Staff Reports*. Federal Reserve Bank of New York. No. 348, pp. 1-37.

Allen, Franklin and Douglas Gale. (2007) "Systemic Risk and Regulation." *The Risks of Financial Institutions*. National Bureau of Economic Research. Chicago: Illinois: University of Chicago Press. Chapter 7, pp. 341-376.

Bank for International Settlements. (2009) *79th Annual Report*. Basel, Switzerland: BIS.

Bartholomew, Phillip and Gary Whalen. (1995) "Fundamentals of Systemic Risk." *Research in Financial Services: Banking, Financial Markets, and Systemic Risk.* Connecticut: JAI Press. Vol. 7, pp. 3-17.

Benmelech, Efraim and Jennifer Dlugosz. (2009) "The Alchemy of CDO Credit Ratings." *Working Paper Series*. National Bureau of Economic Research (NBER). No. 14878, pp. 1-42.

Brunnermeier, Markus, et al. (2009) *The Fundamental Principles of Financial Regulation*. *Geneva Reports on the World Economy 11*. Geneva: Switzerland: ICMB.

Chan-Lau, Jorge A., Marco Espinosa, and Juan Solé. (2009a) "On the Use of Network Analysis to Assess Systemic Financial Linkages." *Working Paper*. International Monetary Fund. (forthcoming)

Chan-Lau, Jorge A., Marco Espinosa, and Juan Solé. (2009b) "CoRisk Measures to Assess Systemic Financial Linkages." *Working Paper*. International Monetary Fund. (forthcoming)

Cifuentes, Rodrigo, et al. (2004) "Liquidity Risk and Contagion." *Working Paper Series*. Bank of England. No. 264, pp. 1-31.

Cohen, Ben and Eli Remolona. (2008) "The Unfolding Turmoil of 2007–2008: Lessons and Responses." *Lessons from the Financial Turmoil of 2007 and 2008*. Reserve Bank of Australia. Sydney, Australia: Pegasus Print Group.

De Nicolo, Gianni and Myron L. Kwast. (2001) "Systemic Risk and Financial Consolidation: Are They Related?" *IMF Working Paper*. No. 02/55, pp. 1-25.

Diamond, Douglas W. and Philip H. Dybvig. (1983) "Bank Runs, Deposit Insurance and Liquidity." *Journal of Political Economy*. Vol. 91, pp. 401-419.

Eee, Khor Hoe and Kee Rui Xiong. (2008) "Asia: A Perspective on the Subprime Crisis." *Finance and Development*. International Monetary Fund (IMF). Vol. 45, No. 2, pp. 19-23.

Eichengreen, Barry. (2008) "Ten Questions about the Subprime Crisis." *Financial Stability Review*. Banque de France. No. 11, pp. 19-28.

Eisenbeis, Robert A. (1997) "International Settlements: A New Source of Systemic Risk?" *Economic Review*. Federal Reserve Bank of Atlanta. Second Quarter, pp. 44-50.

Freixas, Xavier and Jean-Charles Rochet. (1997) *The Microeconomics of Banking*. Cambridge, Massachusetts: MIT Press.

Giesecke, Kay, and Baeho Kim, 2009, "Risk Analysis of Collateralized Debt Obligations." *Working Paper*. Stanford University.

Hellwig, M. (1995) "Systemic Aspects of Risk Management in Banking and Finance." *Swiss Journal of Economics and Statistics*. 131(4/2), pp. 723-737.

Hellwig, M. (1997) "Systemische Risiken im Finanzsektor, In Duwendag, de., Finanzmarkte im Spannungsfeld von Globalisierung" *Regulierung und Geldpolitik*. Berlin: Duncker & Humblot.

Hellwig, M. (1998) "Banks, Markets and the Allocation of Risk in an Economy." *Journal of Institutional and Theoretical Economics*. Vol. 154, No. 1, pp. 328-245.

Kashyap, Anil K., Raghuram G. Rajan, and Jeremy C. Stein. (2008) "Rethinking Capital Regulation." *Federal Reserve Bank of Kansas City Symposium on "Maintaining Stability in a Changing Financial System."* Jackson Hole, Wyoming, August 21-23, 2008.

Kaufman, George G. (1995) "Comment on Systemic Risk." *Research in Financial Services: Banking, Financial Markets, and Systemic Risk*. Greenwich, Connecticut: JAI Press. Vol. 7, pp. 47-52.

Kaufman, George G. and Kenneth E. Scott. (2000) "Does Bank Regulation Retard Or Contribute to Systemic Risk?" *Working Paper Series*. John M. Olin Program in Law and Economics, Stanford Law School. No. 211, pp. 1-29.

Kaufman, George G. and Kenneth E. Scott. (2003) "What Is Systemic Risk, and Do Bank Regulators Retard or Contribute to It?" *The Independent Review*. Vol. VII, No. 3, pp. 371-391.

Kregel, Jan. (2008) "Using Minsky's Cushions of Safety to Analyse the Crisis in the U.S. Subprime Mortgage Market." *The IDEAs Working Paper Series*. No. 4/2008.

Kupiec, Paul and David Nickerson. (2001) "Assessing Systemic Risk Exposure Under Alternative Approaches for Capital Adequacy." *Paper prepared for the Bank of England Conference on "Banks and Systemic Risk."*

Macey, Jonathan R. and Maureen O'Hara. (2003) "Solving the Corporate Governance Problems of Banks: A Proposal." *The Banking Law Journal*. Vol. 120, No. 4, pp. 326-348.

Milgrom, Paul and John Roberts. (1992) *Economics, Organization and Management*. Englewood Cliffs, New Jersey: Prentice Hall.

Morrison, Alan D. (2005) "Credit Derivatives, Disintermediation and Investment Decisions." *Journal of Business*. Vol. 78, pp. 621-647.

President's Working Group on Financial Markets. (1999) "Hedge Funds, Leverage and the Lessons of Long Term Capital Management." *United States Department of Treasury*. Report No. 3097.

Rochet, Jean-Charles and Jean Tirole. (1996) "Interbank Lending and Systemic Risk." *Journal of Money, Credit and Banking*. Vol. 28, No. 4, pp. 733-762.

Rodriguez, R. L. (2008) "Absence of Fear." *Speech to CFA Society*. Available at http://www.fpafunds.com/news_070703_absense_of_fear.asp.

Schwarcz, Steven L. (2008) "Systemic Risk." *The Georgetown Law Journal*. Vol. 97, No. 193, pp. 193-249.

Staub, M. (1998) "Inter-Banken-Kredite und Systemisches Risiko." *Swiss Journal of Economics and Statistics*. Vol. 134, No. 2, pp. 193-230.

Summer, Martin. (2002) "Banking Regulation and Systemic Risk." *Working Paper Series*. Oesterreichische Nationalbank (Austrian Central Bank). No. 57, pp. 1-35.

APPENDIX

1. THE FINANCIAL LINKAGE ESTIMATION PLOTS FOR EACH BANK'S COVAR AND ΔCOVAR OVER TIME

Figure A1: Financial Linkage Estimation of Bank A: CoVaR-ΔCoVaR Plot

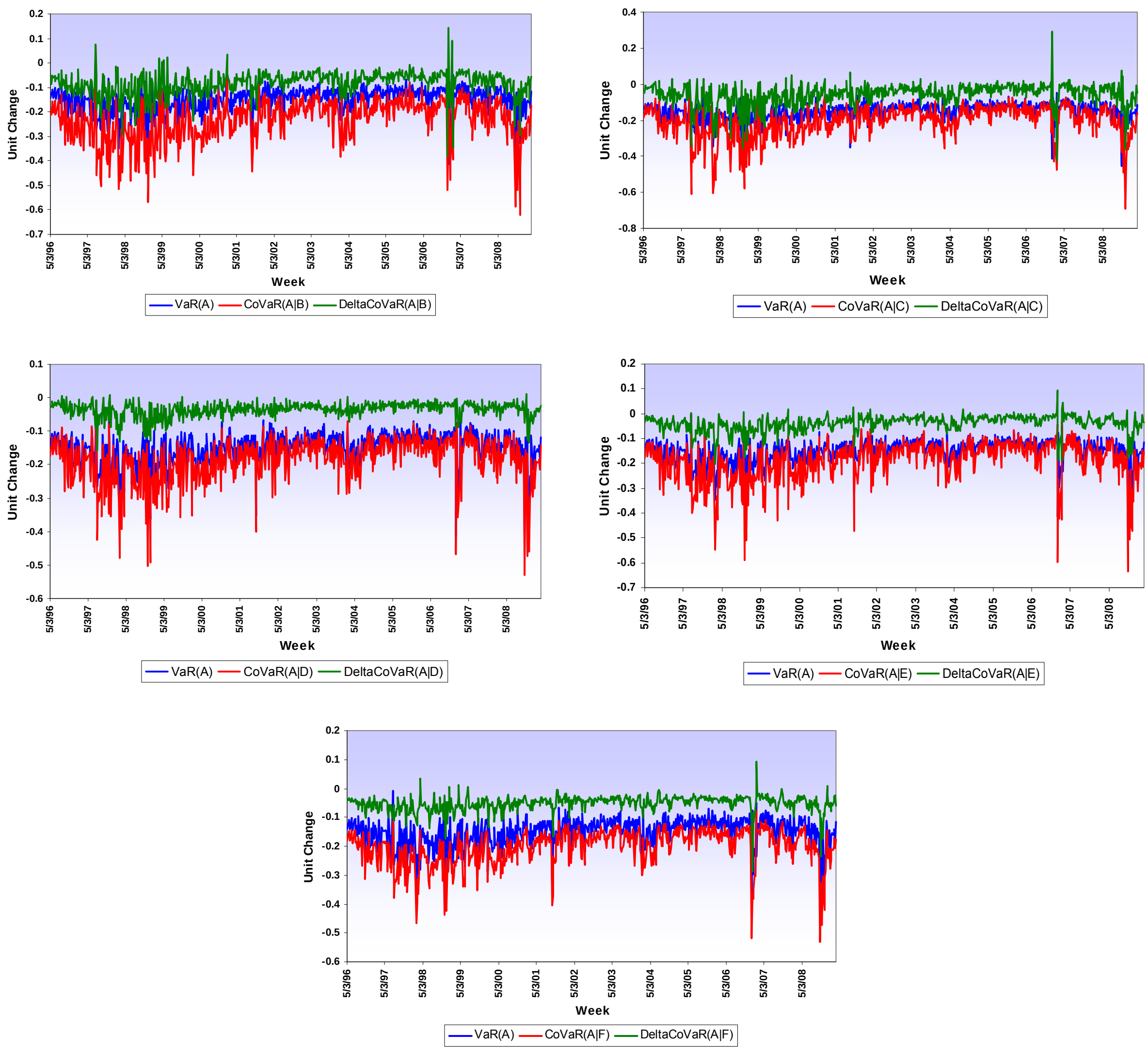


Figure A2: Financial Linkage Estimation of Bank B: CoVaR-ΔCoVaR Plot

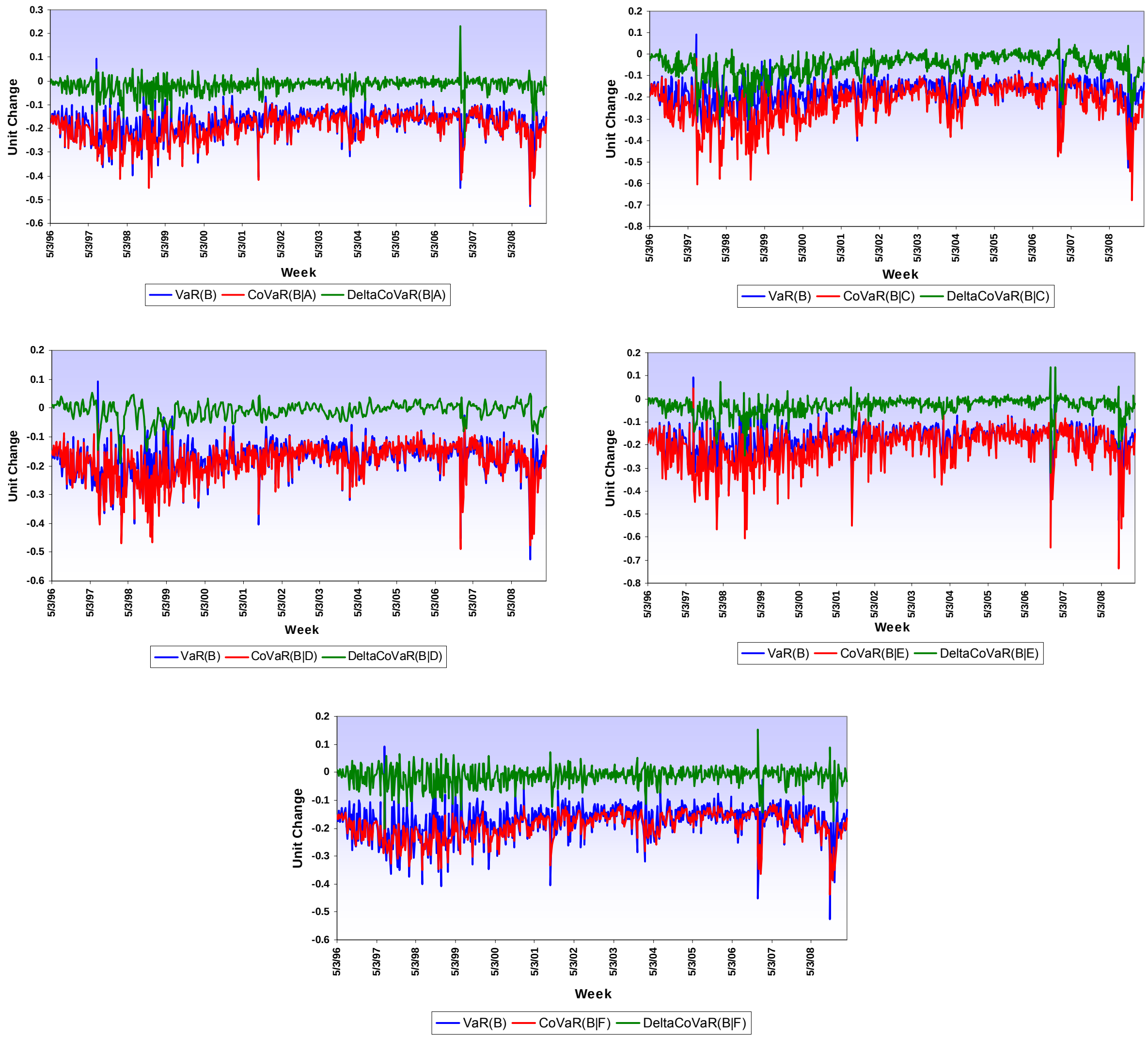
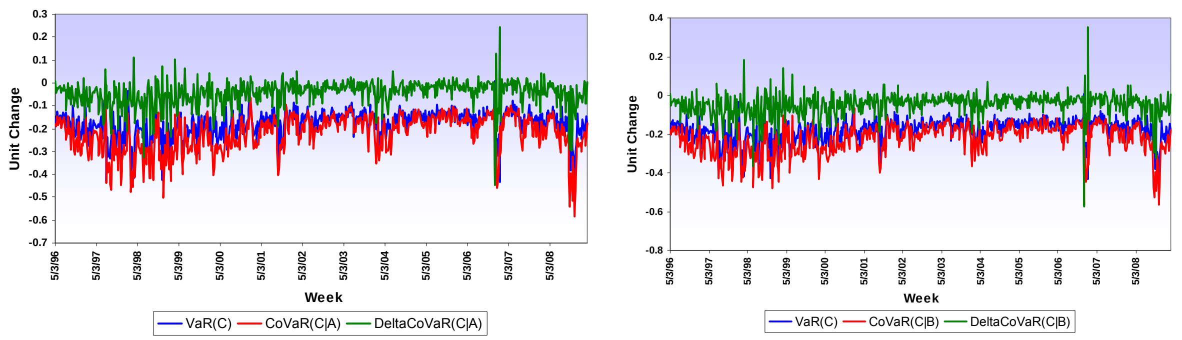


Figure A3: Financial Linkage Estimation of Bank C: CoVaR-ΔCoVaR Plot



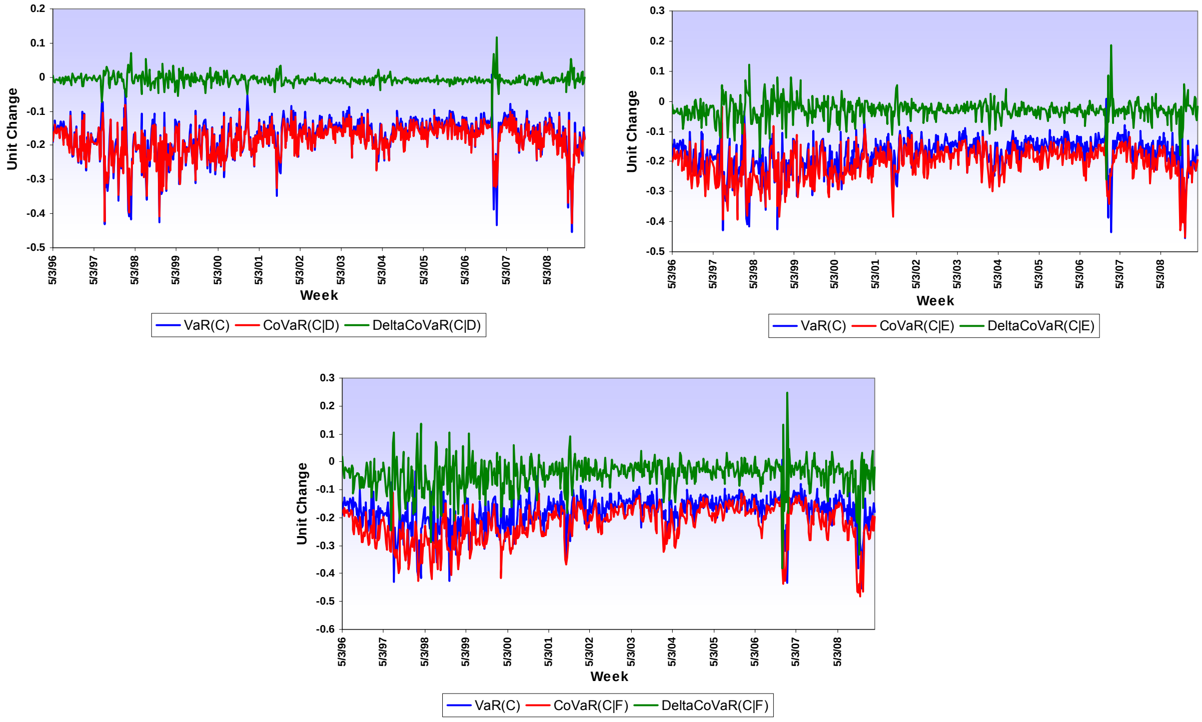
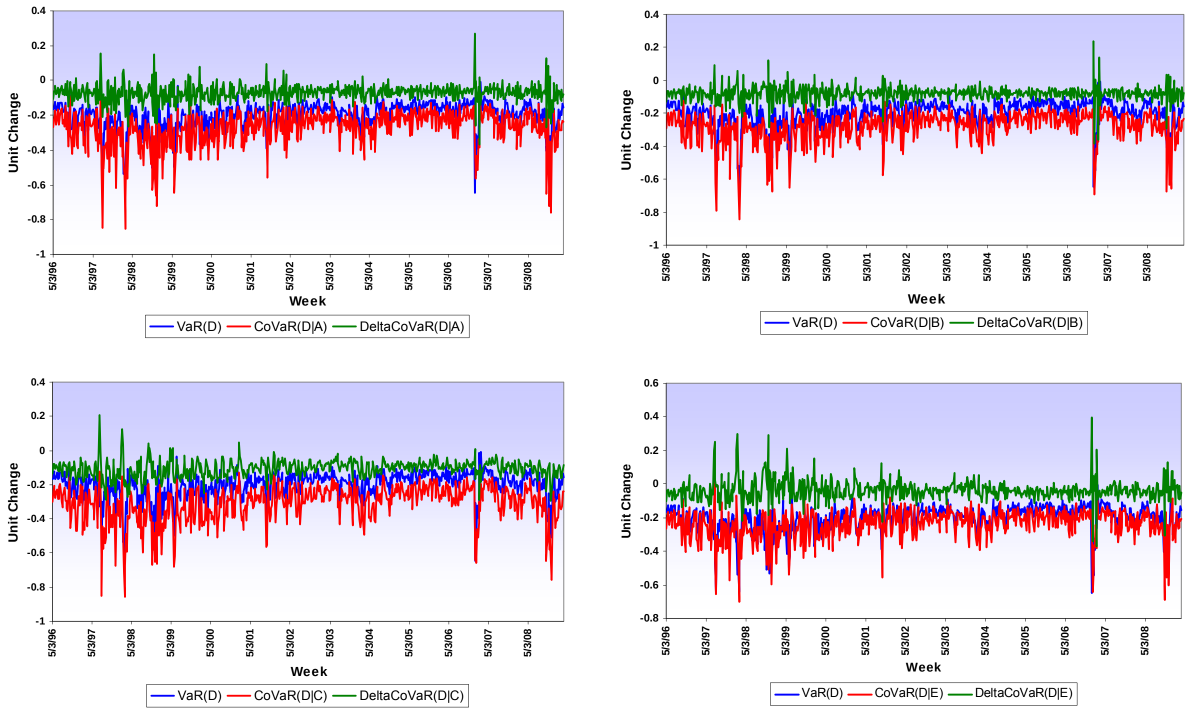


Figure A4: Financial Linkage Estimation of Bank D: CoVaR-ΔCoVaR Plot



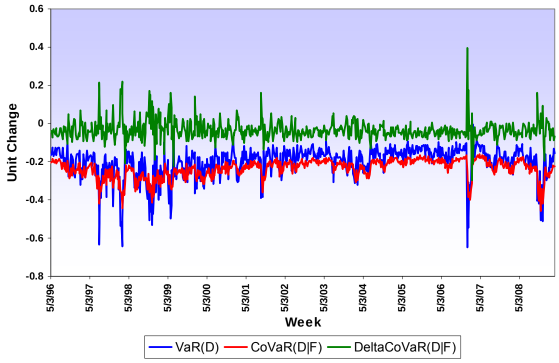
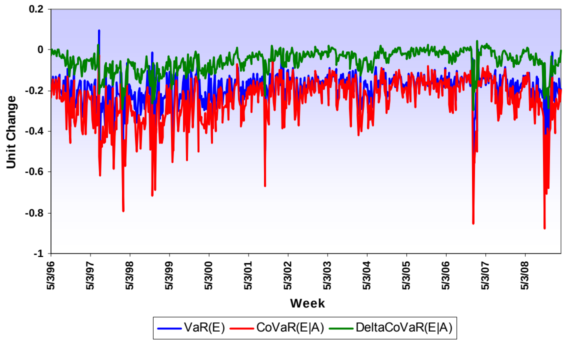
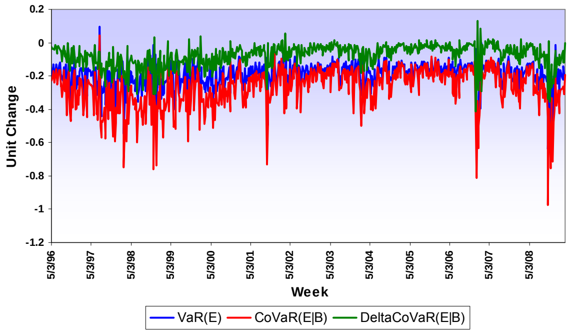
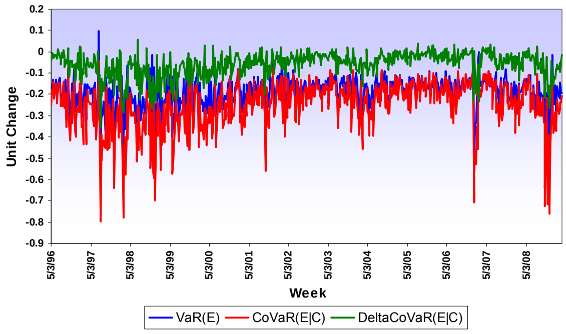
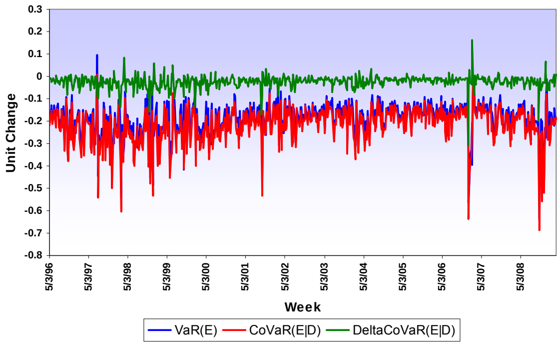


Figure A5: Financial Linkage Estimation of Bank E: CoVaR-ΔCoVaR Plot









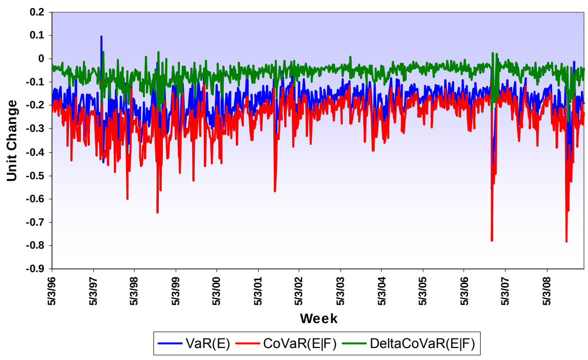
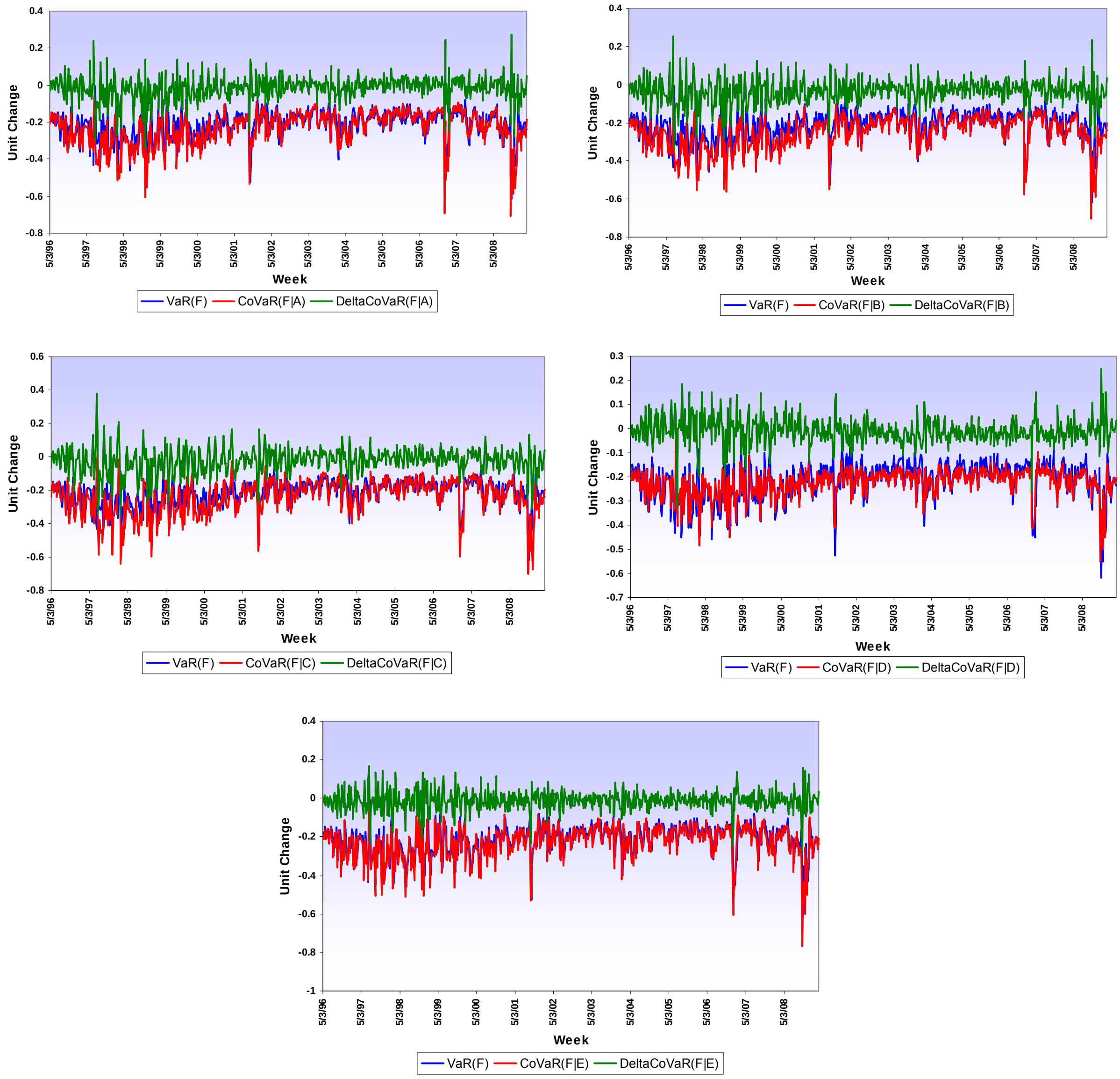


Figure A6: Financial Linkage Estimation of Bank F: CoVaR-ΔCoVaR Plot



2. CORRELATIONS OF ALL BALANCE-SHEET VARIABLES USED IN THE FIXED-EFFECT PANEL DATA REGRESSION OF EACH IMPACTED BANK

Bank A as Impacted Bank

VARIABLES	total loans	interbank assets	interbank deposits	interbank loans	common equity	retained earnings	liabilities on demand
total loans	1.0000						
interbank assets	0.2296	1.0000					
interbank deposits	0.2989	0.3907	1.0000				
interbank loans	0.4895	0.0614	0.5782	1.0000			
common equity	0.7995	0.3364	0.1366	0.3031	1.0000		
retained earnings	0.0364	-0.0890	-0.4093	-0.2540	0.1168	1.0000	
liabilities on demand	0.3484	0.0980	-0.0968	-0.0389	0.4612	0.1274	1.0000

Bank B as Impacted Bank

VARIABLES	total loans	interbank assets	interbank deposits	interbank loans	common equity	retained earnings	liabilities on demand
total loans	1.0000						
interbank assets	0.3837	1.0000					
interbank deposits	0.3721	0.4234	1.0000				
interbank loans	0.5949	0.2586	0.6444	1.0000			
common equity	0.8006	0.4109	0.2319	0.4108	1.0000		
retained earnings	-0.0267	-0.1030	-0.4481	-0.3066	0.0770	1.0000	
liabilities on demand	0.4380	0.1895	-0.0042	0.1564	0.4924	0.1243	1.0000

Bank C as Impacted Bank

VARIABLES	total loans	interbank assets	interbank deposits	interbank loans	common equity	retained earnings	liabilities on demand
total loans	1.0000						
interbank assets	0.7138	1.0000					
interbank deposits	0.3059	0.3415	1.0000				
interbank loans	0.6229	0.3868	0.4617	1.0000			
common equity	0.8517	0.4963	0.1630	0.4683	1.0000		
retained earnings	0.0297	-0.0075	-0.3950	-0.1917	0.1599	1.0000	
liabilities on demand	0.5439	0.4029	-0.0253	0.1280	0.5519	0.1586	1.0000

Bank D as Impacted Bank

VARIABLES	total loans	interbank assets	interbank deposits	interbank loans	common equity	retained earnings	liabilities on demand
total loans	1.0000						
interbank assets	0.2167	1.0000					
interbank deposits	0.3599	0.3947	1.0000				
interbank loans	0.6161	0.2142	0.6750	1.0000			
common equity	0.7546	0.2260	0.1864	0.4061	1.0000		
retained earnings	-0.0676	-0.1300	-0.4514	-0.3473	0.0564	1.0000	
liabilities on demand	0.3336	0.0444	-0.0960	0.0368	0.4297	0.1176	1.0000

Bank E as Impacted Bank

VARIABLES	total loans	interbank assets	interbank deposits	interbank loans	common equity	retained earnings	liabilities on demand
total loans	1.0000						
interbank assets	0.3266	1.0000					
interbank deposits	0.3219	0.3945	1.0000				
interbank loans	0.5972	0.2064	0.6253	1.0000			
common equity	0.8194	0.3323	0.2207	0.4500	1.0000		
retained earnings	-0.0164	-0.1013	-0.4196	-0.2932	0.0490	1.0000	
liabilities on demand	0.4800	0.1731	-0.0702	0.0734	0.5594	0.1432	1.0000

Bank F as Impacted Bank

VARIABLES	total loans	interbank assets	interbank deposits	interbank loans	common equity	retained earnings	liabilities on demand
total loans	1.0000						
interbank assets	0.2654	1.0000					
interbank deposits	0.2702	0.3632	1.0000				
interbank loans	0.5474	0.1467	0.5808	1.0000			
common equity	0.7848	0.2699	0.1255	0.3565	1.0000		
retained earnings	-0.0159	-0.0970	-0.4438	-0.2978	0.0939	1.0000	
liabilities on demand	0.3245	0.0686	-0.1667	-0.0357	0.4297	0.1459	1.0000