Systemic risk and crisis management: A CoVaR approach ☆

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Abstract

This paper examines the effects of a regulator's crisis management on systemic risk as measured by the delta conditional value-at-risk (CoVaR) during the financial crisis in Japan. We evaluate the various management measures primarily in terms of their liquidity provision/capital infusion effects as well as adverse contagion effects. The findings of the study generally support evidence for the liquidity provision/capital infusion effect, but favor the adverse contagion effect for public fund injection programs with multiple recipients. In addition, the management restrictions accompanying injection prrograms or the moral hazard with failure resolution might have aggravated the systemic risk. Furthermore, although we confirm that the average systemic risk of the largest banks is higher than that of other banks, we do not necessarily observe the amplified effects of the former on the latter. Lastly, crisis management does not effectively work for the systemic tail risk.

Keywords: Systemic risk, CoVaR, deposit insurance, prompt corrective action, public fund injection, bank failure, liquidity, contagion, too-big-to-fail policy, tail risk

JEL classification: G21; G28; G18; G14; G32

March 20, 2015

☆The author acknowledges funding support from Grant-in-Aid for Scientific Research.

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1. Introduction

During a financial crisis, we experience a successive sequence of bank failures. A large-scale breakdown of financial institutions has adverse effects on the financial markets and overall economy. A liquidity shortage in a system of interconnected banks and a decline in asset prices through fire sales worsen the stability of financial markets. The failure of one financial institution may trigger the failure of another, leading to a surge in systemic risk. Even under full coverage deposit insurance, failures seem to spill over to others. Regulators, occasionally considered in the past, are now widely considered responsible for managing crises in a manner that does not aggravate systemic risk. This paper examines whether regulators' crisis management had significantly ameliorating effects on the spillover from a distressed bank to the financial markets.

Since the recent global financial crisis, academics and financial regulators have been more highly concerned with the crisis management. However, empirical research on the effects of crisis management on the systemic risk seems under-researched. We broadly define the four types of crisis management: public fund injection (abbreviated as PFI) programs; prompt corrective actions (PCA); failure resolution scheme (FRS), such as purchase and assumption (P&A) agreement; and deposit insurance reforms (DIR) act that implement blanket guarantees in extreme cases. Our analyses focus on the systemic risk and management measures during the Japanese financial crisis in the 1990s and early 2000s, because the prolonged and serious nature of the crisis provides an environment rich in these management measures.

We examine the various hypotheses on the effects of the four measures on systemic risk. First, systemic risk surges because of liquidity shocks in the sense of the celebrated work of Diamond and Dybvig (1983). Liquidity provisions that can be used to pay depositors and to provide liquidity to distressed client borrowers lower the probability of individual runs (Allen and Gale (2000)). In addition, preventing insolvency through capital infusions leads to lower systemic risk (Freixas et al. (2000)). We call these mechanisms liquidity provision/capital infusion effects. Furthermore, liquidity shocks spread through contagion, because financial claims overlap across banks and/or borrowers. Because the interbank links enables the losses of one bank to spread over to other banks, liquidity provisions and/or preventing insolvency of one distressed bank by capital infusions may prevent the contagion of failures, leading to lower systemic risk (Diamond and Rajan (2005) and two papers previously cited). We call this effect an adverse contagion effect.

In PCA and the FRS, these two effects may also be observed. PCA may prevent distressed banks from failing or may mitigate the damages to the financial system through early appropriate orders. The rescue package in which the failed bank is sold to another healthy bank may also prevent contagious failures by smoothly isolating banks at default from the market (Acharya and Yorulmazer (2008), Gorton and Huang (2004), Freixas et al. (2000)). In adiition, under the so-called blanket guarantee, no general creditors of the failed bank incur any losses. Therefore, the blanket guarantee may ameliorate systemic risk in the sense that the insolvency of one bank does not lead to a liquidity shortage of other banks, borrowers, and depositors.

Together with these two effects, we consider the adverse effects of crisis management on systemic risk, such as management restriction effects and risk-shifting effects attributable to moral hazard. We find supportive evidence for the liquidity provision/capital infusion effects in particular for PFI, PCA, and DIR. Our evidence favors the adverse contagion effect rather than the liquidity provision/capital infusion effects for PFI programs with multiple recipients. In the largest PFI program, however, the restrictions on management policy accompanied with PFI might have aggravated the systemic risk, consistent with Bayazitova and Shivdasani (2012). In FRS, the adverse moral hazard effect tend to offset the liquidity provision/capital infusion effect. We find the relatively strong effect of moral hazard in particular for the failure of small banks, because small banks cause herding behaviors and gamble for the subsidies, consistently with the argument of Acharya and Yorulmazer (2007a). The introduction of blanket guarantees and the special public management mitigated the systemic risk contribution. There are no evidence for the adverse effects due to risk-shifting effect due to deposit insurance. Incidentally, we confirmed the positive size effect and negative VaR effect on the systemic risk. Consistently with the aggregate uncertainty of the liquidity, we confirmed that the larger reserves on the Bank of Japan (BOJ) mitigates the systemic risk by providing sufficient liquidity into the market, in line with Holmström and Tirole (1998) and Allen et al. (2009).

In relation to the adverse contagion effect, we examine the rationale and the outcome of too-big-to-fail (TBTF) management. O'Hara and Shaw (1990) find the positive announcement effect of the TBTF policy on the included banks. Demirgüç-Kunt et al. (2013) argue that the limit imposed by a country's public finances are reflected in bank valuation and CDS spread. Although we confirm that the average systemic risk of the largest banks is higher than that of other banks and that the latter is positively associated with the former, we do not necessarily observe the amplified effects of the former on the latter. In addition, when the regulator manages the largest distressed banks, the result does not show clear evidence that systemic risk is calmed.

Lastly, we explore the limitations of crisis management. We observe seven days on average that systemic risk was extremely high. We argue that management does not work effectively for systemic risk in the tail when management should work most effectively. Moreover, crisis management sometimes worsens the systemic risk in the tail.

Many papers propose systemic risk indexes, which are introduced briefly in a later section. We follow Adrian and Brunnermeier (2011), Lopez-Espinoza et al. (2012), and Girardi and Ergün (2013) to use the delta conditional Value-at-Risk (CoVaR) as a systemic risk index. The CoVaR on financial system measures the maximal loss rate of the financial system conditional on the event that certain bank suffers severe losses beyond the VaR. The delta CoVaR is the systemic risk contribution of distressed banks, which is defined as the standardized difference of the CoVaR between the distress and the normal state. It captures the risk spillover effects from a distressed bank to the overall financial system. We use Engle (2002)'s DCC-GARCH (generalized auto-regressive conditional heteroskedastic model with dynamic conditional correlations) model to calculate the CoVaR.

Section 2 describes the regulators' crisis management and our methodology for estimating CoVaR. Section 3 provides the estimation results of various regressions that investigate the relationship between crisis management and systemic risk. In section 4, we introduce the Markov regime switching model to distinguish the extreme systemic risk state from normal state. Using the inferred states, we examine the effectiveness of crisis management during the period of extremely high systemic risk. Section 5 discusses policy implications. Section 6 concludes the paper.

1.1. Related literature

There is a substantial empirical literature on the contagion other than listed above. The banking panics are considered random events or the predictable events in the literature. Gorton (1988) shows that the panics during the U.S. National Banking Era were systematic responses by depositors to changing perceptions of risk. Bae et al. (2003) argue that contagion is predictable. Upper and Worms (2004) argue that the failure of a single bank could lead to the breakdown of 15% of the banking system in Germany. Furfine (2003) argues that federal funds exposures are not large enough to cause a great risk of contagion. These two papers examine the interbank connection of the banks while the contagious behaviors of the depositors are empirically examined in Saunders and Wilson (1996) and Shimizu (2009b) for example. Jorion and Zhang (2009) examine the credit contagion via direct counterparty credit risk on the asset side.

Recently, among four crisis management measures, PFI program has attracted the interest of researchers. Veronesi and Zingales (2010), Bayazitova and Shivdasani (2012), Li (2013), Cornett et al. (2013), Wilson and Wu (2012), Khan and Vyas (2013), and Liu et al. (2013) investigate the outcomes of a PFI program called troubled asset relief program (TARP) during the global financial crisis in the United States. Shimizu (2006) and Montgomery and Shimizutani (2009) examine the PFI program during the Japanese financial crisis. However, these papers are primarily concerned with bank performance, TARP costs, or changes in value rather than systemic risk. One exception is Lopez-Espinosa et al.(2012) investigating the effect of recapitalization on systemic risk using the CoVaR approach. Our results for PFI programs are consistent with theirs.

PCA is investigated in Aggarwal and Jacques (2001), Jones and King (1995), Dahl and Spivey (1995), Cummins et al. (1995), and Benston and Kaufman (1997). Among others, Aggarwal and Jacques (2001) estimate the impact of PCA on both bank capital and credit risk. Almost little evidence exists for the third measure: a FRS. Goodhart and Schoenmaker (1995) summarize FRS in twenty-four countries in the 1980s and 1990s. Brei et al. (2013) examine rescue measures and the bank lending supply during the recent global financial crisis. [1] The last measure, DIR act, which implements a blanket guarantee in an extreme case, is studied in Upper and Worms (2004), Kane and Klingebiel (2004), Hovakimian et al. (2003), Hanazaki and Horiuchi (2003), and Honohan and Klingebiel (2001). Upper and Worms (2004) argue that the financial safety net considerably reduces the danger of contagion. Hovakimian et al. (2003) consider the risk-shifting effect of explicit deposit insurance. Kane and Klingebiel (2004) report the blanket guarantee in twelve countries that experienced crises.

2. Methodology

2.1. Crisis management

Our sample period is from April 1995 to March 2004. In 1995, the Japanese financial system experienced the failure of a bank that was viewed as the start of the subsequent financial crisis. [2] In December 2013, the last failure occurred during the Japanese financial crisis.[3] Our sample is restricted to listed banks. Non-listed banks and other small depository institutions are excluded from our sample.

Table 1 shows the events of crisis management measures taken by the regulator for our sample banks. These events are available in the annual report of the Deposit Insurance Corporation of Japan (DICJ) and are also documented in Shimizu (2009a). We define the event date as its announcement date and identify the date by searching Nikkei Telecom Database (Nikkei Degital Media,

[1]See Acharya and Yorulmazer (2007a) for other unpublished works studying the failure resolution policy.

[2]Nikkei reported that the Ministry of Finance announced the failure of regional bank Hyogo on August 30. Three years before this failure, Toho Sougo Bank failed and was rescued by Iyo Bank. We do not include this event in our sample because of the long interval between the events. Horiuchi and Shimizu (1998) analyze the bank behavior during the pre-crisis period in early 1990s.

[3]One regional bank Ashikaga failed after it received public capital.

Inc.) from one month before the reported official date when the measure was taken.

Table1

In standard textbooks, the systemic risk is broadly defined as any risk that may affect the financial system/market as a whole. Typically, systemic risk surges when the losses or the failure of one bank spread to other banks. Liquidity shortages and/or heightened counterparty credit risk are strikingly observed phenomena, because the losses generate a shortage of liquidity and the value of the debt obligation declines. Given the overlapping nature of financial claims, liquidity shocks spread through contagion (Allen and Gale (2000)). In particular, Eisenberg and Noe (2001) emphasize the interdependence of banks through interbank market transactions. Under the multiple lending relationships prevalent in Japan, the default of large borrowers simultaneously damages more than one bank. In addition, informational contagion occurs because the failure of one bank serves as the signal that predicts the failure of other banks (Acharya and Yorulmazer (2008)). Our systemic risk index, delta CoVaR, captures the potential for such spreading of financial distress across banks by measuring the increase in the tail co-movement.

We now explain how the regulator introduced these measures and how these measures work for systemic risk. The PFI programs allow banks to reinforce equity capital and provide liquidity to the financial system and the recipient bank. The regulator offered new PFI programs several times during our sample period. Among these programs, the largest program was introduced in 1999 (#15 in Table 1). In this program, the fifteen largest banks that were considered relatively healthy but that had substantial influence over the systemic risk applied for the reinforcement of equity capital. [4] The second program was in September 1999. Four relatively weak regional banks reinforced their equity capital. Subsequently, one or a few banks applied simultaneously for the injection program. The total number of approvals are thirteen during the sample period.

As noted in the introduction, in addition to the liquidity provision effect, the infusion has the effect of decreasing the probability of bank runs and lowering systemic risk because it takes the form of preferred stock or debt subordinated to deposits. [5] These effects are at least enjoyed by the recipients. Furthermore, appropriate PFI programs not only prevent distressed banks from going insolvent but also prevent a contagion of failures, because they ameliorate the spillover effect of the liquidity shortage (Allen and Gale (2000), Freixas et al. (2000), Diamond and Rajan (2005), Shin (2008)). In other words, we may observe the adverse contagion effect that non-recipients also enjoy lower systemic risk when other banks participate in the PFI program.

However, the program comes with restrictions on management in Japan and in the United States. In particular, Bayazitova and Shivdasani (2011) stress that restrictions on management compensation caused banks to refuse infusions. In Japan, restrictions on other activities rather than management compensation might trigger turmoil over systemic risk, as emphasized in Shimizu (2006). Importantly, because the regulator has an incentive and is able to make discretionary decisions to promote loans to small and medium-sized firms under certain political pressure, recipient banks might not be able to choose the

[4]The recipients were Daiichi-Kangyo, Fuji, Industrial Bank of Japan, Sanwa, Tokai, Sumitomo, Sakura, Asahi, Daiwa, Yokohama, and five trust banks. The announcement date of this event is the date on which the government decided to inject funds into fifteen banks. Note that we ignore the notorious program introduced just before # 15 because its scale was small relative to this program.

[5]Even under full deposit insurance coverage, depositors may care about the temporary inconvenience of withdrawal until the failure is fully resolved.

optimal amount of loans. Such a restriction may erode systemic risk, because it delays the resolution of their failed borrowers. We call this effect the management restriction effect. [6]

PCA requires early intervention on a timely basis when a bank's capitalization is still positive but not-well capitalized. For example, the regulator orders banks to recapitalize, suspend dividends, restrict asset growth, and prohibit some or all activities (Benston and Kaufman (1997)). The regulator introduced PCA scheme in 1998 and ordered the first PCA to one of the regional banks in April 1999. Eight PCA events are in the sample. The scheme of PCA in Japan is similar to that of U.S., which was enacted by FDICIA in 1991.[7] However, the zones of capitalization might be different between Japan and U.S. [8] Appropriate PCA orders lead to lower systemic risk by preventing the distressed bank from failing or by mitigating damages to the financial system.

However, PCA may induce other banks to increase risk ex ante (Aggarwal and Jacques (2001), Davis and McManus (1991)). Such banks may have greater incentives to gamble for their resurrection when facing a stringent PCA. In addition, as Dahl and Spivey (1995) point out, capacity is limited for distressed banks to correct positions of under-capitalization without appropriate public capital infusion. Therefore, PCA may not work for systemic risk and may have adverse effects. We call this risk-shifting (moral hazard) effects of PCA.

When a bank finally fails, deposit insurance resolves the failure, because private-sector resolution is not always, or not usually, feasible. The regulator usually takes P & A -like resolution policy rather than deposit payoffs. In such rescue package, the failed bank is sold to another healthy bank. This rescuing

[6]Increasing loans to small and medium-sized firms may have an adverse effect because too many bankruptcies of such firms trigger the bank failures.

[7]See Table 1 of Benston and Kaufman (1997) for details.

[8]Additionally, they are different depending on whether banks operates abroad or not in Japan.

bank usually purchases or assumes the assets and liabilities of the failed banks with the aid of a subsidy provided by deposit insurance. The subsidy usually covers the difference between the market values of the assets and liabilities. Deposit insurance sometimes purchases part of assets and deposits of the failed bank. Regulators seek a rescuing bank among candidate banks whose operating area is the same as or adjacent to the failed bank.

Among sixteen FRS, three exceptions exist.[9] When two long-term credit banks failed in 1998 and one regional bank failed in 2003, they were temporarily nationalized.[10] This scheme, officially called special public management, is a bailout policy in the narrow sense. Unlike the other scheme, no value remained to stockholders of these banks.

Similar to PFI and PCA, the FRS may also ameliorate systemic risk if it succeeds in preventing the spillover, provides the liquidity, and eventually to isolate the banks at default from the market (Cordella and Yeyati (2003)). However, the scheme may create moral hazard incentives, cause herding behavior by healthy banks, and increase interbank correlation of asset returns, because subsidies are provided only when many banks fail (Acharya and Yorulmazer (2007a)). In this case, the resolution scheme may have adverse effects on systemic risk. We call this phenomena the moral hazard effect of FRS.

The blanket guarantee was practically implemented through the special fund

[9]We do not distinguish between the resolution scheme of the Ministry of Finance (MOF) from that of the Financial Services Agency (FSA). The latter took the position of the department of financial regulation in the MOF after 1998. The method of the MOF was similar to that of the FSA. However, it is worth while to stress that the failure resolution scheme was underdeveloped and that the aid of a subsidy was implicit rather than explicit. Under the well-known convoy system and the entry-branch regulation, the MOF could provide an implicit subsidy in the form of favorable treatment to the bank that cooperatively rescues a failed bank. Since the subsidy was implicit and the resolution scheme was not explicitly formulated, these arrangements may be considered relatively close to the merger and acquisition procedures of the private-sector.

[10]They are Long-term Credit Bank of Japan, Nippon Credit Bank, and Ashikaga bank. In addition, public fund injections into Resona Bank (# 41) is considered de facto nationalization because Resona Bank issued common equity rather than preferred stock. However, we do not count this occurrence as FRS but PFI.

assistance. The DICJ provides the rescuing bank with amounts of funds over those required for deposit payoffs. [11] When introduced in 1996, the blanket guarantee period was scheduled to end in March 2001. In the DIR act of 2000, the period was extended. The blanket guarantee finally ended in March 2002 except for the settlement account (e.g. ordinary deposits). The reform of 2002 enacted this measure as permanent. [12]

When insurance coverage extends to all liabilities, the market expects that creditors do not incur losses when banks fail at the cost of the regulator and taxpayers. Therefore, the blanket guarantee may ameliorate the systemic risk in the sense that the insolvency of one bank does not lead to a liquidity shortage of any bank, borrower, and depositor. However, as in PCA, the blanket guarantee may also have adverse effects on systemic risk, because creditors lose the incentive to monitor banks and banks can shift risk onto the insurer (Hovakimian et al. (2003), Marcus and Shaked (1984)). This phenomenon is called the risk-shifting effect of deposit insurance.

2.2. Econometric method of delta CoVaR

Many candidates exist for the systemic risk index. Acharya et al. (2010) propose the systemic expected shortfall (SES) and marginal expected shortfall (MES). Lopez et al. (2014) propose the CoMargin, which systematically adjusts collateral requirements on the basis of the CoVaR concept. Huang et al. (2009) propose the "distress insurance premium" indicator, which measures

[11] In addition to the blanket guarantee, the DICJ began to collect special insurance fees in addition to ordinary fees. The total fees became almost seven times as large as the previous ones. The reform also enabled the DICJ to purchase depository claims of failed banks through its subsidiary.

[12] The reform of 1997 was somewhat minor. The framework for new mergers and assistance was introduced but only used for one resolution. The reform of 1998 introduced the receivership of the failed banks, the establishment of a bridge bank, and the temporary nationalization of failed banks.

the expected portfolio loss above the total liabilities. Lehar (2005) proposes the systemic risk index on the assets and the number of banks measured as the probability of systemic crisis. Billio et al. (2012) propose the interconnectedness measure using the principal component analysis. De Jonghe (2010) proposes tail-β measure using extreme value analysis. Each of these measures has advantages and disadvantages. We employ the CoVaR measure simply because VaR is the most familiar concept among the indexes measuring the risk of loss.

The delta CoVaR is estimated in three steps. In step 1, we calculate the daily market return of bank assets using the option pricing formula. In step 2, we estimate the parameters of the bivariate normal distribution of returns for the financial system and each bank by multivariate GARCH model with dynamic conditional correlation. In step 3, we estimate VaR, CoVaR, and delta CoVaR using the estimated parameters in step 2.

In step 1, we calculate market value of asset because the asset VaR is more relevant when we study the systemic risk. When we use equity VaR, the put option value of deposit insurance is ignored. Since regulator's crisis management affects this put option value in various points, we use asset VaR instead of equity VaR. The specific procedure of the step 1 is as follows; The gross return of the bank j at date $t = (1, \cdots T)$ is defined as $R_{jt} = \ln P_{jt} - \ln P_{j,t-1}$, where P_{jt} is the stock price. We estimate asset return X_{jt} using Black-Scholes-Merton formula. Define bank equity value as V_E, asset value V_A, debt value (including deposit insurance) as B, and risk-free discount rate as r. Then, the market value of equity satisfies the formula (Merton (1974, 1977, 1978)) $V_E = V_A N(d_1) - Be^{-rT} N(d_2)$, with $d_1 = \{\ln(V_A/X) + (r + \sigma_A^2/2)T\}(\sigma_A \sqrt{T})$ and $d_2 = d_1 - \sigma_A \sqrt{T}$, where σ_A is the volatility of asset value. Using this formula, we are able to calculate market value of asset on the daily basis. Our method follows one used in Vassalou and Xing (2004). [13] Asset return is defined as $X_{jt} = \ln V_{Ajt} - \ln V_{A,j,t-1}$. We also define the asset return of financial system as $X_{St} = \ln \sum_j V_{Ajt} - \ln \sum_j V_{Aj,t-1}$. Subscript S denotes financial system.

The second step is as follows; We assume that each pair of individual asset return and system return follows bivariate GARCH model with DCC.

$$X_t^j = \mu_t^j + \epsilon_t^j \tag{1}$$

, where $X_t^j = (X_{St}, X_{jt})'$ is the j-th pair of asset return vector, $\mu_t^j = \alpha_0^j + \alpha_1^j X_{t-1}^j$ is the conditional drift term, ϵ_t^j is the error term. This error term follows

$$\epsilon_t^j = (H_t^j)^{1/2} \nu_t^j \tag{2}$$

, where ν_t^j follows bivariate *i.i.d.* joint normal distribution $N(0, I)$. The conditional covariance matrix of ϵ_t^j defined as $H_t = E_{t-1}(\epsilon_t^j \epsilon_t^{j\prime})$ is decomposed into $H_t = D_t^{1/2} R_t D_t^{1/2}$, following Engle (2002). D_t is a diagonal matrix with element being conditional variance of j-th return σ_{jt}^2. R_t is time-varying correlation coefficient matrix with 1 on the diagonal and $\rho_{jS,t}$ off the diagonal.

The variance - covariance matrix of ϵ_t^j is modeled as

$$R_t = diag(Q_t)^{-1/2} Q_t \ diag(Q_t)^{-1/2} \tag{3}$$

$$Q_t = (1 - \lambda_1 - \lambda_2) R + \lambda_1 \left(\hat{\epsilon}_{t-1} \hat{\epsilon}_{t-1}' \right) + \lambda_2 Q_{t-1} \tag{4}$$

The typical element of Q_t is $q_{jS,t}$ satisfying $\rho_{jS,t} = q_{jSt} / \sqrt{q_{jjt} q_{SSt}}$. $\hat{\epsilon}_{t-1}$ is the

[13] The method consists of the following six steps. (1)we estimate σ_{Et}, standard deviation of $R_{j\tau}$ ($\tau = t - 250, \cdots, t$) for each t, (2) Substituting this σ_{Et} as initial value, we compute V_{At} using the formula for past 12 months, (3): we estimate σ_{At} using daily data V_{At} in (2) for the past 12 months, (4) Using σ_{At} in (3), compute V_{At} using the formula for the past 12 months, (5) we repeat (3) and (4) until σ_{At} from two consecutive iterations converge, (6) Using converged σ_{At}, compute daily V_{At} from the formula.

standardized error defined as $D_t^{-1/2}\epsilon_t$. R is quasicorrelation matrix. λ_1 and λ_2 is nonnegative parameters satisfying $0 \leq \lambda_1 + \lambda_2 < 1$. The estimates of μ_t^j and variance covariance matrix H_t are obtained by maximal likelihood estimation method.

The third step is as follows; The CoVaR is defined as

$$Pr\left(X_{St} \leq CoVaR_t^{Sj} \mid X_{jt} \leq VaR_t^j \right) = q \tag{5}$$

, where q is the confidence level. Following Girardi and Ergün (2013), this conditional bivariate normal probability is transformed into joint probability

$$Pr\left(X_{St} \leq CoVaR_t^{Sj} \ , \ X_{jt} \leq VaR_t^j \right) = q^2. \tag{6}$$

The benchmark state is defined as the one sigma region around the conditional mean $\{\mu_{jt} - \sigma_{jt} \leq X_{jt} \leq \mu_{jt} + \sigma_{jt}\}$. The benchmark CoVaR is defined as

$$Pr\left(X_{St} \leq CoVaR_t^{B\,Sj} \ , \ \mu_{jt} - \sigma_{jt} \leq X_{jt} \leq \mu_{jt} + \sigma_{jt} \right) = p_t^j q \tag{7}$$

with p_t^j defined as $Pr\left(\mu_{jt} - \sigma_{jt} \leq X_{jt} \leq \mu_{jt} + \sigma_{jt} \right) = p_t^j$. Finally, delta CoVaR is defined as

$$\Delta CoVaR_t^{Sj} = 100 \times (CoVaR_t^{Sj} - CoVaR_{B,t}^{Sj})/CoVaR_{B,t}^{Sj} \tag{8}$$

The delta CoVaR represents the systemic risk contribution of the distressed bank relative to that of the normal state.

2.3. The baseline regression

We employ daily data on equity prices and the market value of equity from the Nikkei Needs Database. The book value of debt is available quarterly, semiannually, or annually. Book value data are collected from the EoL database and the Nikkei Needs Database. Our basic hypothesis is that the systemic risk contribution of a particular bank decreases when the regulator takes crisis management measures. Our baseline regression equation is defined as

$$\Delta CoVaR_t^{Sj} = x_{jt}\beta + D_{jt}\theta + u_j + v_{jt}, \tag{9}$$

where x_{jt} is a vector of covariates for bank j on date t. Following Adrian and Brunnermeier (2011) and Lopez-Espinosa et al. (2012), we examine volatility in the stock market (Tokyo Stock Exchange), the change in the 10-year JGB rate, the short-maturity yield spread between the overnight call rate and the three-month CD rate, the long-maturity yield spread between the three-month CD rate and the 10-year JGB rate, and the market return (TOPIX). Because no volatility index available existed during the period, stock market volatility is measured as the daily standard deviation of the TOPIX return for the prior week. In addition to these covariate variables, we include VaR, log of asset size, and leverage of each bank, following Girardi and Ergün (2013). Lastly, we include two monetary policy variables, the call rate and the reserves on the BOJ account.

The vector of the dummy variable D_{jt} are the set of dummies corresponding to each crisis management measure. This variable takes the value of 1 during the corresponding period of measures taken and 0 otherwise. The crisis management event period is 30 days, which starts from the event date of announcement. The individual error term u_j and the idiosyncratic error v_{jt} are included in the prior equation.

3. Empirical analyses on systemic risk and crisis management

3.1. Four types of crisis management and systemic risk

Figure 1 shows the time series of the cross sectional average of delta CoVaR at the 5% tolerance level. [14] The vertical lines show the approximate date of the eight major events. Among them are the introduction of the blanket guarantee (#3), the largest PFI(#15), the extension of the blanket guarantee (#27), and the failure of one of the largest banks (#5 and #40). Although these lines and the peaks of the delta CoVaR do not coincide precisely, the peak is sometimes found just around the event date.

Figure 1

Table 2 summarizes the cross-sectional averages of delta CoVaR by year and type of crisis management. The sample mean over the full period is approximately 22%. The 5 and 95 percentiles are 7.7 and 47.5, respectively. The mean was the highest in 1997, and the second highest in 2000. The lower panel compares the summary statistics by type of crisis management. First, the subsample mean of crisis management is smaller than that of no crisis management. Second, the subsample means of PFI and PCA are smaller than that of no crisis management, respectively. These medians show similar tendencies.

Table 2

Table 3 shows the estimation results of equation (9) in two specifications when four dummies are used. First, the coefficients of PFI and PCA are signif-

[14] The average delta CoVaR is used in Gauthier et al. (2012) with a slightly different definition. See equation (9) on page 600.

icantly negative. The systemic risk contribution of the distress of a particular bank declines when the regulator announced either PFI or PCA. The results provide supporting evidence for the liquidity provision/capital infusion effects of these two measures. The significantly positive coefficients of FRS suggest the moral hazard effect. The DIR dummy has no significance in both specifications, suggesting that the effect of preventing a liquidity shortage is offset by the adverse risk-shifting effect.

Table 3

Among the control variables, volatility, yield slope for long maturity, market return, and log of assets have significantly positive impacts on the delta CoVaR. The coefficients for change in JGB rate, short maturity yield spread, VaR, call rate, and log of reserves are significantly negative. These signs are mostly consistent with the intuition and the results in Adrian and Brunnermeier (2011), Lopez-Espinosa et al. (2012), and Girardi and Ergün (2013). Among them, we confirmed the positive size effect and negative VaR effect on systemic risk.

The results on the call rate and BOJ reserves are highly contrasting and interesting. When a lower call rate prevails, the systemic risk contribution increases. However, the BOJ reserve has the opposite sign, which may have implications for the quantitative easing policy that began in March 2001. The larger reserves mitigate systemic risk by providing sufficient liquidity to the market, consistently with the arguments of aggregate uncertainty in Holmström and Tirole (1998) and Allen et al. (2009).

3.2. Individual measures and systemic risk

Table 4 shows the estimation results when forty-two individual event dummies are used. First, eight PFI events have negative impacts on the systemic risk contribution, whereas two have the opposite effect. Surprisingly, the largest program (# 15) has a positive impact on systemic risk. The recipients of this program were the largest banks and those of other programs were mostly smaller regional banks. The largest banks were healthier than other banks with respect to the capital asset ratio. This result provides evidence for the management restriction effect that restrictions on management policy accompanied by PFI would delay the resolution of non-performing loan problems, and that the probability of successive failures would increase. The six coefficients of PCA are significantly negative. The results of these two measures are mostly consistent with the results shown in Table 3.

However, the results of two other measures are quite different. The effects of FRS become ambiguous with four being significantly positive and five significantly negative. This result may suggest that market opinions for the resolution scheme tend to be divided. In the FRS, the adverse moral hazard effect tends to outweigh the liquidity provision/capital infusion effect, but not in PCA and PFI. This relatively strong moral hazard effect might be reasonable, because the market might expect that other small banks with similar characteristics fail when a small bank fails. Those banks cause herding behavior and gamble for subsidies, as suggested in Acharya and Yorulmazer (2007a). Furthermore, among three nationalizations, the first two have no significant effects.

Lastly, three of the DIR dummies have significantly negative coefficients. In contrast to the result in Table 3, the systemic risk contribution of the distress of a bank is mitigated by reforms in 1996, 1998, and 2002. The introductions of a blanket guarantee and special public management mitigated the systemic risk contribution. No evidence is found for the adverse effects attributable to risk-shifting.

Table 4

3.3. Direct and indirect spillover effect

To this point, we supposed that the effect of crisis management on systemic risk is not different across banks regardless of whether or a specific bank is directly affected by the measure. Except for the DIR, these management measures generally have direct and indirect effects. Among the three measures, because the PFI measure has multiple recipients, it is suitable in investigating such heterogeneous effects. Capital infusion not only prevents insolvency of the recipients but also prevent contagion of failures. By adding the new dummy variable to equation (9), we distinguish the liquidity provision/capital infusion effect from the adverse contagion effect.

The dummy c_{jt}^{k} which takes the value of 1 if j-th bank is the recipient of capital injection program k and 0 otherwise, is added to equation (9). The dummy D_{jt}^{k} takes the value of 1 during the event period of program k for any j and 0 otherwise. The former measures the liquidity provision/capital infusion effect, which is a direct spillover effect specific to the recipient, and the latter measures the adverse contagion effect, which is an indirect spillover effect common to all banks when program k is taken.

Table 5

According to Table 5, differences exist between the direct and indirect effects in four events. In the largest injection program (#15), the coefficient for the direct spillover is significantly positive. The banks that applied for the injection increased their contribution to systemic risk more than their counterparts.

This result is consistent with the previous view that, the market expected, management restrictions might delay the resolution of the failed borrowers of the recipients. However, the indirect effect also becomes positive, which might be reasonable, because a surge in the systemic risk of these banks may trigger an overall increase in systemic risk.

In event #32, the direct spillover aggravates systemic risk. However, in two events (#25, 28), the direct spillover is significantly negative and the differences are not found in other two events (#22, 34). The indirect effects are negative except for the event (#15), which is consistent with the previous results. Thus, our results are ambiguous for the differences between the direct and indirect spillovers. Our evidence favors the adverse contagion effect rather than liquidity provision/capital infusion effect for multiple PFI programs. These results may reflect the existence of the management restrictions effect.

3.4. Too-big-to-fail and systemic risk

We further investigate PFI program in 1999 (#15), because the adverse effect was found in the previous tables. This investigation also provides us with an opportunity to evaluate the relationship between the TBTF policy and the systemic risk, because the recipients were the largest banks in Japan. The rationale for the TBTF policy is that the large banks have a significant influence over systemic risk. This rationale also supports the new regulation on globally systemically important financial institutions (G-SIFIs) and/or globally systemically important banks (G-SIBs). Some recipients of this program (#15) are now forming the largest financial groups, three of which are identified as G-SIBs (Mitsubishi UFJ FG, Mizuho FG, and Sumitomo Mitsui FG).

In Table 3, we confirmed the size effect of the delta CoVaR. We take a step further, and consider that the average delta CoVaR of the largest banks affects the delta CoVaR of other banks. The largest banks are defined as the city banks and long-term credit banks.[15] To disentangle the influential effect of the largest banks, we use the two-step estimation method. In the first stage, we estimate the delta CoVaR of the largest banks, using a subsample of these banks. Then, we predict the daily average of these delta CoVaRs, which is called the largest banks' delta CoVaR. In the second stage, we estimate eq. (9) by adding the largest banks' delta CoVaR.

In addition to event $15, we examine the events to which one of the largest banks is related. These events are events #5, #8, #13, #14, #40, and #41.[16] In these estimations, we use a subsample consisting of 30 days before and after each of the event date. We define a crisis management dummy which takes the value of 1 after the event and 0 otherwise, and use the cross term of the largest banks' delta CoVaR and the crisis management dummy as the regressor.

We consider two TBTF hypotheses. The first hypothesis is that the largest banks' delta CoVaR has amplified effects on the delta CoVaR of other banks. Statistically, the coefficient of the largest banks' delta CoVaR is predicted to be greater than 1. The second hypothesis is that crisis management related to one or some of the largest banks has an ameliorating effect on the delta CoVaR of other banks.

Table 6

Table 6 displays the estimates of the second stage. The coefficients of the

[15] They are Daiichi Kangyo (Mizuho), Hokkaido Takushoku, Tokyo, Sakura, Mitsubishi Tokyo UFJ (Mitsubishi, Mitsubishi Tokyo), Fuji (Mizuho), Sumitomo (Mitsui Sumitomo), Daiwa (Resona), Sanwa (UFJ), Tokai, Asahi, Industrial Bank of Japan, Long-term Credit Bank of Japan (Shinsei), Nippon Credit Bank (Aozora), Mitsubishi UFJ FG, Resona Holdings, Mitsui Sumitomo FG, Mizuho FG.

[16] #5 and #8: Failures of Hokkaido Takushoku Bank, #13: Failure of Industrial Bank of Japan, #14: Failure of Nippon Credit Bank, #40:Failure of Resona Bank, #41: PFI of Resona Bank. In #5, the merger by the rescuing bank was canceled. After two months, the assets of Hokkaido Takushoku were sold to other rescuing banks. See also Shimizu (2009a) for more details.

largest banks' delta CoVaR are mostly significantly positive and are greater than 1 for the three events (#5, #8, and #15). These amplified effects of the largest banks' systemic risk support the first TBTF hypothesis. However, we find no amplified effects in the other four events. In the lower panel, we report the subsample means of the delta CoVaRs, before and after the events depending on whether they are the largest banks or other banks. Apparently, the delta CoVaRs of the largest banks are greater than those of smaller banks, whose differences are statistically significant, both before and after the event. Therefore, although the largest banks' delta CoVaR is influential in that they are higher than the average of other banks, we do not necessarily observe the amplified effects of the largest banks' systemic risk.

At the bottom of Table 6, we see the statistically significant differences of the subsample means for smaller banks before and after the events related to the largest banks. However, we find no clear evidence of the second hypothesis. Two coefficients of the cross term of the management dummy and the largest banks' delta CoVaR are significantly positive, two are significantly negative, and the other three are not significant. We observe no systematic change after the management measures are taken.

4. Extreme systemic risk state and delta CoVaR

4.1. Markov regime switching model and systemic risk

The systemic risk is most serious when the delta CoVaRs are extremely high, i.e., in the tail. We consider the daily average of the delta CoVaR:

$$ADC_t = \sum_j \Delta CoVaR_t^{Sj} / N_t \tag{10}$$

as the system wide risk representing the degree of comovements in the tail, where N_t is the number of banks. Crisis management should work most effectively for such states.

The system-wide state of extreme systemic risk is identified by the Markov regime-switching model by Hamilton (1989). We consider the three states, $s_t = \{1, 2, 3\}$ with the transition probability π_{tij} from i to state j. We infer the probability of state i $Pr(s_t = i \,|\, ADC_t, \ldots, ADC_{t-3})$ given the available information. We specify the model by assuming that each regime differs in their means of ADC_t, which corresponds to the intercepts and the three lags of ADC_t in the real equation.

In the same way, we also consider the state identification for the average delta CoVaR with a negative sign.

$$ADC_t^n = \sum_{j \in \Delta CoVaR_t^{Sj} < 0} \Delta CoVaR_t^{Sj} / N_t^n, \tag{11}$$

where N_t^n is the number of banks with negative delta CoVaRs. This investigation is motivated by the finding in Bae et al. (2003) and Lopez-Espinosa et al. (2012). The former argue that the evidence that contagion is stronger for extreme negative returns than for extreme positive return is mixed. The latter argue that asymmetries based on the sign of bank returns play an important role in capturing the sensitivity of systemic risk. Allen et al. (2012) also argue that extremely high levels of systemic risk in the banking sector impact the macroeconomy. Instead of return, we examine the negative average delta CoVaR. As Table 2 shows, the ADCs themselves are positive. However, many delta CoVaRs have a negative sign. Even if it is negative, a large absolute value indicates that the system-wide influence cannot be ignored.

The delta CoVaR can be negative when the returns of bank j are negatively correlated with the system returns. Suppose that the market perceives that crisis management succeeds in the sense that the financial system becomes relatively more stable. Then, the return of this bank may continue to worsen each until the exit, whereas the market return of the financial system may improve. In this case, as the bank becomes more distressed, the absolute value of the CoVaR of the financial system becomes smaller. Then, we may have a negative delta CoVaR. The states for negative delta CoVaR are defined as the state 4, 5, and 6. Regime switching is estimated for a negative delta CoVaR, independently of the regimes $\{1, 2, 3\}$ to avoid complexity.

The upper panel of Table 7 shows the coefficients of intercepts and the lags of ADC. In the lower panel, we report the Markov transition probability from state to state. Among states $\{1, 2, 3\}$, the intercept is the greatest for state 1. Among states $\{4, 5, 6\}$, the intercept has the largest absolute value for state 6. We call the former an extreme positive systemic risk state and the latter an extreme negative systemic risk state. If the state was 2 yesterday, the probability that the state is 1 today is 1.2%. If the state was 4 yesterday, the probability that the state is 6 today is 2.8%. In such sense, both states correspond to the tail in each of Markov process.

Table 7

We identify the inferred state at t as the most probable state;

$$\hat{s}_t = \max_i Pr(s_t = i \,|\, ADC_t, \ldots, ADC_{t-3}) \tag{12}$$

Using this, we identify the positive and negative extreme systemic risk period as $T^P = \{t : \hat{s}_t = 1\}$ and $T^N = \{t : \hat{s}_t = 6\}$, respectively. In the bottom of the table, we report the frequencies of the inferred states.

4.2. Crisis management during extreme systemic risk period

In Table 8, we investigate whether crisis management works more effectively in the tail. The upper panel indicates the number of days with a positive/negative extreme systemic risk and with crisis management. We report the days for each year and their total. We observe that a positive extreme systemic risk state is most frequent in 1996. On average, seven extreme states occur during a year. However, because they are the tail events, a small number of days has an extreme state.

In the regression analyses, we do not distinguish each crisis management measure. The crisis management dummy takes the value of 1 if a management measure is taken. Another dummy is defined to represent a period of extreme systemic risk and takes the value of 1 if $t \in T^P = \{\tau : \hat{s}_\tau = 1\}$ or $t \in T^N = \{\tau : \hat{s}_\tau = 6\}$. These two dummies are crossed to generate eight dummies. Two dummies are excluded to avoid perfect collinearity, which are no crisis management under normal state with respect to positive and negative states.

In the middle panel, we report the sensitivities of the six dummies. In the first column, we estimate eq. (9) using these dummies for the entire period. The sensitivity of the crisis management in the tail is higher relative to those of no crisis management under the normal systemic risk ((A) or (D)). In addition, the sensitivity of crisis management under normal systemic risk is lower than no crisis management under the same condition ((B) or (E)). The lower panel reports the test statistics for the equality of the sensitivities. In the tail, the sensitivity of crisis management is not statistically different from that of no crisis management ((A) = (C), (D) = (F)). Thus, crisis management does not effectively work for systemic risk in the tail. In addition, given crisis management, we confirm that the sensitivity in the tail is statistically different from that of the normal state ((A) $\neq$ (B), (D) $\neq$ (E)).

To check robustness, we consider the yearly estimation using the generalized method of moments (GMM). The sensitivity signs have approximately similar tendencies as those of the first column. However, the signs of crisis management under the normal states become ambiguous. In 1996 and 1999, at the tail of both positive and negative systemic risks, the sensitivity of the crisis management is statistically higher than that of no crisis management. This result may suggest that the crisis management sometimes worsens the systemic risk in the tail.

Table 8

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5. Discussions: Policy implications for future crisis management

In summary, our analyses mostly provide supportive evidence for the liquidity provision/capital infusion effects and the adverse contagion effects of crisis management. However, we also find a few exceptions, such as the moral hazard and the management restriction. There is little evidence on the amplified effects of the spillover and on the effectiveness during the extreme systemic risk period. In reality, the regulators managed the Japanese financial crisis through trial and error. Therefore, the results might be surprising to some of the readers. One should be very careful when applying these results to future crisis management for the following reasons. First, our results are limited in that we examine only a relatively short period after the announcements. It is difficult for us to capture the long-run effects because we experience the successive failures and management events during the crisis. Second, information on some of the FRS and/or the DIR acts acts under legislation were reported in the newspapers before the announcements. Identification of the event date is crucial for our analyses.

Third, our sample only comprises listed banks. Many non-listed banks with stocks that does not trade on exchanges and credit cooperatives that are not incorporated exist. In particular, many failures of very small credit cooperatives occurred during the Japanese financial crisis. Because these cooperatives are very small and the transmission of volatility through stock market is cut off, the spillover effects of each institution may be also considered small. However, the contagious failures may result from small shocks (Cifuentes et al. (2005)). In addition, as Acharya and Yorulmazer (2007b) stress, the too-many-to-fail problem might be important during a crisis, because crisis management may trigger successive failures through herding.

Fourth, in relation to the first point, the fiscal cost of deposit insurance and the long-run effects of bailout should be considered when designing a proper crisis management scheme. According to the Annual Report of the DICJ, the amount of reserves (accumulated amount of insurance fees) fell into a deficit in 1996 and recovered to surplus eventually in 2010. The deficit was financed through government bonds and guarantees granted by the government, which amounted to 17 trillion yen (Shimizu (2009)). In the long-run, soft bailout schemes are usually criticized, because they may invoke risk-shifting moral hazard behavior (Cordella and Yeyati (2003)). However, in reality, more important is that regulatory policy may distort the long-run efficiency of financial institutions under the weak governance of stockholders in Japan. Because the regulators are primarily concerned with prudence from the viewpoint of depositors, which is called the representative hypothesis in Dewatripont and Tirole (1994), weak governance may sacrifice efficiency, along the line with Hanazaki and Horiuchi (2003). The low efficiencies of Japanese banks might suggest that the management may believe that it can be bailed out by being merely prudent. The proper compensation schemes should be accompanied by crisis management (Osano (2002)).

The Basel III proposed macroprudential regulation frameworks from the viewpoint of the importance of systemic risk (Gauthier et al. (2012), Tarashev et al. (2009)). Except for deposit insurance, the regulations and crisis managements might not be aimed at the system level, but, instead, at the individual bank level during our sample period. We did not have any reliable measure of systemic risk on which regulators base crisis management. As Figure 1 suggests, the several peaks of systemic risk do not seem to coincide with events that are considered influential. Under the macroprudential capital regulation , if we could measure the systemic risk more precisely, intensively managing a crisis might become less necessary.

6. Conclusion

This paper examined the relationship between systemic risk contribution and the four types of crisis management during the financial crisis in Japan. We find empirical evidence that the liquidity provision/capital infusion as crisis management helped calming down the systemic risk. However, in some cases, there are the adverse effects due to the management restrictions and the moral hazard. The systemic risk diminishes for non-recipients of PFI programs as well. We also find the rationale for the TBTF policy, but do not find clear evidence for the amplified effects. In addition, the effectiveness of crisis management disappears in the tail of systemic risk. Thus, crisis management played the important role in stabilizing systemic risk during the financial crisis, but its effectiveness is limited, depending on the imposed restrictions and the circumstances in which the method taken. The analyses suggest that it is necessary to have the crisis management method properly stabilizing the financial system.

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Table 1: Events of crisis managements

Event id	Year	Event date	Category	Institutions	Notes
1	1995	19950830	Failure	Regional bank (Hyogo)	
2	1996	19960330	Failure	Regional bank (Taiheyo)	
3		19960619	Deposit insurance act reform		Special assistance (Blanket guarantee), Special insurance fee, Repurchase of deposittory claims
4		19961121	Failure	Regional bank (Hanwa)	Order of suspending operation
5	1997	19970906	Failure	City bank (Hokkaido Takushoku)	Merger cancellation
6		19971009	Failure	Regional bank (Fukutoku and Naniwa)	Merger
7		19971014	Failure	Regional bank (Kyoto Kyoei)	Operation transderred
8		19971117	Failure	City bank (Hokkaido Takushoku)	
9		19971126	Failure	Regional bank (Tokuyo City)	
10		19971213	Deposit insurance act reform		Assistance for special merger
11	1998	19980515	Failure	Regional bank (Hanshin Midori)	Merger
12		19981003	Deposit insurance act reform		Receiver, bridge bank, and special public management (temporary
13		19981023	Failure	Long-term bank (Long-Term Credit Bank of Japan)	Nationalized
14		19981212	Failure	Long-term bank (Nippon Credit Bank)	Nationalized
15	1999	19990313	Public funds injection	fifteen institutions	
16		19990408	Failure	Regional bank (Kokumin)	
17		19990412	Prompt Corrective Action	Regional bank (Kofuku)	
18		19990522	Prompt Corrective Action	Regional bank (Hokkaido)	
19		19990601	Prompt Corrective Action	Regional bank (Tokyo Sowa)	
20		19990629	Prompt Corrective Action	Regional bank (Namihaya)	
21		19990705	Prompt Corrective Action	Regional bank (Niigata Chuo)	
22		19990914	Public funds injection	four institutions	
23		19991126	Public funds injection	Regional bank (Kumamoto Family)	
24	2000	20000210	Public funds injection	Long-term bank (Long-Term Credit Bank of Japan)	
25		20000225	Public funds injection	Regional bank (Hokkaido)	
26		20000428	Prompt Corrective Action	Regional bank (Chiba Kogyo)	
27		20000524	Deposit insurance act reform		Extending the period of blanket guarantee
28		20000901	Public funds injection	two Regional banks (Chiba Kogyo, Yachiyo)	
29		20000906	Public funds injection	Long-term bank (Nippon Credit Bank)	
30		20000928	Prompt Corrective Action	Regional bank (Senshu)	
31	2001	20010302	Public funds injection	Regional bank (Kansai Sawayaka)	
32		20010309	Public funds injection	two Regional banks (Kinki Osaka, Higashi Nihon)	
33		20010323	Public funds injection	Regional bank (Gifu)	
34		20011127	Public funds injection	three Regional banks (Fukuoka City, Kyushu, Wakayama)	
35		20011228	Failure	Regional bank (Ishikawa)	
36	2002	20020104	Prompt Corrective Action	Regional bank (Chubu)	
37		20021212	Deposit insurance act reform		Blanket guarantee of account for settlement
38	2003	20030220	Failure	Regional bank (Chubu)	
39		20030401	Public funds injection	Regional bank (Kanto Tsukuba)	
40		20030517	Failure	City bank (Resona)	Nationalized
41		20030611	Public funds injection	City bank (Resona)	
42		20031206	Failure	Regional bank (Ashikaga)	Nationalized

(Note): PFI (public fund injection program), PCA (prompt corrective action), FRS (failure resolution scheme), DIR(deposit insurance act reform). Sample period : Apr. 3rd, 1995-Mar. 31, 2004. Event day is identified by Nikkei Shimbun. (Source): Annual report of Deposit Insurance Corporation in Japan.

Table 2: Summary statistics of delta CoVaR

Year	Number of banks	Cross sectional average of Delta CoVaR for each year					
		Mean	S.D.	5%	Median	95%	Number of days
1995	108	20.3	7.2	12.9	18.8	31.6	186
1996	108	21.4	13.0	10.4	19.6	35.9	247
1997	107	38.1	21.7	17.8	30.9	84.7	245
1998	107	25.0	10.6	14.0	22.5	44.8	247
1999	104	14.6	15.6	-9.1	15.2	41.8	245
2000	103	25.2	16.9	7.5	20.6	62.4	248
2001	101	19.0	11.4	6.6	16.6	43.2	246
2002	93	23.6	23.0	5.3	17.8	70.1	246
2003	91	14.8	17.1	4.0	12.9	30.0	245
2004	89	17.7	7.6	8.0	16.8	30.1	60
Full sample period		22.0	14.4	7.7	19.2	47.5	221.5

Crisis management	Mean	S.D.	5%	Median	95%	Number of days
None	23.6	17.9	7.8	19.7	56.178	1558
Four types	19.5 ***	15.1	-2.8 ***	17.2 ***	45.585 ***	657
PFI	19.7 ***	15.3	5.8	15.1 ***	58.553	205
PCA	12.9 ***	19.0	-11.5 ***	10.3 ***	45.585	128
Fail	21.9	13.1	7.7	19.8	41.245 **	230
DIR	22.1	9.8	6.1	20.6	38.941	94

(Note) Sample period : Apr. 3, 1995- Mar. 31, 2004. Table shows mean, standard deviation (S.D.), 5 percentile, median, 95 percentile. Number of days is on operating basis. The results of significance test on the difference of means, 5%, 50%, and 95% are reported. *, **, *** denotes the significance level of 10, 5, 1%, respectively.

Table 3 : Delta CoVaR and four types of crisis management: Panel data estimation

Dep. Var.	Delta CoVaR	
Market variables	(i)	(ii)
Volatility	5.475***	4.612***
	(0.770)	(0.899)
Change in JGB rate	-15.18*	-6.442**
	(8.087)	(2.844)
Yield spread (Long)	4.448***	4.930***
	(0.974)	(1.420)
Yield spread (Short)	-1.316	-7.337**
	(3.084)	(3.694)
Market return	15.43*	15.73*
	(8.153)	(8.753)
Bank variables		
VaR		-100.5***
		(26.55)
Log of asset		12.25***
		(3.152)
Leverage		52.83
		(50.80)
Monetary policy variables		
Call rate		-7.267***
		(2.689)
Log of Reserve		-4.733***
		(1.287)
Crisis management variables		
PFI	-3.756***	-5.317***
	(1.150)	(1.232)
PCA	-11.16***	-12.27***
	(2.846)	(3.054)
FRS	1.454	2.226**
	(0.989)	(1.086)
DIR	-0.451	-1.331
	(1.357)	(1.561)
Constant	11.85***	-171.6**
	(3.264)	(76.14)
Observations	138,104	109,612
Number of bank	80	63
Std. Dev. of Individual error	22.24	11.96
Std. Dev. of Idiosyncratic error	58.61	49.67
Rho	0.126	0.0548
Wald Chi (zero coeffs)	113.9	133.6
p-value	0.00	0.00

(Notes) The random effects panel data models are estimated. Reported in parentheses are robust standard errors. *, **, or *** denotes 10%, 5%, 1% significance level, respectively.

Table 4 :Delta CoVaR and individual measures of crisis management

Dep. Var.: Delta CoVaR

Event	Type	Coef.	Event	Type	Coef.	Event	Type	Coef.	Event / Var.	Coef.
1	F	-11.07***	16	F	18.97***	31	I	-23.54***	Volatility	3.821***
		(2.027)			(5.157)			(7.204)		(0.885)
2	F	22.95***	17	P	-8.759	32	I	-6.390	Change in jgb rate	-5.447*
		(6.550)			(6.996)			(6.838)		(3.060)
3	D	-8.102***	18	P	-12.68**	33	I	23.34***	Yield spread (Long)	3.448**
		(2.320)			(6.011)			(6.756)		(1.587)
4	F	-7.510***	19	P	-18.62***	34	I	-8.567***	Yield spread (Short)	-12.90***
		(2.645)			(5.710)			(1.975)		(4.414)
5	F	-1.104	20	P	-14.98***	35	F	1.527*	Market return	10.96
		(3.214)			(3.243)			(0.797)		(7.279)
6	F	-11.24***	21	P	-25.50***	36	P	-9.105***	VaR	-94.72***
		(3.330)			(5.389)			(1.760)		(24.94)
7	F	3.013	22	I	-18.90***	37	D	-8.137***	Log of asset	11.97***
		(3.001)			(3.068)			(1.606)		(2.731)
8	F	1.852	23	I	-5.259***	38	F	-6.254***	Leverage	39.84
		(3.676)			(1.980)			(2.356)		(52.69)
9	F	9.741***	24	I	2.292	39	I	-6.397***	Call rate	-6.023**
		(1.743)			(2.042)			(2.289)		(2.441)
10	D	2.626	25	I	-12.97***	40	F	-2.234	Reserve	-4.813***
		(1.826)			(2.028)			(1.890)		(1.353)
11	F	3.574	26	P	10.20*	41	I	-5.502***	Constant	-150.1**
		(4.612)			(5.393)			(1.265)		(72.17)
12	D	-6.710***	27	D	3.970	42	F	-6.879***		
		(2.120)			(4.173)			(2.276)	Observations	109,612
13	F	2.251	28	I	-16.50***				Number of bank	63
		(1.675)			(4.098)				Std. Dev. of Individual error	9.726
14	F	-2.401	29	I	3.687				Std. Dev. of Idiosyncratic	49.26
		(2.557)			(3.479)				Rho	0.0375
15	I	9.701***	30	P	-11.30***				Wald Chi (zero coeffs)	3983
		(3.650)			(2.329)				p-value	0

(Notes) Types of crisis management are public fund injection program (I), prompt corrective action (P), failure resolution scheme (F), and deposit insurance act reform (D). The random effects panel data models are estimated. Reported in parentheses are robust standard errors. *, **, or *** denotes 10%, 5%, 1% significance level, respectively.

Table 5 : Delta CoVaR and direct/indirect spillover: Panel data estimation

Dep. Var.= Delta CoVaR Event	15	22	25	28	32	34
Indirect spillover dummy	10.81***	-16.81***	-9.178***	-12.22***	-8.886***	-6.582***
	(4.073)	(3.109)	(1.978)	(3.082)	(2.697)	(1.909)
Direct spillover dummy	21.24**	5.312	-39.57***	-10.07***	5.822**	2.671
	(9.587)	(4.890)	(1.655)	(2.925)	(2.631)	(2.257)
Observations	109,612	109,612	109,612	109,612	109,612	109,612
Number of bank	63	63	63	63	63	63
Std. Dev. of Individual	11.94	11.64	11.97	11.79	11.95	11.99
Std. Dev. of Idiosyncratic	49.74	49.74	49.75	49.75	49.76	49.76
Rho	0.0545	0.0519	0.0548	0.0532	0.0546	0.0549
Wald Chi (zero coeffs)	214.8	130.5	9.900e+06	1.433e+06	12691	3841
p-value	0	0	0	0	0	0

(Notes) Subsample of public fund injection that has multiple recipients are used. Indirect spillover dummy takes 1 for all banks during the event days. Direct spillover dummy takes 1 for the recipient bank only during the event days. The random effects panel data models are estimated. Reported in parentheses are robust standard errors. *, **, or *** denotes 10%, 5%, 1% significance level, respectively. The coefficients for the market variables and bank variables are omitted in the table.

Table 6: Delta CoVaR and TBTF: panel data IV estimation

Event id	5	8	13	14	15	40	41
Year	1997	1997	1998	1998	1999	2003	2003
Largest banks' delta CoVaR	1.348***	1.199*	0.258*	-0.524***	1.340***	0.071***	-0.025
	-0.46	-0.656	-0.147	-0.201	-0.136	-0.017	-0.032
Crisis management dummy X	-0.378***	0.742***	-0.061***	0.075	1.104	0.004	0.013**
Largest banks' delta CoVaR	-0.115	-0.108	-0.015	-0.055	-0.859	-0.013	-0.005
Volatility	-13.463**	-6.147	-0.742	26.182***	-3.501	-28.826***	0.839
	-6.12	-4.093	-0.844	-7.831	-5.461	-7.275	-2.349
Change in JGB rate	-37.341	84.798***	-33.135***	92.332***	14.49	4.309	3.948
	-24.629	-27.39	-10.351	-35.67	-10.924	-9.847	-31.584
Yield spread (Long)	87.788***	-19.478***	-24.943***	-79.818***	65.598***	13.102**	6.722
	-19.12	-7.396	-8.96	-27.254	-9.71	-6.359	-4.522
VaR	-0.608***	-0.181	-0.516***	-0.795***	-0.037	-0.914***	-0.565**
	-0.188	-0.159	-0.086	-0.261	-0.15	-0.196	-0.234
Constant	-102.167***	24.964***	10.328*	-21.229*	-45.799***	16.907***	-4.291
	-21.75	-5.811	-5.845	-11.818	-13.234	-3.763	-6.112
Observations	3293	3237	3232	3084	3262	2938	2939
Number of bank	58	58	57	57	57	51	51
Std. Dev. of Individual error	30.29	24.15	13.99	11.89	20.42	10.47	9.367
Std. Dev. of Idiosyncratic error	33.94	31.13	16.9	16.49	43.22	13.86	13.62
Rho	0.443	0.376	0.407	0.342	0.182	0.363	0.321
Wald Chi (zero coeffs)	51.78	281.8	133.9	95.77	206.9	42	60.33
Subsample means of delta CoVaR							
Largest banks, before the event	41.37	57.73	52.55	47.27	54.28	57.37	62.35
Other banks, before the event	19.08	12.13	17.58	12.84	13.9	10.06	17.93
Largest banks, after the event	46.31	61.61	47.91	50.78	92.61	65.15	41.14
Other banks, after the event	15.68	28.89	13.47	12.26	29.7	13.16	10.71
t-test							
Before, Largest=other	***	***	***	***	***	***	***
After, Largest = other	***	***	***	***	***	***	***
Largest, Before=after					***		
Other, Before =after	**	***	***		***	**	*

(Notes) Subsample of banks other than largest banks are used. Largest banks' delta CoVaR is endogenized by estimating it in the first stage (not reported). The reported second stage uses the predicted value of the largest banks' delta CoVaR. The selected events is related to the largest banks. Crisis management dummy takes one after each event or 0 otherwise. Reported in parentheses are robust standard errors. *, **, or *** denotes 10%, 5%, 1% significance level, respectively.

Table 7: Average delta CoVaR: Markov regime switching model

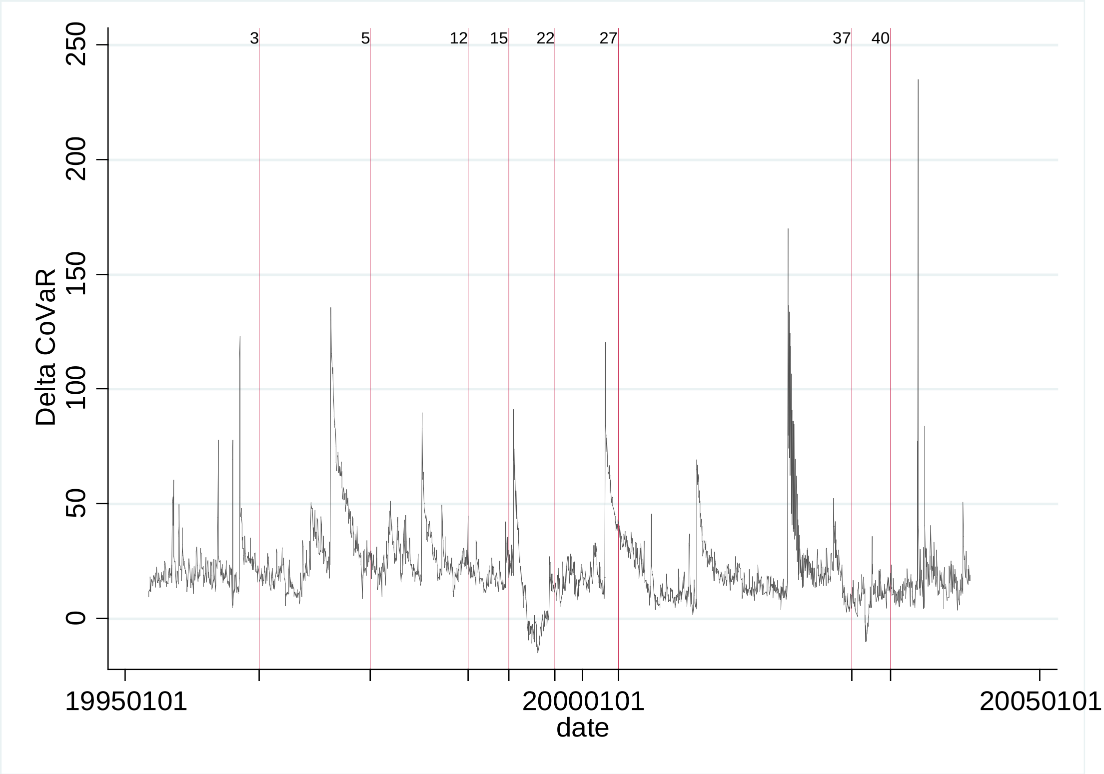
	Average delta CoVaR			Average negative delta CoVaR		
Regime	1	2	3	4	5	6
Variables						
Intercept	57.310	4.113	0.445	-1.378	-0.445	-22.280
	(10.323)***	(0.623)***	(0.181)*	(0.495)**	(0.164)**	(8.506)**
Lag 1	0.110	0.173	0.676	0.479	0.617	0.128
	(0.128)	(0.040)***	(0.020)***	(0.034)***	(0.042)***	(0.191)
Lag2	0.057	0.851	0.164	0.440	0.142	0.027
	(0.138)	(0.028)***	(0.023)***	(0.034)***	(0.043)***	(0.420)
Lag3	-0.319	-0.134	0.088	0.020	0.181	0.480
	(0.241)	(0.032)***	(0.015)***	(0.030)	(0.034)***	(0.543)
Residual standard error	40.299	6.146	2.911	5.938	2.361	17.357
Multiple R-squared	0.000	0.000	0.000	0.000	0.000	0.000
Transition probability matri	1	2	3	4	5	6
1	0.609	0.012	0.012			
2	0.109	0.529	0.177			
3	0.282	0.459	0.810			
4				0.896	0.075	0.417
5				0.075	0.920	0.094
6				0.028	0.004	0.490
Frequencies of the most probable state						
	56	366	1790	1086	1091	35

Table 8 : Crisis management during extremely high systemic risk: GMM panel data estimation

Fiscal Year	ALL	1996	1997	1998	1999	2000	2001	2002	2003
Number of days									
all	2215	247	245	247	245	248	246	246	245
Positive extreme state	56	14	3	4	3	2	6	5	9
Negative extreme state	35	3	2	8	4	4	8	3	3
Crisis management	657	64	71	72	132	106	57	32	102
positive extreme	15	5	0	0	2	1	6	0	1
negative extreme	13	3	1	0	4	1	4	0	0
Sensitivities									
(A) Crisis management, positive extreme	34.462***	82.422***			47.630***	31.010*	37.928**		23.124**
	(8.098)	(29.115)			(7.120)	(17.900)	(15.235)		(9.132)
(B) Crisis management, positive normal	-4.460***	10.075**	1.459	-0.763	-2.243	-5.948***	20.274***	9.237**	-0.119
	(0.795)	(4.841)	(2.904)	(1.152)	(2.212)	(2.038)	(5.921)	(4.524)	(1.591)
(C) No crisis management, positive extre	36.292***	32.187	40.382***	27.506***	24.866***	84.569***		53.944***	12.746
	(9.357)	(30.281)	(3.988)	(3.883)	(5.768)	(10.673)		(6.961)	(9.574)
(D) Crisis management, negative extreme	36.561***	86.006**	4.996		26.856***	-5.682	41.073**		
	(8.611)	(41.465)	(7.228)		(5.954)	(9.528)	(20.677)		
(E) Crisis management, negative normal	-4.701***	8.477	0.968	-1.113	-3.035**	-5.619***	20.149***	9.124**	0.322
	(0.750)	(5.829)	(3.139)	(1.107)	(1.535)	(1.822)	(5.680)	(4.441)	(1.518)
(F) No crisis management, negative extre	32.771***		8.848**	25.465***		24.498***	-1.670	40.177***	0.005
	(4.537)		(3.475)	(4.821)		(4.062)	(2.436)	(5.872)	(4.056)
Test for the equality of coefficients									
(A)=(C)	0.079	5.986			9.858	6.142			0.630
p-value	0.779	0.014			0.002	0.013			0.427
(A)=(B)	25.210	6.733			56.660	4.092	2.562		6.392
p-value	0.000	0.009			0.000	0.043	0.109		0.012
(D)=(F)	0.135		0.202			10.18	4.135		
p-value	0.714		0.653			0.001	0.042		
(D)=(E)	24.030	3.150	0.424		26.080	0.000	1.515		
p-value	0.000	0.076	0.515		0.000	0.995	0.218		

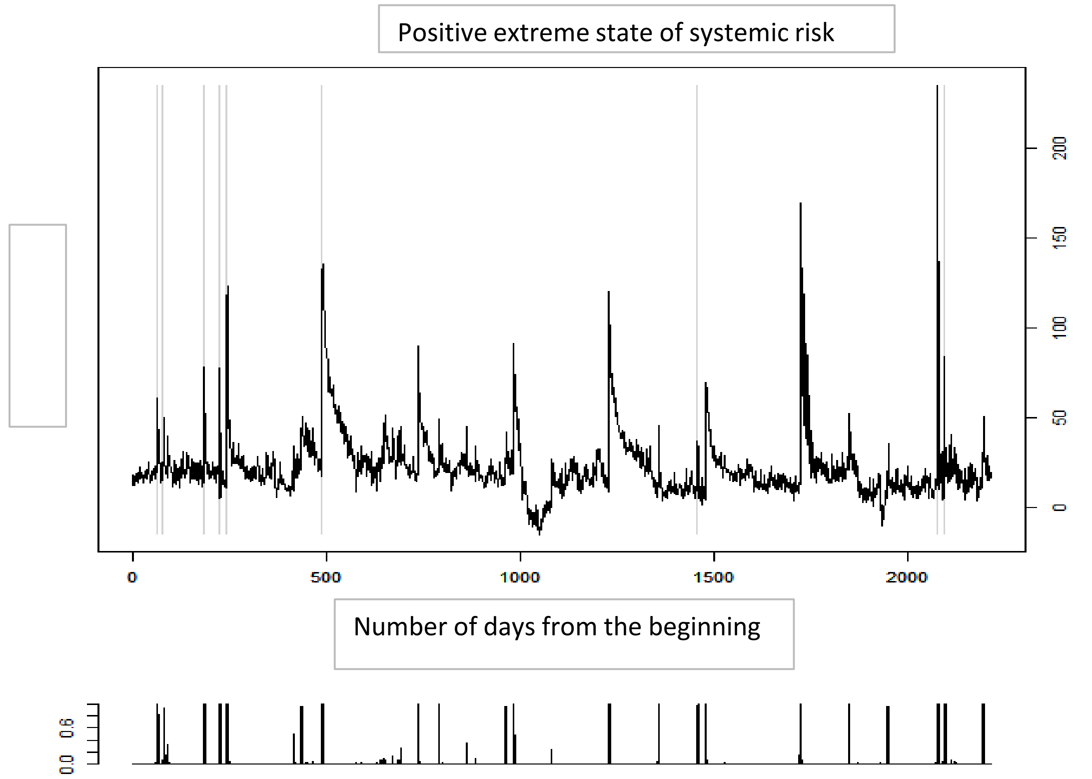
(Notes) Using the inferred states by the Markov regime switching model, we identify the extreme state and normal state for average delta CoVaR and average negative delta CoVaR, respectively. We divide each state into two for each average delta CoVaR, depending on the crisis management dummy. The base state is set to no crisis management and normal state. Subsample of public fund injection that has multiple recipients are used. Indirect spillover dummy takes 1 for all banks during the event days. Direct spillover dummy takes 1 for the recipient bank only during the event days. The random effects panel data models are estimated. Reported in parentheses are robust standard errors. *, **, or *** denotes 10%, 5%, 1% significance level, respectively. In the bottom, we report the Wald statistics for the equaliry of the coefficients for each dummy.

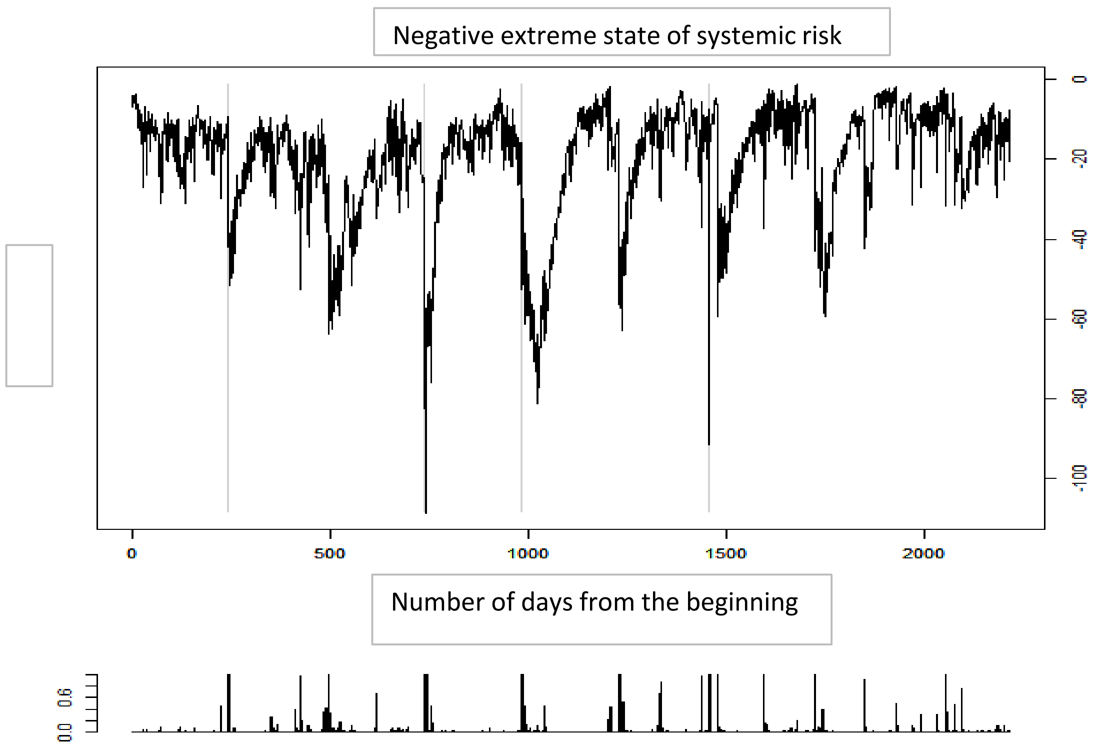
Figure 1: Cross sectional average of daily delta CoVaR



(Note) : Delta CoVaR (%) is the standardized difference of CoVaR of financial systemi in normal state and that of distressed state of each bank.

Figure 2: Average delta CoVaR and markov states for extreme systemic risk





(Note) The grey lines in the large graph shows the exterme state for each. The small graphs show the inferred probability of extreme state.