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# Empirical Evidence on "Systemic as a Herd": The Case of Japanese Regional Banks

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## Abstract

We examine a sample of Japanese regional banks and explore whether exposure to market risk factors affects systemic risk through a banks' portfolio composition or revenue source, using Adrian and Brunnermeier's (2016) CoVaR to proxy for systemic risk. We find evidence of "systemic as a herd" behavior among Japanese regional banks, as portfolio and revenue components associated with market activities exert positive and significant impacts on systemic risk by generating higher comovement among banks, even though they reduce standalone bank risk through portfolio diversification. Further, the marginal effect of an increase in a given banks' market-related components on systemic risk is larger when the share of the corresponding components is already high among other banks. Our results have important implications from the macro-prudential perspective.

*JEL classification:* D21; G28; G32; G38; G62

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## 1. Introduction

Systemic banking crises tend to be costly, with costs often exceeding that imposed by individual bank failures. Therefore, more attention is being paid to forestalling systemic crises and mitigating their impact. As opposed to the question of “too-big-to-fail”, which has attracted much scrutiny, the problem of “systemic as a herd”, whereby institutions which are not individually systemically important behave in a similar way and are thus exposed to common risks, has attracted relatively less attention. However, “systemic as a herd” behavior increases the probability of joint failure among herding institutions and thus can have financial stability implications. In this paper, we investigate “systemic as a herd” behavior, specifically, the effect of portfolio and revenue source diversification on both systemic and standalone bank risk.

The question of how financial institutions' portfolio composition or revenue source affects standalone bank risk is a topic of active research. Stiroh (2004, 2006) concludes that greater reliance on non-interest income, particularly trading revenue, is associated with higher risk across commercial banks.<sup>1</sup> Other research finds support, albeit limited to hypothetical scenarios, for the risk reduction benefits of diversification. Employing simulated mergers between banks and non-bank financial firms, Laderman (2000) finds that diversification into insurance activities could reduce the variation in return on assets and also banks' probability of bankruptcy. By constructing synthetic portfolios between 1981 and 1989, Wall, Reichert and Mohanty (1993) find that banks could enjoy higher returns and lower risk, by diversifying to a small extent into non-banking activities.

While previous research sheds light on the implications of portfolio composition or revenue structure for individual banks, research on its systemic risk implications is limited.<sup>2</sup> One way in which banks' portfolio composition or revenue structure could affect systemic risk is through exposure to common factors, such as market fluctuations. If banks are similarly exposed to market-related factors through their portfolio

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<sup>1</sup> DeYoung and Roland (2001) present similar findings.

<sup>2</sup> For example, Brunnermeier, Dong and Palia (2012) examine the effect of non-traditional, non-interest income activities on systemic risk, and report that non-interest income components make a larger contribution compared to traditional banking activities, such as lending.

composition or revenue structure, these common exposures increase the risk that many banks could fail together and lead to a system-wide problem.<sup>3</sup>

In this paper, we investigate the effect of portfolio composition and revenue structure on both systemic risk and standalone bank risk, employing Japanese regional bank data. Specifically, we ask whether increased securities holdings and reliance on non-interest income among Japanese regional banks will affect systemic risk and standalone bank risk. Since securities investments are more likely associated with common factors, compared with traditional lending activities, higher exposure to market-related components such as securities investments could render a bank more correlated with other banks. The higher correlation could result even though regional banks may not be interconnected directly, through the interbank lending market, for example. This phenomena is termed “systemic as a herd” in Adrian and Brunnermeier (2016).<sup>4</sup> We use a recently developed measure, Adrian and Brunnermeier (2016)'s CoVaR to proxy for systemic risk. In this paper, we ask if CoVaR, which captures the common exposure to exogenous aggregate macroeconomic risk factors, is in agreement with the idea that Japanese regional banks could be behaving in a manner consistent with “systemic as a herd”.

The novelty of our paper is twofold. First, previous papers have focused on interbank exposures or funding structures as a source of systemic risk. While we

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<sup>3</sup> There are theoretical studies on the effect of portfolio diversification on systemic risk. For example, Acharya and Yorulmazer (2007) coined the term “too-many-to-fail” to describe the situation where a regulator finds it optimal to bail out some or all banks that face bankruptcy as a result of their herd behavior and common exposure to risks. Similarly, Farhi and Tirole (2012) show that if central banks have no choice but to intervene when systemic implications are present, banks will be incentivized to take on more correlated risk. Restating the problem facing an individual bank, it would appear to be “unwise to play safely while everyone else gambles”. Exploring a different transmission channel, Wagner (2010) shows that diversification could lead to increased similarity in banks’ portfolios and expose them to the same risks, which causes a rise in the probability that banks fail simultaneously.

<sup>4</sup> The concept of “systemic as a herd” is further clarified below. Consider a case where a large number of small financial institutions are not interconnected directly (e.g. absence of lender and borrower relationships) but are exposed to the same risk factors because they hold similar positions or rely on similar funding sources. Since each financial institution is small, its distressed state or failure may not necessarily trigger a systemic crisis. However, if the source of distress is common to a large number of financial institutions, a common risk event could cause them to enter a distressed state simultaneously. The vulnerability of the entire financial system to a crisis state is thus heightened.

acknowledge the importance of those factors, our paper takes a different approach, exploring how revenue source and portfolio composition can also play a role. To our knowledge, this is the first paper that documents that the portfolio composition of banks – namely the securities-to-assets ratio – also has an impact on systemic risk. Second, we employ data for Japanese regional banks, which are neither considered to be individually systemically important nor strongly interconnected, but have exhibited a tendency to increase their securities holdings and non-interest income over time, mainly due to the decrease in loan demand and profitability. The potential for “systemic as a herd” behavior is thus present – Japanese regional banks are ideal candidates for testing the validity and relevance of this concept.

Our main empirical findings are as follows. First, we find that increased securities holdings or dependence on non-interest income increase our measure of systemic risk (CoVaR). Further, while these factors reduce standalone bank risk (VaR), a component of systemic risk, they raise the systemic risk coefficient, a parameter that captures the linkage between the individual bank's tail risk and aggregated tail risk. This implies that although increases in securities holdings and non-interest income may not increase standalone bank risk, it may have the side-effect of rendering the financial system as a whole more vulnerable. Second, we find that the marginal effects of securities holdings or dependence on non-interest income on systemic risk depend on other banks' portfolio composition or revenue structure. Specifically, the more banks increase their reliance on non-interest income and securities holdings in aggregate, the more an increase in these factors at a given bank will exert a marginal effect on systemic risk. This implies that when banks which are not individually systemically important behave in a similar way and thus exposed to common risk, systemic risk could increase to a greater extent, compared to the case where such behavior is confined to a limited number of banks.

The remainder of the paper is organized as follows. Section 2 outlines the measure of systemic risk we use. Section 3 discusses the data, our CoVaR estimation framework and main results. Section 4 presents an extended model and additional results. Section 5 concludes.

## 2. Measure of systemic risk

To gauge systemic risk, we employ a recently developed measure, Adrian and Brunnermeier's (2016) CoVaR. While an individual banks' idiosyncratic risk is typically measured by its standalone VaR, Adrian and Brunnermeier (2016) emphasize the importance of an individual banks' contribution to systemic risk. CoVaR allows time-varying estimates of the systemic risk contribution for each bank to be generated. This methodology has been applied in a number of macro-prudential studies (e.g. Brunnermeier et al, 2012; López-Espinosa et al, 2012; Zhang et al, 2014).

CoVaR is defined as the maximum loss that can be expected in a certain portfolio for a given confidence level, given the maximum loss expected in another portfolio at a specific confidence level. In our context, it is the additional amount of risk that the financial system is subject to when the aforementioned bank is in a distressed state, as opposed to being in its median state.

Formally, we denote  $CoVaR_{\lambda,t}^{system|c(X_t^i)}$  by the  $\lambda$  % quantile VaR of the financial system conditional on some event  $C(X^i)$  of bank  $i$ . In our paper,  $C(X^i)$  refers to the case when the individual bank stock return is at its  $\lambda$  % bottom level. Equivalently,  $CoVaR_{\lambda,t}^{system|c(X_t^i)}$  is defined by the  $\lambda$  % quantile conditional probability distribution:

$$\Pr\left(-X_t^{system} \leq CoVaR_{\lambda,t}^{system|c(X_t^i)} | C(X_t^i)\right) = \lambda\%,$$

where  $X_t^{system}$  and  $X_t^i$  denote the respective portfolio returns. Given this,  $\Delta CoVaR_{\lambda,t}^{system|i}$  is defined as portfolio  $i$ 's contribution to systemic risk:

$$\Delta CoVaR_{\lambda,t}^{system|i} = CoVaR_{\lambda,t}^{system|-X^i=VaR_{\lambda}^i} - CoVaR_{\lambda,t}^{system|-X^i=VaR_{50}^i}.$$

$\Delta CoVaR_{\lambda,t}^{system|i}$  is the difference between the CoVaR of the financial system when financial institution  $i$  is in its distressed state (when its losses  $X^i$  equal the  $\lambda$  % quantile

of its VaR), and the CoVaR of the financial system when financial institution  $i$  is in its median state (when its losses  $X^i$  equal the 50% quantile of its VaR).

The CoVaR methodology requires the estimation of VaR for individual banks and any system portfolio in our sample. The key step in the CoVaR methodology is to estimate the conditional comovement measure. Following Adrian and Brunnermeier (2016), we compute the predicted value of an aggregate regional bank loss on the loss of a particular bank  $i$  for the 5% quantile. We estimate systemic risk coefficient  $\delta_{\lambda,t}^i$  via quantile regression, as proposed by Koenker and Bassett (1978). Specifically, we solve the following equation:

$$\min_{\alpha_{\lambda}^i, \delta_{\lambda}^i, \beta_{\lambda}^i} \sum_t \begin{cases} (1 - \lambda\%) |X_t^{system} - \alpha_{\lambda}^i - \beta_{\lambda}^i M_{t-1} - \delta_{\lambda}^i X_t^i| & \text{if } (X_t^{system} - \alpha_{\lambda}^i - \beta_{\lambda}^i M_{t-1} - \delta_{\lambda}^i X_t^i) \geq 0 \\ \lambda\% |X_t^{system} - \alpha_{\lambda}^i - \beta_{\lambda}^i M_{t-1} - \delta_{\lambda}^i X_t^i| & \text{if } (X_t^{system} - \alpha_{\lambda}^i - \beta_{\lambda}^i M_{t-1} - \delta_{\lambda}^i X_t^i) < 0 \end{cases}$$

where  $M_t$  denotes a state variable. In this expression, the existence of risk spillover is captured by estimating parameter  $\delta_{\lambda}^i$ : for non-zero values of this parameter, the left tail of the system distribution can be predicted by observing the given distribution of a bank's returns. Our specification utilizes TOPIX stock returns as a state variable. Parameters are estimated using daily data with a rolling sample of 126 business days (half-year).

Applying the definition of value at risk, it can be seen that the  $\lambda\%$  quantile of CoVaR can be computed from the  $\lambda\%$  quantile of bank  $i$  VaR.  $\Delta\text{CoVaR}$  is then derived according to the equation below, by taking the difference between VaR for bank  $i$  at the  $\lambda\%$  quantile and VaR for the same bank in its median state.

$$\Delta\text{CoVaR}_{\lambda,t}^i = \delta_{\lambda,t}^i \underbrace{\left( \text{VaR}_{i,t}(\lambda) - \text{VaR}_{i,t}(50\%) \right)}_{=\Delta\text{VaR}_{i,t}(\lambda)}$$

Figure 1 displays the estimated 5% quantile  $\Delta\text{CoVaR}$  of Japanese regional banks in the sample period April 1996 to March 2016.<sup>5</sup> In terms of bank coverage, we selected

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<sup>5</sup> The sample period is determined based on the availability of bank level data mentioned in Section 3. This sample period is sufficiently long in Japan's case, as it includes the late 1990s banking crisis

59 regional banks whose equity prices are available from 1996 or earlier.<sup>6</sup> A clear uptrend can be observed since the mid-2000s. After peaking in 2008,  $\Delta\text{CoVaR}$  declined, but did not fall back to the levels observed pre-2000. To get a better idea of the drivers of  $\Delta\text{CoVaR}$ , we decomposed  $\Delta\text{CoVaR}$  into its constituent components  $-\Delta\text{VaR}$  and the systemic risk coefficient  $\delta$ . Figure 2 shows that  $\Delta\text{VaR}$  – which represents banks’ own risk, unsurprisingly peaked in 2008, but did not exhibit a clear uptrend or downtrend over time. The picture for the systemic risk coefficient (Figure 3) is very different. Since around 2000, the systemic risk coefficient of regional banks has exhibited an uptrend, showing that comovement among regional banks has risen markedly.

CoVaR, our measure of systemic risk, has desirable properties that render it suitable for measuring the systemic risk contribution of each individual bank. In particular, the CoVaR measure satisfies the clone property – splitting one large individually systemically important institution into  $n$  clones leaves CoVaR unchanged. The CoVaR of each of the  $n$  clones is identical to that of the original institution. We can treat the clones as systemic as part of a herd – since all  $n$  clones are exposed to exactly the same risk factors, should a common factor cause any one of the  $n$  institutions to fall into distress, all  $n$  institutions will be in distress as well.

### 3. Methodology and results

#### 3.1 Data

In this section, we explore the determinants of systemic risk as presented in Section 2. Two primary sources of data are used for this purpose: (i) bank-level accounting data, used to analyze the nexus between systemic risks and bank characteristics, and (ii) macro state variables that control for variation not directly related to financial system risk exposures. All bank-level accounting data are obtained from Bank of Japan’s internal data source. For bank-level variables, we employ log-transformed total assets,

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(Hutchison and McDill, 1999). Here, we use semiannual data, instead of daily data.

<sup>6</sup> We excluded banks that have been consolidated or experienced bankruptcy.



which captures bank size ( $\log(asset)_{i,t}$ ), securities-to-assets ( $StoA_{i,t}$ ), loans-to-assets ( $LtoA_{i,t}$ ) and the non-interest income-to-income ratio ( $NtoI_{i,t}$ ), which represent banks' balance sheet and revenue source exposures.<sup>7</sup>

The loans-to-assets ratio shows how reliant a bank is on traditional lending activities. In the case of Japanese regional banks, loans are largely extended to households or firms in the operating area of the bank, and thus the loans-to-assets ratio represents a risk factor more attributable to a specific bank. The securities-to-assets ratio is a measure of a bank's exposure to market risk factors, which may be driven by common factors.<sup>8</sup> The non-interest income-to-interest income ratio is a proxy for the extent to which a bank is reliant on non-traditional activities, such as fees and commissions income related to investment trusts, relative to traditional deposit and lending activities.

As for macro state variables, we employ Japanese stock market volatility<sup>9</sup> (30-day historical volatility of the TOPIX index); the Japanese yen "TED spread" (i.e. 3-month Yen LIBOR less 3-month JGB yields); excess return of the real estate sector over the financial sector (using TOPIX subsector returns); TOPIX returns; 3-month JGB yields; and the term spread (10-year JGB yields less 3-month JGB yields), following Adrian and Brunnermeier (2016). All data are measured as semiannual averages, except for 3-month JGB yields and the term spread, where the first difference in semiannual averages is employed. Table 1 presents summary statistics of the data employed.

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<sup>7</sup> Other potential variables of interest include non-core liabilities, which is often linked to financial system vulnerability (Shin, 2011). However, this variable does not suit our empirical exercise as deposits form a very large share of funding for our sample banks.

<sup>8</sup> Acharya and Yorulmazer (2007) consider a two asset model comprising a bank-specific asset and a common asset. In our empirical analysis, loans, which comprise banks' main portfolio, are considered to be more bank-specific, while securities are considered to have more common asset characteristics.

<sup>9</sup> While Adrian and Brunnermeier (2016) employ implied volatility calculated from options prices, due to data limitations, we employ historical stock return volatility computed with daily data instead.

### 3.2 Determinants of systemic risk

To analyze how the characteristics of banks affect both standalone and systemic bank risk, we run regressions employing CoVaR estimated earlier.

López-Espinosa et al. (2012) find that for a set of large international banks, the share of short-term wholesale funding is a key determinant of systemic risk episodes. In contrast, this paper sheds light on the effects of two other potentially important elements of systemic risk: revenue source and portfolio structure. To investigate this, we perform regressions with bank fixed effects of the individual bank's systemic risk contribution ( $\Delta CoVaR_{\lambda,t}^i$ ) on the following bank-specific variables: log-transformed total asset size ( $\log(asset)_{i,t-1}$ ); non-interest income-to-interest income ratio ( $NtoI_{i,t-1}$ ); securities holdings-to-assets ratio ( $StoA_{i,t-1}$ ); loans-to-assets ratio ( $LtoA_{i,t-1}$ ); and a set of macro state variables ( $X_{t-1}$ ).

$$\begin{aligned} \Delta CoVaR_{\lambda,t}^i = & \alpha_1 + \alpha_2 \log(asset)_{i,t-1} + \alpha_3 NtoI_{i,t-1} + \alpha_4 StoA_{i,t-1} \\ & + \alpha_5 LtoA_{i,t-1} + \alpha X_{t-1} + Bank_i + \epsilon_{i,t} \end{aligned} \quad (1)$$

where  $Bank_i$  denotes a bank fixed effect.

These bank-specific variables may exert their effects on  $\Delta CoVaR_{\lambda,t}^i$  through two different channels.  $\Delta CoVaR_{\lambda,t}^i$  could have increased because the amount of risk borne by individual banks ( $\Delta VaR_{i,t}(\lambda)$ ) increased. Alternatively,  $\Delta CoVaR_{\lambda,t}^i$  could have increased because the comovement between banks ( $\delta_{\lambda,t}^i$ ) strengthened. To better understand the factors contributing to systemic risk  $\Delta CoVaR_{\lambda,t}^i$ , we conduct a similar exercise on its constituent elements  $\Delta VaR_{i,t}(\lambda)$  and  $\delta_{\lambda,t}^i$ , respectively:

$$\begin{aligned} \Delta VaR_{i,t}(\lambda) = & \beta_1 + \beta_2 \log(asset)_{i,t-1} + \beta_3 NtoI_{i,t-1} + \beta_4 StoA_{i,t-1} \\ & + \beta_5 LtoA_{i,t-1} + \beta X_{t-1} + Bank_i + \epsilon_{i,t} \end{aligned} \quad (2)$$

$$\begin{aligned} \delta_{\lambda,t}^i = & \gamma_1 + \gamma_2 \log(asset)_{i,t-1} + \gamma_3 NtoI_{i,t-1} + \gamma_4 StoA_{i,t-1} + \gamma_5 LtoA_{i,t-1} \\ & + \gamma X_{t-1} + Bank_i + \epsilon_{i,t} \end{aligned} \quad (3)$$

### 3.3 Estimation results

The first column of Table 2 reports the benchmark estimation results with  $\Delta CoVaR_{\lambda,t}^i$  in equation (1). For comparison, the second column presents estimation results where the loans-to-assets ratio is excluded from the explanatory variables. In the benchmark estimation, the ratio of non-interest income to interest income as a revenue source exhibits significantly positive explanatory effects, suggesting that higher dependence on non-interest income leads to an increase in systemic risk. A possible reason is that non-interest income mainly consists of fees and commissions related to investment trusts, which are likely to be driven by common market factors, such as stock prices. Similarly, the ratio of securities to assets has significantly positive explanatory power. Since securities are exposed to market risk, banks that hold securities are exposed to market risk and thereby susceptible to common shocks. Therefore, a higher ratio of securities to assets elevates systemic risk. In the benchmark estimation, the loans-to-assets ratio has a significantly positive impact on systemic risk. However, as shown in Table 3, the coefficient of the securities-to-assets ratio is significantly higher than the coefficient on the loans-to-assets ratio, which means that a portfolio shift from loans to securities tends to increase systemic risk on the whole.

When the loans-to-assets ratio is excluded from the estimation, the securities-to-assets ratio retains positive explanatory power, but the coefficient becomes somewhat smaller. This may be attributed to omitted variable bias, as the omitted loans-to-assets ratio is negatively correlated with the securities-to-assets ratio. The coefficients of the other explanatory variables are nearly unaffected by the exclusion of the loans-to-assets ratio.

The third and fourth column of Table 2 show the estimation results for  $\Delta VaR_{i,t}(\lambda)$  in equation (2). The non-interest income-to-interest income ratio and the ratio of securities to assets are negative and statistically significant. Since the coefficients on those ratios are negative, an increase in those ratios contributes to a decrease in standalone bank risk.

The fifth and sixth column of Table 2 show the estimation results for the systemic risk coefficient  $\delta_{\lambda,t}^i$  in equation (3). We find that the coefficients on the ratio of non-interest income to interest income and the ratio of securities to assets are positive and statistically significant, both when the loans-to-assets ratio is included as an explanatory variable and when it is not.

The estimation results presented above for  $\Delta CoVaR_{\lambda,t}^i$ ,  $\Delta VaR_{i,t}(\lambda)$  and the systemic risk coefficient  $\delta_{\lambda,t}^i$  suggest that the determination of systemic risks depends crucially on portfolio composition and revenue structure. Greater reliance on non-interest income or a higher proportion of market securities in a given bank's asset base strengthens comovement between banks. The strengthened comovement between banks in turn raises CoVaR, our measure of systemic risk.

To ascertain the extent to which portfolio composition and revenue structure affect the systemic risk coefficient  $\delta_{\lambda,t}^i$  and  $\Delta CoVaR_{\lambda,t}^i$ , we compute the contributions that each of the variables make to the increase in the systemic risk coefficient  $\delta_{\lambda,t}^i$  and  $\Delta CoVaR_{\lambda,t}^i$  between the fiscal 1996-2006 subperiod average and the fiscal 2007-2015 subperiod average. The results, shown in Table 4, indicate that changes in  $StoA_{i,t-1}$  and  $NtoI_{i,t-1}$  from the first sub-period to the second account for approximately 40 percent of the increase of both the systemic risk coefficient and  $\Delta CoVaR_{\lambda,t}^i$ .<sup>10</sup> While the two variables are not the dominant factors behind the increase in the systemic risk coefficient  $\delta_{\lambda,t}^i$  and  $\Delta CoVaR_{\lambda,t}^i$ , they account for a substantial portion of the increase.

Our results have some interesting implications. While an increase in securities holdings or the non-interest income ratio reduces individual banks' VaR significantly, they strengthen the tail dependency among banks and increase systemic risk. This implies that although each bank's attempt to diversify risks by increasing their reliance on non-traditional income sources and by holding more market securities could be optimal in the sense of minimization of its own risk, their strategy could lead to an

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<sup>10</sup> Even if the negative contribution from the decrease in  $LtoA_{i,t-1}$  partially offsets the contribution from the increase in  $StoA_{i,t-1}$ , the cumulative net effect of change in portfolio composition and revenue structure accounts for more than one-third of the total increase in the systemic risk coefficient and  $\Delta CoVaR_{\lambda,t}^i$  respectively.

unintended increase in the level of systemic risk. Our results could therefore be capturing the idea that individual banks are behaving "systemic as a herd". These results are consistent with Wagner (2010), which shows that even though diversification in income source and portfolio composition pursued by each financial institution reduces each institution's individual probability of failure, it makes systemic crises more likely. Overall, it suggests that business activities associated with market risk should be assessed more stringently from the macro-prudential perspective, because such activities can raise systemic risk, which entails a negative externality.

#### **4. Extended model**

The previous section confirmed that exposure to common risk factors present in securities holdings or non-interest income raise systemic risk by strengthening the comovement between banks, not by raising standalone bank risk, at least in the sample period examined. However, the same result – that systemic risk increases when the exposure of individual banks to market-related factors grows – may not hold generally. It is possible to conceive a situation where the comovement between a given bank and other banks in the financial system falls. For example, if a given bank increases its securities holdings or non-interest income ratio in a situation where the securities-to-assets ratio or non-interest income-to-interest income ratio among the majority of banks in the financial system is limited, the revenue or profit structure of the bank in question could become more dissimilar to that of other banks. Conversely, if those ratios among the majority of banks are already high, an increase in securities holdings or reliance on non-interest income could strengthen comovement between banks and thus raise systemic risk. The effect on systemic risk of a change in portfolio composition or revenue structure at a given bank thus depends on the portfolio composition and revenue structure at other banks. To analyze this, this section presents a simple model and the results of additional empirical exercises.

#### 4.1 A simple model of comovement

Consider two banks, Bank  $i$  and Bank  $j$ , which are conducting two different activities. The first activity they engage in is market-related activity, which includes investments in securities and commission-based non-interest income. The other activity is traditional loans, which generates interest income. Earnings from those activities at period  $t$  are denoted by  $X_{i,t}$  and  $Y_{i,t}$ , respectively. It is assumed that these activities are governed by hierarchical-factor models:

$$X_{i,t} = \rho_X F_{X,t} + \sqrt{1 - \rho_X^2} \epsilon_{X_{i,t}},$$

$$Y_{i,t} = \rho_Y F_{Y,t} + \sqrt{1 - \rho_Y^2} \epsilon_{Y_{i,t}},$$

where  $F_{X,t}$  denotes a market factor that both banks are exposed to,  $F_{Y,t}$  denotes a loan factor that both banks share, and  $\rho_X$  and  $\rho_Y$  denote correlation coefficients whose absolute values are no more than 1. Both factors are linked by the underlying macro-factor  $F_t$ :

$$F_{X,t} = \beta_X F_t + \epsilon_{F_{X,t}},$$

$$F_{Y,t} = \beta_Y F_t + \epsilon_{F_{Y,t}}.$$

In the above,  $\epsilon_{F_{X,t}}$  and  $\epsilon_{F_{Y,t}}$  are uncorrelated idiosyncratic factors for the market factor and the loan factor, and  $\epsilon_{X_{i,t}}$  and  $\epsilon_{Y_{i,t}}$  are uncorrelated idiosyncratic factors inherent in Bank  $i$ 's market related activities and loan activities respectively. Bank  $i$ 's income  $B_{i,t}$  and Bank  $j$ 's income  $B_{j,t}$  are given by:

$$B_{i,t} = \omega_{X,i} X_{i,t} + (1 - \omega_{X,i}) Y_{i,t},$$

$$B_{j,t} = \omega_{X,j} X_{j,t} + (1 - \omega_{X,j}) Y_{j,t},$$

$\omega_{X,i}$  and  $\omega_{X,j}$  are Bank  $i$  and  $j$ 's weights on market-related activities, respectively. The covariance between  $B_{i,t}$  and  $B_{j,t}$  is obtained as follows:

$$\text{Cov}(B_{i,t}, B_{j,t}) = r_{i,1} r_{j,1} \text{Var}(F_t) + r_{i,2} r_{j,2} \text{Var}(\epsilon_{F_{X,t}}) + r_{i,3} r_{j,3} \text{Var}(\epsilon_{F_{Y,t}}),$$

where, for  $k = i, j$ ,

$$r_{k,1} = \omega_{X,k}\rho_X\beta_X + (1 - \omega_{X,k})\rho_Y\beta_Y,$$

$$r_{k,2} = \omega_{X,k}\rho_X,$$

$$r_{k,3} = (1 - \omega_{X,k})\rho_Y.$$

Clearly,  $Cov(B_{i,t}, B_{j,t})$  depends on both  $\omega_{X,i}$  and  $\omega_{X,j}$ . Next, the effect of changes in  $\omega_{X,i}$  on the covariance is obtained as follows:

$$\begin{aligned} \frac{\partial Cov(B_{i,t}, B_{j,t})}{\partial \omega_{X,i}} &= (\rho_X\beta_X - \rho_Y\beta_Y)\{\omega_{X,j}\rho_X\beta_X + (1 - \omega_{X,j})\rho_Y\beta_Y\}Var(F_t) \\ &+ \rho_X^2\omega_{X,j}Var(\epsilon_{F_{X,t}}) - \rho_Y^2(1 - \omega_{X,j})Var(\epsilon_{F_{Y,t}}) \geq 0 \end{aligned}$$

The first order derivative shows that the sign of the derivative is not conclusive, and depends on the other Bank  $j$ 's weight on market-related activities,  $\omega_{X,j}$ . To analyze the relationship between the effect of a change in Bank  $i$ 's weight  $\omega_{X,i}$  on the covariance and bank  $j$ 's weight  $\omega_{X,j}$ , we calculate a cross partial derivative with respect to  $\omega_{X,i}$  and  $\omega_{X,j}$ ,  $\frac{\partial^2 Cov(B_{i,t}, B_{j,t})}{\partial \omega_{X,i}\partial \omega_{X,j}}$  is given by:

$$\begin{aligned} \frac{\partial^2 Cov(B_{i,t}, B_{j,t})}{\partial \omega_{X,i}\partial \omega_{X,j}} & \\ &= (\rho_X\beta_X - \rho_Y\beta_Y + \rho_Y^2\beta_Y^2)^2Var(F_t) + \rho_X^2Var(\epsilon_{F_{X,t}}) + \rho_Y^2Var(\epsilon_{F_{Y,t}}) > 0 \end{aligned} \quad (4)$$

As shown in equation (4) above, the sign of the cross partial derivative is always positive, which indicates that whether a bank's behavior leads to an increase in covariance or not depends on the behavior of other banks. Specifically, the marginal effect of Bank  $i$ 's weight on market-related activity  $\omega_{X,i}$  on the covariance increases with an increase in Bank  $j$ 's weight,  $\omega_{X,j}$ . According to equation (4), when Bank  $j$ 's weight on market-related activity is large, an increase in Bank  $i$ 's weight on market-related activity increases comovement to a large extent. Conversely, the equation suggests that when Bank  $j$ 's weight on market-related activity is small, an

increase in Bank  $i$ 's market-related activity can lead to a smaller covariance. In this case, the increase in Bank  $i$ 's weight on  $X$  increases the compositional difference between the two banks' portfolios, which leads to diversification in the financial system as a whole.

## 4.2 Empirical exercise

### *Estimation Model*

Given the predictions from the simple model, we incorporate the following variables representing the behavior of other banks.

$$\overline{StoA}_{i,t} \equiv \frac{\sum_{j \neq i} StoA_{j,t}}{n}$$

$$\overline{LtoA}_{i,t} \equiv \frac{\sum_{j \neq i} LtoA_{j,t}}{n}$$

$$\overline{NtoI}_{i,t} \equiv \frac{\sum_{j \neq i} NtoI_{j,t}}{n}$$

As shown above, each variable is defined as the simple average of the respective ratios for all sample banks except for Bank  $i$ . The average values represent the overall portfolio composition or revenue source of other banks for a given bank. With these variables, we estimate the determinants of systemic risk coefficient  $\delta_{\lambda,t}^i$ , which represents comovement between banks:

$$\begin{aligned} \delta_{\lambda,t}^i = & \gamma_1 + \gamma_2 \log(asset)_{i,t-1} + \gamma_3 NtoI_{i,t-1} + \gamma_4 NtoI_{i,t-1} \times \overline{NtoI}_{i,t-1} \\ & + \gamma_5 StoA_{i,t-1} + \gamma_6 StoA_{i,t-1} \times \overline{StoA}_{i,t-1} + \gamma_7 LtoA_{i,t-1} \\ & + \gamma_8 LtoA_{i,t-1} \times \overline{LtoA}_{i,t-1} + \gamma X_{t-1} + Bank_i + \epsilon_{it} . \end{aligned} \quad (5)$$

In this estimation, the marginal effects of  $NtoI_{i,t-1}$ ,  $StoA_{i,t-1}$  and  $LtoA_{i,t-1}$  on the systemic risk coefficient depend on the variables representing the aggregate behavior of banks, namely,  $\overline{NtoI}_{i,t-1}$ ,  $\overline{StoA}_{i,t-1}$  and  $\overline{LtoA}_{i,t-1}$ , respectively:

$$\frac{\partial \delta_{\lambda,t}^i}{\partial NtoI_{i,t-1}} = \gamma_3 + \gamma_4 \overline{NtoI}_{i,t-1} , \quad (6)$$



$$\frac{\partial \delta_{\lambda,t}^i}{\partial StoA_{i,t-1}} = \gamma_5 + \gamma_6 \overline{StoA_{i,t-1}} \quad , \quad (7)$$

$$\frac{\partial \delta_{\lambda,t}^i}{\partial LtoA_{i,t-1}} = \gamma_7 + \gamma_8 \overline{LtoA_{i,t-1}} \quad . \quad (8)$$

Recall from equation (4) that whether a bank's behavior leads to an increase in comovement or not depends on the aggregate behavior of other banks. Consistent with that prediction, equations (6) to (8) show that the marginal effect of each variable on the systemic risk coefficient depends on the average level of the variable in the financial system as a whole. Since this level is state dependent, the marginal effect of a change in an individual banks' variable on the systemic risk coefficient is state dependent as well.

### ***Estimation results***

The first column of Table 5 presents the estimation results for equation (5), which includes interaction terms. The second column shows the estimation results when the loans-to-assets ratio is excluded from the explanatory variables. As shown in both columns, goodness-of-fit improves compared with Table 2. As for the marginal effects of the non-interest income ratio and securities-to-assets ratio, coefficients  $\gamma_3$  and  $\gamma_5$  in equations (6) and (7) respectively are significantly negative, while  $\gamma_4$  and  $\gamma_6$  are significantly positive. The results are consistent with the prediction of equation (4) from subsection 4.1. According to the estimation results, the marginal effects of the securities-to-assets ratio  $StoA_{i,t-1}$  and non-interest income-to-interest income ratio  $NtoI_{i,t-1}$  on systemic risk coefficient  $\delta_{\lambda,t}^i$  increase as the overall ratio of securities to assets  $\overline{StoA_{i,t-1}}$  and non-interest income-to-interest income ratio  $\overline{NtoI_{i,t-1}}$  in regional banks rise. When the aggregate securities holdings of banks on the whole are small, the marginal effect of an increase in securities holdings in any given bank on systemic risk will be negative. This is because an increase in securities holdings in any given bank will increase the heterogeneity of bank portfolios and thereby decrease systemic risk. On the other hand, when the aggregate securities holdings of banks on the whole are large, the marginal effect of an increase in securities holdings in any given bank on systemic risk will be positive. In sum, the more banks increase the

securities-to-assets ratio in aggregate, the larger the marginal effect of increasing the securities-to-assets ratio at a given bank will be on systemic risk. A similar argument applies to the non-interest income-to-interest income ratio. Such effects are observed because the variables  $NtoI_{i,t-1}$  and  $StoA_{i,t-1}$  are closely related to market risks, which are common to all banks.

By contrast, the coefficients on the terms related to the loan-to-assets ratio,  $LtoA_{i,t-1}$  and  $LtoA_{i,t-1} \times \overline{LtoA_{i,t-1}}$  in equation (8), are found to be not significant. Contrary to  $NtoI_{i,t-1}$  and  $StoA_{i,t-1}$ , which are related to market risks common to all banks, loans extended by regional banks are exposed more to idiosyncratic risk factors, such as region-specific factors. Therefore, the loan-to-assets ratio is not found to be a significant driver of the systemic risk coefficient  $\delta_{\lambda,t}^i$ .

Figures 4 and 5 plot the marginal effects on the systemic risk coefficient of the securities-to-assets ratio and non-interest income-to-interest income ratio respectively, as indicated by equation (6) and (7). It can be observed that the marginal effect of the securities-to-assets ratio and the non-interest income-to-interest income ratio are increasing over time as banks are increasing their securities holdings and dependence on non-interest income.

In particular, Figure 4 shows that the marginal effect of the securities-to-assets ratio  $StoA_{i,t-1}$  on the systemic risk coefficient  $\delta_{\lambda,t}^i$  has turned positively significant in the recent period. This is because the aggregate ratio of securities to assets held by regional banks  $\overline{StoA_{t-1}}$  increases over time. As shown in Figure 5, the marginal effect of non-interest income-to-interest income  $NtoI_{i,t-1}$  on the systemic risk coefficient  $\delta_{\lambda,t}^i$  is also noteworthy. Until the early-2000s, the marginal effect was negatively significant. This implies that when a given regional bank increased its reliance on non-interest income in that time period, its comovement with other regional banks fell. However, from around 2010 onward, there was a distinct upward shift in the marginal effect, and it became significantly positive in the most recent period. This implies that in the later period, an increase in reliance on non-interest income at a given regional bank causes its comovement with other regional banks to rise, since other regional banks are already

highly reliant on non-interest income, rendering their revenue source more exposed to a common factor.

As stated above, we obtain empirical findings that are consistent with the predictions of the model presented earlier in this section. That is, systemic risk could increase when a bank's exposure to common factors, such as market risk, increases. In particular, systemic risk could increase to a greater extent when other banks' exposure to the same common factors is already high.

## **5. Conclusion**

As banks hold a larger share of securities and shift toward non-traditional sources of income, namely non-interest income, standalone bank risk may be lowered through portfolio diversification, although systemic risk may increase through reduced diversity among banks. In this paper, we ask if there is evidence that individual banks pursue diversification of their own portfolios and revenue sources, producing at the same time the unintended side effect of increased exposure to common risks.

By examining the relationship between a measure of systemic risk, CoVaR, and the income sources and portfolio compositions for a set of Japanese regional banks, we find that increased exposure of bank portfolios to market risks and greater reliance on non-traditional income sources associated with market activities raise systemic risk, even though they reduce standalone bank risk. Further, we find that the marginal effect of an increase in a given banks' market-related components on systemic risk is larger when the share of the corresponding components is already high among other banks. Although regional banks are individually non-systemic, they have the potential to behave "systemic as a herd", whereby common shocks generate losses across distinct financial institutions with similar portfolio holdings, and cause these financial institutions to respond in a similar manner. It should be noted that the adverse effect of diversification in our paper does not originate from contagion through interbank linkages – whether or not a bank fails does not depend on direct exposure to other banks.

Rather, the common shock is transmitted through comovements in asset holdings and income sources.

Our paper is an empirical complement to theory on the potential costs and limits of diversification (Wagner, 2010). It suggests that contrary to common belief, it is not desirable for banks to pursue diversification to the maximum extent possible, since “systemic as a herd” behavior could increase the vulnerability of the financial system.

From a macro-prudential perspective, it is essential to address the externality associated with greater vulnerability to joint failure stemming from “systemic as a herd” behavior. For example, Goodhart and Wagner (2012) suggest introducing a surcharge on existing capital requirements depending on how correlated their overall activities are with the rest of the financial system. Alternatively, current risk weights could be redefined to penalize activities that are more exposed to common risk factors, while keeping average capital requirements unchanged. Such policies may render banks that have more potential for “systemic as a herd” behavior less risky, since they will be made to hold more capital.

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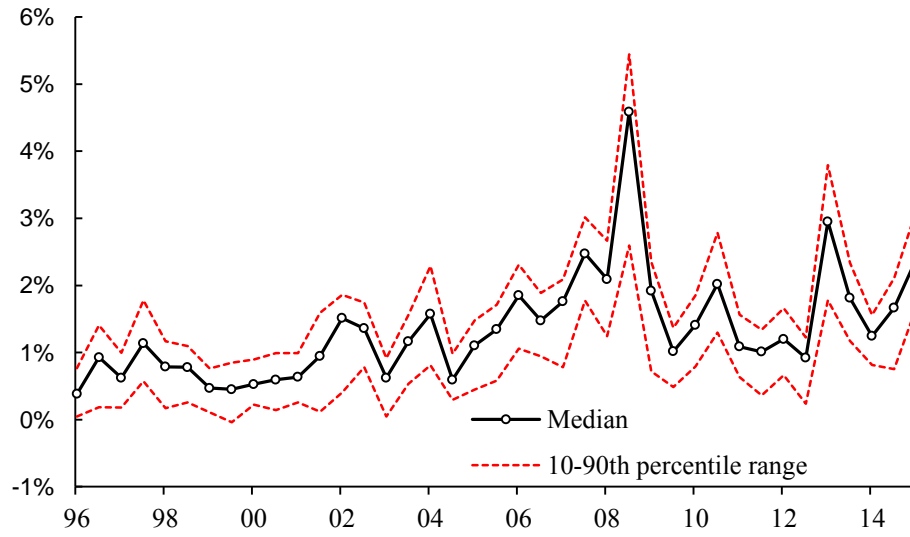
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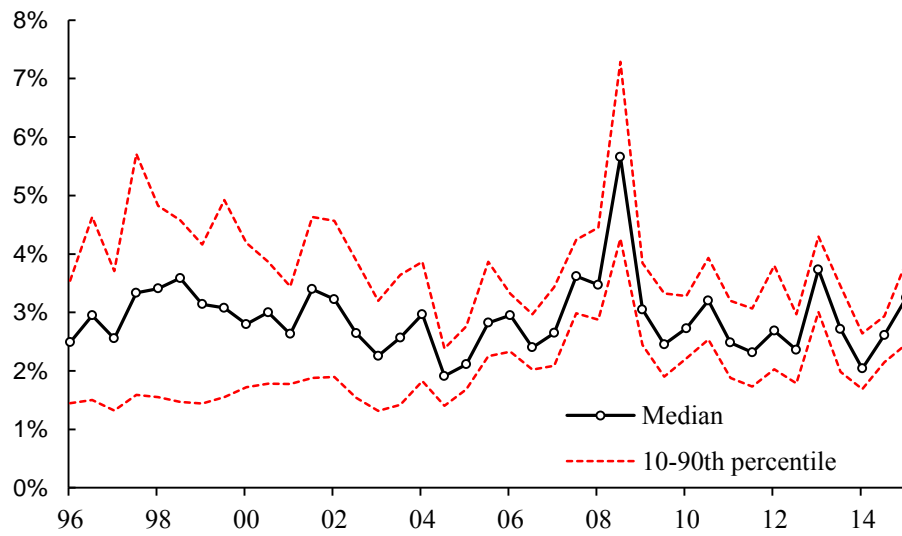
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Figure 1:  $\Delta\text{CoVaR}$



Note: The solid line shows the median  $\Delta\text{CoVaR}$  (5<sup>th</sup> percentile) among our sample of regional banks. The dash lines show the 10<sup>th</sup>-90<sup>th</sup> percentile range of  $\Delta\text{CoVaR}$  among regional banks, representing the cross-sectional variation of  $\Delta\text{CoVaR}$  at each point in time. Semiannual data is presented (fiscal year basis).

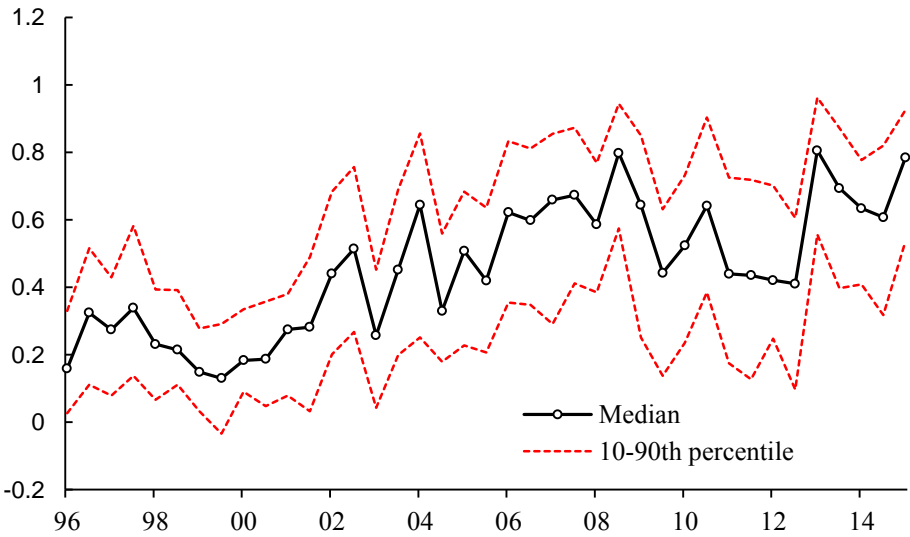
Figure 2: Decomposition of  $\Delta\text{CoVaR} - \Delta\text{VaR}$  component



Note: The solid line shows the median  $\Delta\text{VaR}$  (individual bank risk, 5<sup>th</sup> percentile) among our sample of regional banks. The dash lines show the 10<sup>th</sup>-90<sup>th</sup> percentile range of  $\Delta\text{VaR}$  among regional banks, representing the cross-sectional variation of  $\Delta\text{VaR}$  at each point in time. Semiannual data is presented (fiscal year basis).



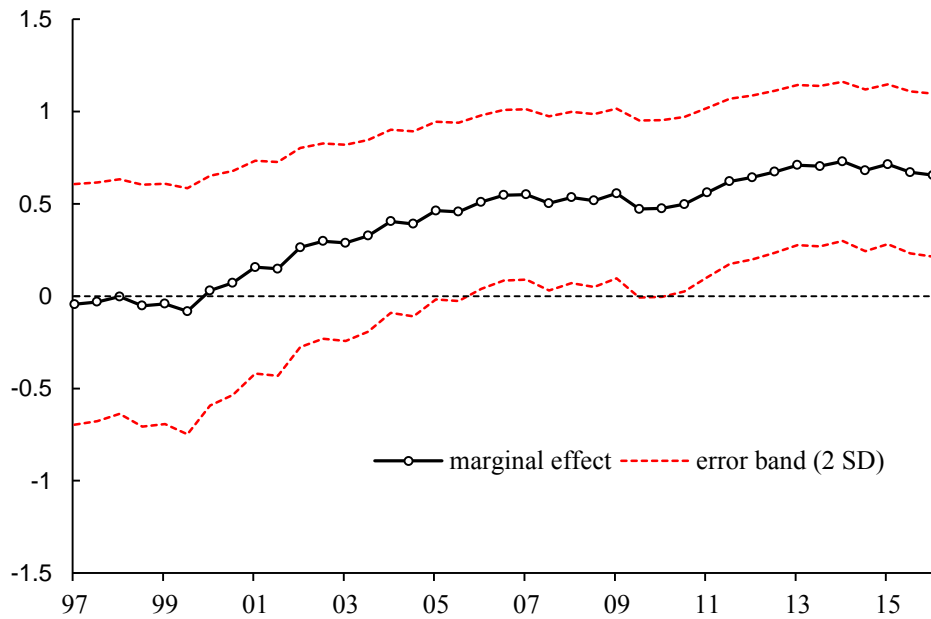
Figure 3: Decomposition of  $\Delta\text{CoVaR}$  - systemic risk coefficient  $\delta$



Note: The solid line shows the median systemic risk coefficient among our sample of regional banks. The dash lines show the 10<sup>th</sup>-90<sup>th</sup> percentile range of the systemic risk coefficient among regional banks, representing the cross-sectional variation of the systemic risk coefficient at each point in time. Semiannual data is presented (fiscal year basis).

Figure 4: Marginal effect of securities-to-assets ratio on systemic risk coefficient

$$\frac{\partial \delta_{\lambda,t}^i}{\partial StoA_{i,t-1}} = \gamma_5 + \gamma_6 \overline{StoA}_{t-1},$$

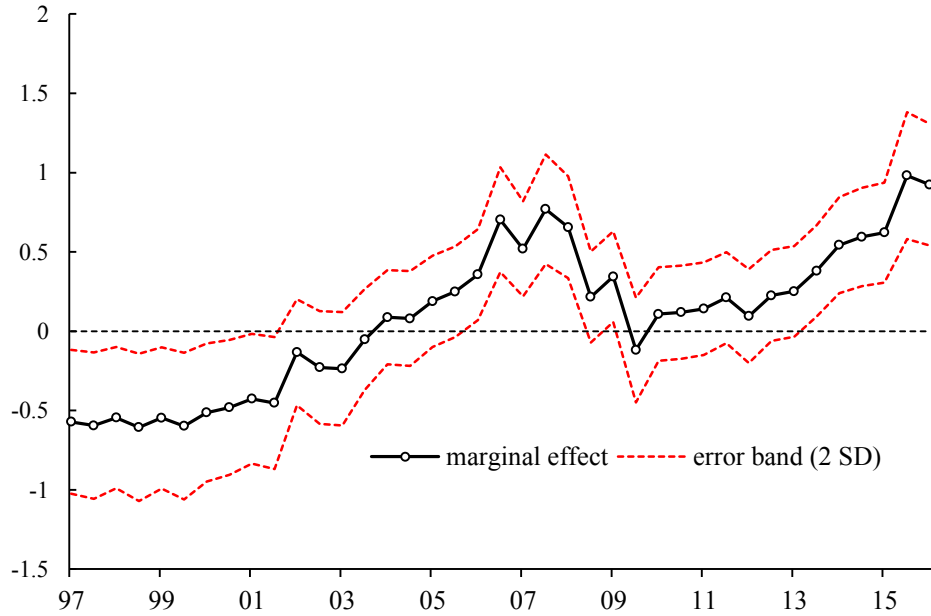


Note: Semiannual data is presented (fiscal year basis).  $\overline{StoA}_{t-1}$  is defined as  $\frac{\sum_{j=1}^n StoA_{j,t-1}}{n}$ .

The estimated coefficients in first column of table 5 are used for the calculation.

Figure 5: Marginal effect of non-interest income-to-interest income ratio on systemic risk coefficient

$$\frac{\partial \delta_{\lambda,t}^i}{\partial Ntoi_{i,t-1}} = \gamma_3 + \gamma_4 \overline{Ntoi}_{t-1},$$



Note: Semiannual data is presented (fiscal year basis).  $\overline{Ntoi}_{t-1}$  is defined as  $\frac{\sum_{j=1}^n Ntoi_{j,t-1}}{n}$ .

The estimated coefficients in first column of table 5 are used for the calculation.

Table 1: Summary statistics

1.1 Bank-level variables

	mean	median	S.D.	min.	max
log(asset)	14.696	14.693	0.747	12.667	16.537
NtoI	0.105	0.101	0.067	-0.284	0.783
LtoA	0.658	0.66	0.067	0.475	0.829
StoA	0.244	0.238	0.072	0.046	0.460

1.2 Macro state variables

	mean	median	S.D.	min.	max
3 month JGB (%)	0.17	0.10	0.19	-0.06	0.61
Term spread (% pt)	1.20	1.21	0.51	0.25	2.79
TED spread (% pt)	0.13	0.10	0.10	0.04	0.45
TOPIX return (%)	0.05	0.10	2.61	-5.18	5.86
TOPIX real estate excess return (%)	0.90	0.73	2.40	-4.61	6.14
TOPIX volatility (%)	20.40	19.64	6.36	10.81	48.86

Note: log(asset) is the log-scaled total asset size; NtoI is the non-interest income-to-interest income ratio; LtoA is the loans-to-assets ratio and StoA is the securities-to-assets ratio. The term spread is computed as the difference between the yield on 10-year JGBs and 3-month JGBs. The “TED spread” is computed as the difference between the 3-month Yen LIBOR and the 3-month JGB yield. The TOPIX real estate excess return is computed as the return of the TOPIX real estate subsector less the return of the TOPIX financial subsector. TOPIX volatility refers to 30-day historical volatility, calculated from daily equity price data. All data are at semiannual frequency. Data for the macro state variables are from Bloomberg.

Table 2: Regression results -  $\Delta\text{CoVaR}$ ,  $\Delta\text{VaR}$  and systemic risk coefficient

	$\Delta\text{CoVaR}$				$\Delta\text{VaR}$				systemic risk coefficient: $\delta$			
<i>NtoI</i>	0.024	***	0.024	***	-0.016	***	-0.016	***	0.821	***	0.812	***
	[0.004]		[0.004]		[0.005]		[0.005]		[0.155]		[0.157]	
<i>LtoA</i>	0.019	***			-0.007				0.857	***		
	[0.005]				[0.007]				[0.255]			
<i>StoA</i>	0.041	***	0.031	**	-0.014	**	-0.01	**	1.561	***	1.091	**
	[0.004]		[0.003]		[0.006]		[0.005]		[0.206]		[0.129]	
$\log(\text{asset})$	0.019	***	0.018	***	-0.001		-0.001		0.676	***	0.627	***
	[0.001]		[0.001]		[0.002]		[0.002]		[0.050]		[0.051]	
TOPIX volatility	0.077	***	0.077	***	0.088	***	0.088	***	0.394	***	0.396	***
	[0.004]		[0.004]		[0.005]		[0.005]		[0.122]		[0.123]	
TED spread	0.008	***	0.009	***	0.008	***	0.008	***	0.21	**	0.248	***
	[0.002]		[0.002]		[0.003]		[0.003]		[0.082]		[0.080]	
TOPIX real estate excess return	-0.017	***	-0.016	***	-0.016	**	-0.017	**	-0.15		-0.111	
	[0.005]		[0.005]		[0.007]		[0.007]		[0.279]		[0.277]	
TOPIX return	-0.029	***	-0.029	***	-0.01		-0.01		-1.121	***	-1.117	***
	[0.006]		[0.006]		[0.008]		[0.008]		[0.273]		[0.272]	
3-month JGB change	0.008	***	0.008	***	0.005	**	0.005	**	0.097		0.101	
	[0.001]		[0.001]		[0.002]		[0.002]		[0.084]		[0.084]	
Term spread	0.003	***	0.003	***	0.002	*	0.002	*	0.111	***	0.124	***
	[0.001]		[0.001]		[0.001]		[0.001]		[0.039]		[0.038]	
constant	-0.316	***	-0.286	***	0.037		0.027		-11.007	***	-9.596	***
	[0.025]		[0.018]		[0.034]		[0.026]		[0.801]		[0.746]	
Bank fixed effects	yes		yes		yes		yes		yes		yes	
R-squared	0.657		0.655		0.419		0.419		0.289		0.286	
Observations	2242		2242		2242		2242		2242		2242	

Note: \*, \*\* and \*\*\* denote significance at the 10, 5, and 1 percent levels, respectively. Heteroscedasticity-robust standard errors are displayed in parentheses.

Table 3: Comparison of coefficients

	$\Delta\text{CoVaR}$		systemic risk coefficient: $\delta$	
<i>StoA – LtoA</i>	0.0223 ***		0.7035 ***	
	[0.0038]		[0.156]	

Note: \*\*\* denotes significance at the 1 percent level. Heteroscedasticity-robust standard errors are displayed in parentheses.

Table 4: Contribution to change in systemic risk coefficient  $\delta$  and  $\Delta\text{CoVaR}$

		Contribution		
		<i>NtoI</i>	<i>StoA</i>	<i>LtoA</i>
Change in $\delta$	0.248	0.027	0.083	-0.025
Change in $\Delta\text{CoVaR}$	0.00902	0.000791	0.00281	-0.00056

Note: To obtain the change in  $\delta$  and  $\Delta\text{CoVaR}$ , the difference between the fiscal year 2007-2015 averages and the fiscal year 1996-2006 averages are computed. The contributions of *NtoI*, *StoA*, and *LtoA* are calculated based on the change in their sub-sample averages and parameters in first and fifth column of Table 2.

Table 5: Regression results with interaction terms

	systemic risk coefficient: $\delta$	
<i>Ntol</i>	-1.882 ***	-2.234 **
	[0.466]	[0.433]
<i>Ntol</i> $\times$ $\overline{Ntol}$	18.667 ***	20.791 ***
	[3.806]	[3.278]
<i>LtoA</i>	1.699	
	[1.069]	
<i>LtoA</i> $\times$ $\overline{LtoA}$	-1.985	
	[1.506]	
<i>StoA</i>	-1.426 **	-2.702 **
	[0.643]	[0.561]
<i>StoA</i> $\times$ $\overline{StoA}$	7.485 ***	11.249 ***
	[1.946]	[1.796]
$\log(asset)$	0.133	0.107
	[0.082]	[0.075]
TOPIX volatility	0.342 ***	0.349 ***
	[0.117]	[0.118]
TED spread	0.213 **	0.165 **
	[0.097]	[0.079]
TOPIX real estate excess return	0.007	-0.003
	[0.279]	[0.272]
TOPIX return	-1.058 ***	-1.066 ***
	[0.280]	[0.280]
3-month JGB change	-0.101	-0.106
	[0.093]	[0.091]
Term spread	0.079 *	0.07 *
	[0.042]	[0.038]
constant	-1.981	-1.219
	[1.308]	[1.172]
Bank fixed effects	yes	yes
R-squared	0.323	0.323
Observations	2242	2242

Note: \*, \*\* and \*\*\* denote significance at the 10, 5, and 1 percent levels, respectively. Heteroscedasticity-robust standard errors are displayed in parentheses.