Systemic Risk and the Fallacy of Composition: Empirical Evidence from Japanese Regional Banks*

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We examine a sample of Japanese regional banks and explore whether exposure to market risk factors affects systemic risk through banks' portfolio composition or revenue source, using Adrian and Brunnermeier's (2016) CoVaR to proxy for systemic risk. We find that the securities investment and fee- and commission-related activities of Japanese regional banks exert positive and significant effects on systemic risk by generating higher co-movement among banks, even though they reduce standalone bank risk through portfolio diversification. Further, the marginal effect of an increase in common risk factors on systemic risk is larger when other banks are already highly exposed to common risk factors. We interpret the results as suggestive of "fallacy of composition," since the behavior of individual banks could be individually optimal but collectively has an unwelcome systemic effect. Our results have important implications from the macroprudential perspective.

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1. Introduction

In a speech that explores the nexus between the microprudential and macroprudential dimensions of financial stability, Crockett (2000) argues that ensuring the soundness of each and every institution in the financial system is not a sufficient condition for ensuring financial stability. Authorities also need to take into account the effect of the collective behavior of institutions on economic outcomes, since "actions that may seem desirable or reasonable from the perspective of individual institutions may result in unwelcome system outcomes" (Crockett 2000). The authorities could fall prey to a "fallacy of composition" if they focus solely on limiting the likelihood of failure of individual institutions, without considering the endogenous systemic effect that arises from their collective behavior. The desire to guard against unwelcome system outcomes, even as the soundness of each institution is maintained with *microprudential* policy, has been the primary motivation for *macroprudential* policy.

In this paper, we investigate whether the concept of "fallacy of composition" has empirical support. We seek to uncover evidence that attempts by individual institutions to lower standalone bank risk generate collective behavior that has an unwelcome systemwide effect. To do this, we analyze the standalone and systemic risk implications of portfolio and revenue source choices at the individual bank level.

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. DeYoung and Roland (2001) also find that replacing traditional lending activities with fee-based activities is associated with higher revenue volatility. DeYoung and Torna (2013) show that the probability of distressed bank failure declines with pure fee-based nontraditional activities such as securities brokerage and insurance sales, but increases with asset-based nontraditional activities such as venture capital, investment banking, and asset securitization. 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 nonbanking activities.

Previous studies on determinants of systemic risk typically focus on the effect on funding structure, bank size, and leverage, which are often targeted at large banks. Therefore, the determinants of systemic risk are associated with interconnectedness or degree of influence of each bank due to bank size or funding volume. Gai, Haldane, and Kapadia (2011) develop a theoretical network model of interbank lending and show that financial network concentration can amplify the fragility of the financial system. Langfield, Liu, and Ota (2014) analyze the funding and exposure network of interbank transactions and argue that funding provided by investment banks may trigger widespread liquidity shortages. López-Espinosa et al. (2013) report that unstable funding is the main factor driving systemic risk. Also, López-Espinosa et al. (2012) find that short-term wholesale funding is a key determinant in triggering systemic risk episodes. Laeven, Ratnovski, and Tong (2016) find that systemic risk grows with bank size and is inversely related to bank capital adequacy.

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 composition or revenue structure, these common exposures increase the risk that many banks could fail together and lead to a systemwide problem. Theoretical studies have explored 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.

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 fee and commission 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. We use a recently developed systemic risk measure, Adrian and Brunnermeier's (2016) CoVaR, to proxy for systemic risk. For the "fallacy of composition" to apply to Japanese regional banks, a general reduction in standalone bank risk should be accompanied by the higher correlation between regional banks, such that systemic risk increases.

The novelty of our paper is twofold. First, while some theoretical papers show that "fallacy of composition" effects can be present in a financial system (Wagner 2010; Beale et al. 2011), empirical evidence on such an effect is difficult to come by. Our paper seeks to provide empirical evidence of "fallacy of composition" effects in a financial system, shedding light on the effects of banks' portfolio composition and revenue source choices, on both standalone risks and systemwide risks. The above point distinguishes our study from existing research. Our paper relates to Brunnermeier, Dong, and Palia (2012). They analyze the effects of nontraditional activities on systemic risk in a sample of U.S. banks and claim that nontraditional activities such as trading activities increase systemic risk, but do not elucidate their effects on standalone risks. On the other hand, our paper argues that securities investment reduces standalone bank risk but increases systemic risk. Importantly, we claim that the action that seems desirable from the perspective of an individual bank may have an unwelcome systemic effect. We attribute such a "fallacy of composition" effect to increased co-movement between banks, generated from securities holdings and reliance on fee and commission income.

Second, unlike previous papers[1] which have typically employed data on large banks and focused on interconnectedness (i.e., interbank exposures or funding structures) as a source of systemic risk, our paper employs data on smaller banks and explores how exposures to common risks (i.e., investment in securities and reliance on fee and commission income) can play a role. Specifically, we study a sample of Japanese regional banks. Although Japanese regional banks account for about 40 percent of loan volumes in the Japanese financial system in aggregate, they are neither individually systemic nor strongly interconnected. Japanese regional banks have exhibited a tendency to increase securities investment and their reliance on fees and commission income over time, mainly due to decreased loan demand in their operating areas and declining profitability of traditional banking activities. Such behavior, intended to diversify portfolio and revenue sources, increases the exposure of regional banks to common risk factors, potentially increasing the vulnerability of the banking system to common risk factors.[2]

Our main empirical findings are as follows. First, we find that increased securities holdings or dependence on fee and commission income increases our measure of systemic risk (CoVaR).[3] 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 fee and commission 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 fee and commission income on systemic risk depend on other banks' portfolio composition or revenue structure. Specifically, the more banks

[1]See, for example, López-Espinosa et al. (2012, 2013), Langfield, Liu, and Ota (2014), and Laeven, Ratnovski, and Tong (2016).

[2]Although Cai, Saunders, and Stefeen (2014) report that syndicated loan portfolios also increase exposure to common risks, such loans do not account for a large portion of the regional banks' loan portfolio.

[3]As shown in section 3.4, we obtain similar results with an alternative measure of systemic risk, the marginal expected shortfall (MES).

increase their reliance on fee and commission income and securities holdings in aggregate, the more increase in these factors at a given bank will exert a marginal effect on systemic risk. This implies that when banks are exposed to common risk, systemic risk could increase to a greater extent than in 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 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 bank's idiosyncratic risk is typically measured by its standalone VaR, Adrian and Brunnermeier (2016) emphasize the importance of an individual bank's 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 macroprudential studies (e.g., Brunnermeier, Dong, and Palia 2012; López-Espinosa et al. 2012; Zhang et al. 2015; Laeven, Ratnovski, and Tong 2016).

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 λ percent 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 λ percent bottom level. Equivalently, $CoVaR_{\lambda,t}^{system|c(X_t^i)}$ is defined by the λ percent 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 λ percent 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 percent 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 co-movement 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 percent 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:

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

where M_t denotes a state variable. In this expression, the existence of risk spillover is captured by estimating parameter δ_λ^i: for nonzero 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 (Tokyo Stock Price Index) 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 λ percent quantile of CoVaR can be computed from the λ percent quantile of bank i VaR. ΔCoVaR is then derived according to the equation below, by taking the difference between VaR for bank i at the λ percent quantile and VaR for the same bank in its median state.

$$\Delta CoVaR^i_{\lambda,t} = \delta^i_{\lambda,t} \underbrace{(VaR_{i,t}(\lambda) - VaR_{i,t}(50\%))}_{=\Delta VaR_{i,t}(\lambda)}$$

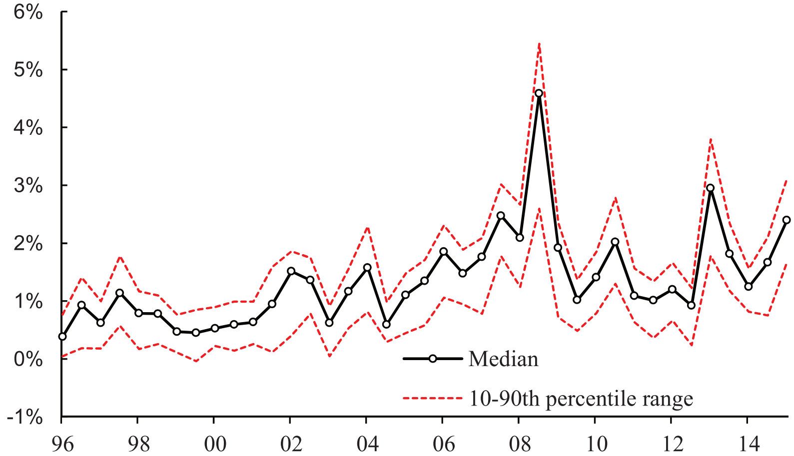
We then calculated CoVaR for a sample of Japanese regional banks. Regarding bank coverage, we include 59 regional banks whose equity prices are available from 1996 or earlier (see table A.1 in appendix A).[4] We focus solely on regional banks in this paper, since our aim is to understand whether and how the common exposure of regional banks could have an unwelcome systemic effect, thereby shedding light on a potential "fallacy of composition" problem. We excluded larger banks, such as global systemically important banks (G-SIBs). Since those banks are large and highly interconnected, they are likely to be individually systemically important, even without taking common exposures into consideration.

Figure 1 displays the estimated 5 percent quantile ΔCoVaR of Japanese regional banks in the sample period April 1996 to March 2016.[5] A clear uptrend can be observed since the mid-2000s. After peaking in 2008, ΔCoVaR declined, but it did not fall back to the levels observed pre-2000. To get a better idea of the drivers of ΔCoVaR, following Benoit et al. (2017), we decomposed ΔCoVaR into its constituent components—ΔVaR and the systemic risk coefficient δ. Figure 2 shows that ΔVaR—which represents banks' own tail risk (Benoit et al. 2017)—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 co-movement among regional banks has risen markedly.

[4]We excluded banks that have been consolidated or experienced bankruptcy.

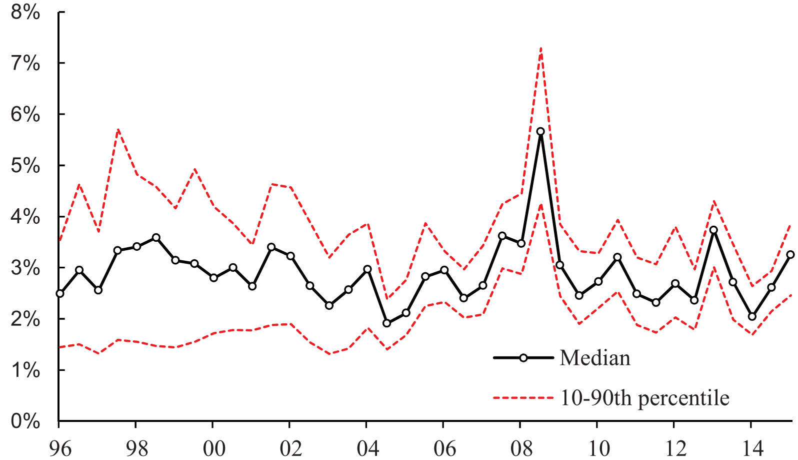
[5]The sample period is determined based on the availability of bank-level data mentioned in section 3. This sample period is sufficiently long in Japan's case, as it includes the late 1990s banking crisis (Hutchison and McDill 1999). Here, we use semiannual data instead of daily data.

Figure 1. ΔCoVaR



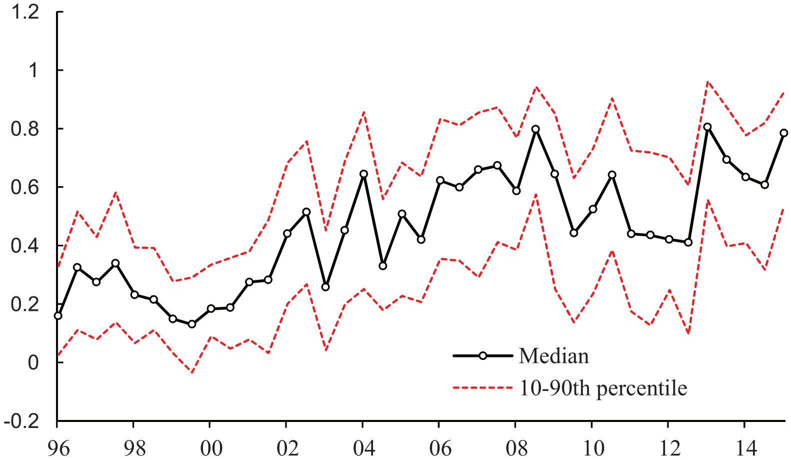
Notes: The solid line shows the median ΔCoVaR (5th percentile) among our sample of regional banks. The dashed lines show the 10th–90th percentile range of ΔCoVaR among regional banks, representing the cross-sectional variation of ΔCoVaR at each point in time. Semiannual data are presented (fiscal year basis).

Figure 2. Decomposition of ΔCoVaR: ΔVaR Component



Notes: The solid line shows the median ΔVaR (individual bank risk, 5th percentile) among our sample of regional banks. The dashed lines show the 10th–90th percentile range of ΔVaR among regional banks, representing the cross-sectional variation of ΔVaR at each point in time. Semiannual data are presented (fiscal year basis).

Figure 3. Decomposition of ΔCoVaR: Systemic Risk Coefficient δ



Notes: The solid line shows the median systemic risk coefficient among our sample of regional banks. The dashed lines show the 10th–90th 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 are presented (fiscal year basis).

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 based on the Japanese Bankers Association's database. For bank-level variables, we employ log-transformed total assets, which captures bank size ($\log(asset)_{i,t}$), securities to assets ($StoA_{i,t}$), loans to assets ($LtoA_{i,t}$), the ratio of fee and commission income to interest income ($FCtoI_{i,t}$), equity to assets ($EtoA_{i,t}$), and deposit to debt ($DtoD_{i,t}$). These variables represent banks' balance sheet and revenue source exposures (see appendix B for data definitions).

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.[6,7] The ratio of fee and commission income to interest income is a proxy for the extent to which a bank is reliant on nontraditional income sources, mainly fees and commission income related to investment trusts, relative to traditional deposit and lending income sources.[8] The equity-to-assets ratio, defined as the ratio of net assets to total assets, measures the (inverse) degree of a bank's leverage. The deposit-to-debt ratio, being the size of bank retail deposits (deposits excluding current deposits and negotiable certificates of deposit) relative to total debt (total liability = total assets – net assets), serves as an indicator of a bank's funding stability.

As for macro state variables, we employ Japanese stock market volatility[9] (30-day historical volatility of the TOPIX index); the Japanese yen "TED spread" (i.e., three-month yen LIBOR less three-month Japanese government bond (JGB) yields); excess return of the real estate sector over the financial sector (using TOPIX subsector returns); TOPIX returns; three-month JGB yields; and the term spread (10-year JGB yields less three-month JGB yields), following Adrian and Brunnermeier (2016). All data are measured as semiannual averages, except for three-month JGB yields and the

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[6]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.

[7]Ideally, we would want to analyze different types of securities separately, to better understand the contribution from different market risk factors (De Young and Torna 2013). Due to data constraints, we use only the total amount of securities as a share of assets as one of the bank-level variables.

[8]On average, fees and commissions related to those items account for more than 70 percent of total fee and commission income. The balance comprises fees on foreign exchange and money transfers.

[9]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.

Table 1. Summary Statistics

	Mean	**Median**	**S.D.**	**Min.**	**Max.**
A. Bank-Level Variables					
Log(asset)	14.696	14.693	0.747	12.667	16.537
Fee and Commission Income to Interest Income (FCtoI)	0.105	0.101	0.067	−0.284	0.783
Loans-to-Assets (LtoA)	0.658	0.660	0.067	0.475	0.829
Securities-to-Assets (StoA)	0.244	0.238	0.072	0.046	0.460
Equity-to-Assets (EtoA)	0.050	0.049	0.011	0.001	0.088
Deposit-to-Debt (DtoD)	0.902	0.904	0.039	0.719	0.979
B. Macro State Variables					
Three-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

Notes: Log(asset) is the log-scaled total asset size; the term spread is computed as the difference between the yield on 10-year JGBs and three-month JGBs. The "TED Spread" is computed as the difference between the three-month yen LIBOR and the three-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.

term spread, where the first difference in semiannual averages is employed. Table 1 presents summary statistics of the data employed.

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 ($\Delta CoVaR^i_{\lambda,t}$) on the following bank-specific variables: log-transformed total asset size ($\log(asset)_{i,t-1}$); equity-to-assets ratio ($EtoA_{i,t-1}$); deposit-to-debt ratio ($DtoD_{i,t-1}$); ratio of fee and commission income to interest income ($FCtoI_{i,t-1}$); ratio of securities holdings to assets ($StoA_{i,t-1}$); loans-to-assets ratio ($LtoA_{i,t-1}$); and a set of macro state variables (X_{t-1}).

$$\begin{aligned}\Delta CoVaR^i_{\lambda,t} = {} & \alpha_1 + \alpha_2 \log(asset)_{i,t-1} + \alpha_3 EtoA_{i,t-1} + \alpha_4 DtoD_{i,t-1} \\ & + \alpha_5 FCtoI_{i,t-1} + \alpha_6 StoA_{i,t-1} + \alpha_7 LtoA_{i,t-1} + \alpha X_{t-1} \\ & + Bank_i + \epsilon_{i,t}, \end{aligned} \tag{1}$$

where $Bank_t$ denotes bank fixed effect.

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

$$\begin{aligned}\Delta VaR_{i,t}(\lambda) = {} & \beta_1 + \beta_2 \log(asset)_{i,t-1} + \beta_3 EtoA_{i,t-1} + \beta_4 DtoD_{i,t-1} \\ & + \beta_5 FCtoI_{i,t-1} + \beta_6 StoA_{i,t-1} + \beta_7 LtoA_{i,t-1} + \beta X_{t-1} \\ & + Bank_i + \epsilon_{i,t}, \end{aligned} \tag{2}$$

$$\begin{aligned}\delta^i_{\lambda,t} = {} & \gamma_1 + \gamma_2 \log(asset)_{i,t-1} + \gamma_3 EtoA_{i,t-1} + \gamma_4 DtoD_{i,t-1} \\ & + \gamma_5 FCtoI_{i,t-1} + \gamma_6 StoA_{i,t-1} + \gamma_7 LtoA_{i,t-1} + \gamma X_{t-1} \\ & + Bank_i + \epsilon_{i,t}. \end{aligned} \tag{3}$$

3.3 Estimation Results

The first column of table 2 reports the benchmark estimation results with $\Delta CoVaR^{i}_{\lambda,t}$ 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 fee and commission income to interest income as a revenue source exhibits significantly positive explanatory effects, suggesting that higher dependence on fee and commission income leads to an increase in systemic risk. A possible reason is that fee and commission 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 effect 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 columns of table 2 show the estimation results for $\Delta VaR_{i,t}(\lambda)$ in equation (2). The ratio of fee and commission income to interest income 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 columns of table 2 show the estimation results for the systemic risk coefficient $\delta^{i}_{\lambda,t}$ in equation (3). We find that the coefficients on the ratio of fee and commission income to interest

Table 2. Regression Results: ΔCoVaR, ΔVaR, and Systemic Risk Coefficient

	ΔCoVaR		**ΔVaR**		**Systemic Risk Coefficient: δ**	
FCtoI	0.021***	0.021***	−0.011***	−0.011***	0.690***	0.681***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.146)	(0.147)
LtoA	0.016***		−0.008		0.736***	
	(0.005)		(0.007)		(0.256)	
StoA	0.039***	0.030***	−0.015**	−0.010**	1.447***	1.039**
	(0.004)	(0.003)	(0.006)	(0.005)	(0.203)	(0.125)
EtoA	0.096***	0.098***	−0.141***	−0.142***	4.540***	4.643**
	(0.017)	(0.017)	(0.037)	(0.037)	(0.754)	(0.763)
DtoD	0.005	0.007	0.027***	0.026***	0.227	0.327
	(0.005)	(0.005)	(0.009)	(0.009)	(0.291)	(0.286)
Log(*asset*)	0.017***	0.017***	0.003	0.003	0.610***	0.572***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.057)	(0.058)
TOPIX Volatility	0.076***	0.076***	0.089***	0.089***	0.332***	0.330***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.122)	(0.122)
TED Spread	0.009***	0.010***	0.007***	0.007***	0.252***	0.286***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.081)	(0.078)
TOPIX Real Estate Excess Return	−0.019***	−0.018***	−0.016**	−0.016**	−0.214	−0.186
	(0.005)	(0.005)	(0.007)	(0.007)	(0.277)	(0.276)
TOPIX Return	−0.024***	−0.024***	−0.015*	−0.016*	−0.897***	−0.885***
	(0.006)	(0.006)	(0.008)	(0.008)	(0.270)	(0.269)
Three-Month JGB Change	0.006***	0.006***	0.007***	0.007***	0.022	0.023
	(0.001)	(0.001)	(0.002)	(0.002)	(0.084)	(0.084)
Term Spread	0.002***	0.002***	0.002*	0.002*	0.089***	0.098***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.039)	(0.038)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.662	0.660	0.427	0.427	0.298	0.296
Observations	2,242	2,242	2,242	2,242	2,242	2,242

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

Table 3. Comparison of Coefficients

	ΔCoVaR	**Systemic Risk Coefficient: δ**
StoA – LtoA	0.0225*** (0.0037)	0.711*** (0.155)

Notes: *** denotes significance at the 1 percent level. Heteroskedasticity-robust standard errors are displayed in parentheses.

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 $\Delta CoVaR^i_{\lambda,t}$, $\Delta VaR_{i,t}(\lambda)$ and the systemic risk coefficient $\delta^i_{\lambda,t}$ suggest that the determination of systemic risks depends crucially on portfolio composition and revenue structure. Greater reliance on fee and commission income or a higher proportion of market securities in a given bank's asset base strengthens co-movement between banks. The strengthened co-movement 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 $\delta^i_{\lambda,t}$ and $\Delta CoVaR^i_{\lambda,t}$, we compute the contributions that each of the variables make to the increase in the systemic risk coefficient $\delta^i_{\lambda,t}$ and $\Delta CoVaR^i_{\lambda,t}$ between the fiscal 1996–2006 subperiod average and the fiscal 2007–15 subperiod average. The results, shown in table 4, indicate that changes in $StoA_{i,t-1}$ and $FCtoI_{i,t-1}$ from the first subperiod to the second account for approximately 40 percent of the increase of the systemic risk coefficient and 30 percent of the increase of $\Delta CoVaR^i_{\lambda,t}$, respectively.[10] While the two variables are not the dominant factors behind the increase in the systemic risk coefficient $\delta^i_{\lambda,t}$ and $\Delta CoVaR^i_{\lambda,t}$, they account for a substantial portion of the increase.

[10] 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 30 percent of the total increase in the systemic risk coefficient and more than 25 percent of $\Delta CoVaR^i_{\lambda,t}$, respectively.

Table 4. Contribution to Change in Systemic Risk Coefficient δ and ΔCoVaR

		Contribution		
		NtoI	***StoA***	***LtoA***
Change in δ	0.248	0.023	0.077	−0.022
Change in ΔCoVaR	0.00902	0.000704	0.00206	−0.00048

Notes: To obtain the change in δ and ΔCoVaR, the difference between the fiscal year 2007–15 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 subsample averages and parameters in the first and fifth columns of table 2.

Our results have some interesting implications. While an increase in securities holdings or the fee and commission 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 nontraditional 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 unintended increase in the level of systemic risk. Our results could therefore be capturing a "fallacy of composition" effect in which lower risk for individual banks translates into higher (not lower) risk for the financial system.[11] These results are consistent with Wagner (2010), who 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

[11] Our results do not preclude the possibility that individual banks may be incentivized to take on correlated risks in the presence of moral hazard (Acharya and Yorulmazer 2007; Farhi and Tirole 2012). When a large number of banks fail due to correlated risk-taking behavior, regulators may find it ex post optimal to bail out failed banks. If financial market participants perceive an increased probability of bailout in the event of future bank distress, the measured risk of individual banks as observed in financial markets can decrease. Hett and Schmidt (2013) reported that market discipline (i.e., the extent to which firm-specific risk characteristics are reflected in market prices) eroded in the United States during the 2008 financial crisis, especially for investment banks and large financial institutions.

risk should be assessed more stringently from the macroprudential perspective, because such activities can raise systemic risk, which entails a negative externality.

3.4 Alternative Systemic Risk Measure

The earlier part of this paper employs CoVaR and its components to analyze the determinants of systemic risk. Although CoVaR is a widely employed measure of systemic risk, there is a debate on whether CoVaR is an adequate systemic risk measure (Zhang et al. 2015; Danielsson et al. 2016). To ascertain the robustness of our results, we run a separate set of regressions, substituting CoVaR for an alternative systemic risk measure, namely, marginal expected shortfall (MES) developed by Acharya et al. (2017). MES gauges the sensitivity of returns of individual financial institutions to an extreme event affecting the entire market, and can be expressed as follows:

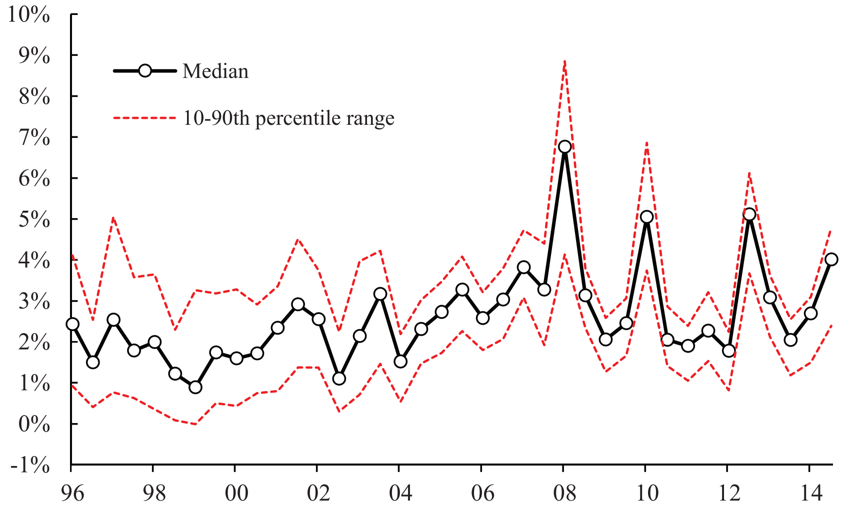
$$MES^{i}_{\lambda,t} = E(-X_{i,t}|X^{system}_{t} \leq VaR^{System}_{\lambda,t}).$$

In the above, MES captures individual bank i's expected losses when the return of the financial system is less than or equal to λ percent quantile of its VaR. Both CoVaR and MES address different aspects of tail dependency, as they uncover different facets of the association between individual-bank and overall returns. If banks become more exposed to common factors, such common factors should be expected to show up in both systemic risk measures.

Figure 4 displays the estimated 5 percent quantile MES of Japanese regional banks in the sample period April 1996 to March 2016. Similar to ΔCoVaR, a clear uptrend can be observed since the mid-2000s. After peaking in 2008, MES generally declined, but it did not fall back to the levels observed pre-2000. To explore the determinants of MES, we perform a regression with bank fixed effects similar to equation (1).

$$\begin{aligned} MES^{i}_{\lambda,t} = {} & \varphi_1 + \varphi_2 \log(asset)_{i,t-1} + \varphi_3 EtoA_{i,t-1} + \varphi_4 DtoD_{i,t-1} \\ & + \varphi_5 FCtoI_{i,t-1} + \varphi_6 StoA_{i,t-1} + \varphi_7 LtoA_{i,t-1} + \varphi X_{t-1} \\ & + Bank_i + \epsilon_{i,t} \end{aligned} \tag{4}$$

Figure 4. Marginal Expected Shortfall (MES)



Notes: The solid line shows the median marginal expected shortfall among our sample of regional banks. The dashed lines show the 10th–90th percentile range of marginal expected shortfall among regional banks, representing the cross-sectional variation of the systemic risk coefficient at each point in time. Semiannual data are presented (fiscal year basis).

The first column of table 5 reports the estimation results with $MES^i_{\lambda,t}$ in equation (4). The second column presents estimation results which exclude the loans-to-assets ratio from the explanatory variables. In both cases, the results are similar to those obtained in the ΔCoVaR case, suggesting that our earlier results are robust to different measures of systemic risk. Both the ratio of fee and commission income to interest income and the securities-to-assets ratio exhibit significantly positive explanatory effects, suggesting that higher dependence on fee and commission income and a higher share of securities holdings leads to an increase in systemic risk as measured by MES. Although the loans-to-assets ratio is significantly positive in the benchmark case, the coefficient of the securities-to-assets ratio is significantly higher than the coefficient on the loans-to-assets ratio (table 6), implying that a portfolio shift from loans to securities tends to increase systemic risk on the whole.

Table 5. Regression Results: MES

	MES	
FCtoI	0.013**	0.017**
	(0.006)	(0.007)
LtoA	0.008	
	(0.011)	
StoA	0.037***	0.034***
	(0.010)	(0.008)
EtoA	0.229***	0.230***
	(0.038)	(0.038)
DtoD	−0.005	−0.004
	(0.012)	(0.012)
Log(*asset*)	0.020***	0.020***
	(0.003)	(0.003)
TOPIX Volatility	0.004	0.004
	(0.006)	(0.006)
TED Spread	0.049***	0.049***
	(0.003)	(0.005)
TOPIX Real Estate Excess Return	0.010	0.010
	(0.011)	(0.011)
TOPIX Return	0.051***	0.051***
	(0.015)	(0.015)
Three-Month JGB Change	0.031***	0.031***
	(0.003)	(0.003)
Term Spread	0.006***	0.006***
	(0.002)	(0.002)
Bank Fixed Effects	Yes	Yes
R-squared	0.304	0.304
Observations	2,242	2,242

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

4. Extended Model

The previous section confirmed that exposure to common risk factors present in securities holdings or fee and commission income raise systemic risk by strengthening the co-movement between banks, not

Table 6. Comparison of Coefficients

	MES
$StoA - LtoA$	0.0291*** (0.00875)

Notes: *** denotes significance at the 1 percent level. Heteroskedasticity-robust standard errors are displayed in parentheses.

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 co-movement between a given bank and other banks in the financial system falls. For example, if a given bank increases its securities holdings or fee and commission income ratio in a situation where the securities-to-assets ratio or the ratio of fee and commission income to interest income 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 fee and commission income could strengthen co-movement 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 Co-movement

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 fee and commission 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 ρ_X and ρ_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's and bank j's weights on market-related activities, respectively. The covariance between $B_{i,t}$ and $B_{j,t}$ is obtained as follows:

$$\begin{aligned} Cov(B_{i,t}, B_{j,t}) = r_{i,1} r_{j,1} Var(F_t) + r_{i,2} r_{j,2} Var(\epsilon_{F_X,t}) \\ + r_{i,3} r_{j,3} Var(\epsilon_{F_Y,t}), \end{aligned}$$

where, for $k = i, j$,

$$\begin{aligned} r_{k,1} &= \omega_{X,k}\rho_X\beta_X + (1-\omega_{X,k})\rho_Y\beta_Y, \\ r_{k,2} &= \omega_{X,k}\rho_X, \\ r_{k,3} &= (1-\omega_{X,k})\rho_Y. \end{aligned}$$

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:

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

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, $\omega_{X,i}$. 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

$$\begin{aligned}\frac{\partial^2 Cov(B_{i,t}, B_{j,t})}{\partial \omega_{X,i}\partial\omega_{X,j}} &= (\rho_X\beta_X - \rho_Y\beta_Y + \rho_Y^2\beta_Y^2)^2\, Var(F_t) \\ &\quad + \rho_X^2\, Var(\epsilon_{F_X,t}) + \rho_Y^2\, Var(\epsilon_{F_Y,t}) > 0. \qquad (5)\end{aligned}$$

As shown in equation (5) 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 (5), when bank j's weight on market-related activity is large, an increase in bank i's weight on market-related activity increases co-movement 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

4.2.1 Estimation Model

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

$$\overline{StoA_{-i,t}} \equiv \frac{\sum_{j\neq i} StoA_{j,t}}{n}$$
$$\overline{LtoA_{-i,t}} \equiv \frac{\sum_{j\neq i} LtoA_{j,t}}{n}$$
$$\overline{FCtoI_{-i,t}} \equiv \frac{\sum_{j\neq i} FCtoI_{j,t}}{n}.$$

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 $\delta^i_{\lambda,t}$, which represents co-movement between banks:

$$\begin{aligned}\delta^i_{\lambda,t} &= \gamma_1 + \gamma_2 \log(asset)_{i,t-1} + \gamma_3 EtoA_{i,t-1} + \gamma_4 DtoD_{i,t-1} \\ &\quad + \gamma_5 FCtoI_{i,t-1} + \gamma_6 FCtoI_{i,t-1} \times \overline{FCtoI_{-i,t-1}} + \gamma_7 StoA_{i,t-1} \\ &\quad + \gamma_8 StoA_{i,t-1} \times \overline{StoA_{-i,t-1}} + \gamma_9 LtoA_{i,t-1} + \gamma_{10} LtoA_{i,t-1} \\ &\quad \times \overline{LtoA_{-i,t-1}} + \gamma X_{t-1} + Bank_i + \varepsilon_{i,t}. \end{aligned} \tag{6}$$

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

$$\frac{\partial \delta^i_{\lambda,t}}{\partial FCtoI_{i,t-1}} = \gamma_5 + \gamma_6 \overline{FCtoI_{-i,t-1}}, \tag{7}$$

$$\frac{\partial \delta^i_{\lambda,t}}{\partial StoA_{i,t-1}} = \gamma_7 + \gamma_8 \overline{StoA_{-i,t-1}}, \tag{8}$$

$$\frac{\partial \delta^i_{\lambda,t}}{\partial LtoA_{i,t-1}} = \gamma_9 + \gamma_{10} \overline{LtoA_{-i,t-1}}. \tag{9}$$

Recall from equation (5) that whether a bank's behavior leads to an increase in co-movement or not depends on the aggregate behavior of other banks. Consistent with that prediction, equations (7)–(9) 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 bank's variable on the systemic risk coefficient is state dependent as well.

4.2.2 Estimation Results

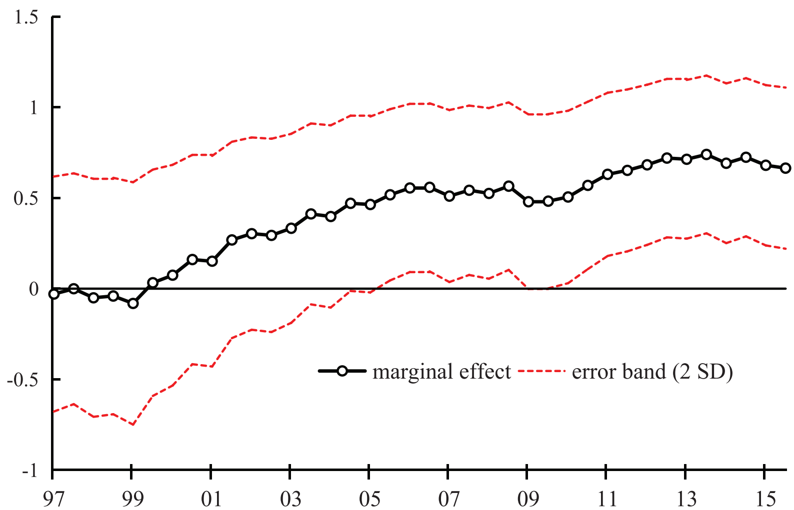
The first column of table 7 presents the estimation results for equation (6), which includes interaction terms. The second column shows the estimation results when the loans-to-assets ratio is excluded from the explanatory variables. As shown in both columns, goodness of fit improves compared with table 2. As for the marginal effects of the fee and commission income ratio and securities-to-assets ratio, coefficients γ_3 and γ_5 in equations (7) and (8), respectively, are significantly negative, while γ_4 and γ_6 are significantly positive. The results are consistent with the prediction of equation (5) from subsection 4.1. According to the estimation results, the marginal effects of the securities-to-assets ratio $StoA_{i,t-1}$ and the ratio of fee and commission income to interest income $FCtoI_{i,t-1}$ on systemic risk coefficient $\delta^i_{\lambda,t}$ increase as the overall ratio of securities to assets $\overline{StoA_{-i,t-1}}$ and of fee and commission income to interest income $\overline{FCtoI_{-i,t-1}}$ 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 ratio of fee and commission income to interest income. Such effects are observed because the variables $FCtoI_{i,t-1}$ and

Table 7. Regression Results of Systemic Risk Coefficient with Interaction Terms

	Systemic Risk Coefficient: δ	
FCtoI	−1.751***	−1.914***
	(0.479)	(0.434)
$FCtoI \times \overline{FCtoI}$	17.416***	18.791***
	(4.003)	(3.407)
LtoA	1.426	
	(1.097)	
$LtoA \times \overline{LtoA}$	−1.615	
	(1.540)	
StoA	−1.441**	−2.395***
	(0.644)	(0.551)
$StoA \times \overline{StoA}$	7.569***	10.324***
	(1.951)	(1.785)
EtoA	1.670**	1.870***
	(0.744)	(0.756)
DtoD	0.051	0.137
	(1.951)	(0.294)
Log(*asset*)	0.139	0.122
	(0.089)	(0.081)
TOPIX Volatility	0.323***	0.326***
	(0.117)	(0.118)
TED Spread	0.221**	0.185**
	(0.097)	(0.077)
TOPIX Real Estate Excess Return	−0.031	−0.044
	(0.281)	(0.272)
TOPIX Return	−0.985***	−0.975***
	(0.279)	(0.278)
Three-Month JGB Change	−0.116	−0.125
	(0.093)	(0.090)
Term Spread	0.072*	0.063*
	(0.042)	(0.038)
Bank Fixed Effects	Yes	Yes
R-squared	0.324	0.324
Observations	2,242	2,242

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

Figure 5. Marginal Effect of Securities-to-Assets Ratio on Systemic Risk Coefficient: $\frac{\partial \delta^i_{\lambda,t}}{\partial StoA_{i,t-1}} = \gamma_7 + \gamma_8 \overline{StoA_{t-1}}$



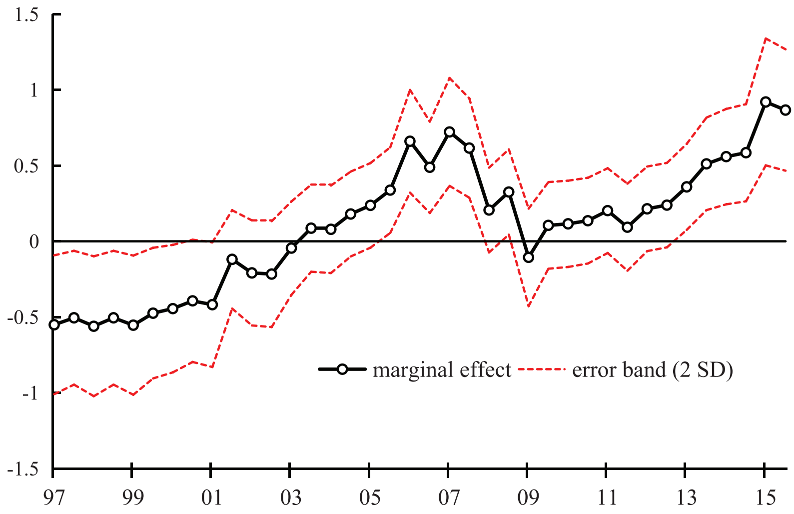
Notes: Semiannual data are presented (fiscal year basis). $\overline{StoA_{t-1}}$ is defined as $\frac{\sum_{j=1}^{n} StoA_{j,t-1}}{n}$. The estimated coefficients in the first column of table 7 are used for the calculation.

$StoA_{i,t-1}$ are closely related to market risks, which are common to all banks.

By contrast, the coefficients on the terms related to the loans-to-assets ratio, $LtoA_{i,t-1}$ and $LtoA_{i,t-1} \times \overline{LtoA_{-i,t-1}}$ in equation (9), are found to be not significant. Contrary to $FCtoI_{i,t-1}$ 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 loans-to-assets ratio is not found to be a significant driver of the systemic risk coefficient $\delta^i_{\lambda,t}$.

Figures 5 and 6 plot the marginal effects on the systemic risk coefficient of the securities-to-assets ratio and the ratio of fee and commission income to interest income, respectively, as indicated by equations (7) and (8). It can be observed that the marginal effect of the securities-to-assets ratio and the ratio of fee and commission income to interest income are increasing over time as banks

Figure 6. Marginal Effect of Ratio of Fee and Commission Income to Interest Income on Systemic Risk Coefficient: $\boldsymbol{\frac{\partial \delta^i_{\lambda,t}}{\partial FCtoI_{i,t-1}} = \gamma_5 + \gamma_6 \overline{FCtoI_{t-1}}}$



Notes: Semiannual data are presented (fiscal year basis). $\overline{FCtoI_{t-1}}$ is defined as $\frac{\sum_{j=1}^{n} FCtoI_{j,t-1}}{n}$. The estimated coefficients in the first column of table 7 are used for the calculation.

are increasing their securities holdings and dependence on fee and commission income.

In particular, figure 5 shows that the marginal effect of the securities-to-assets ratio $StoA_{i,t-1}$ on the systemic risk coefficient $\delta^i_{\lambda,t}$ 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 6, the marginal effect of the ratio of fee and commission income to interest income $FCtoA_{i,t-1}$ on the systemic risk coefficient $\delta^i_{\lambda,t}$ 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 fee and commission income in that time period, its co-movement 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 fee and commission income at a given regional bank causes its co-movement with other regional banks to rise, since other regional banks are already highly reliant on fee and commission 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 fee and commission 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 fee and commission income raise systemic risk, even though they reduce standalone bank risk. Further, we find that the marginal effect of an increase in a given bank's such components on systemic risk is larger when the share of the corresponding components is already high among other banks. The evidence points to a "fallacy of composition" effect among Japanese regional banks, such that the common response of individual institutions to reduce standalone bank risks generates an unwelcome endogenous effect on systemic risks. It should be noted that the "fallacy of composition" 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 securities holdings and fee and commission income.

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 to reduce standalone bank risk. Indeed, the "fallacy of composition" implies that the vulnerability of the financial system could well increase if individual banks collectively choose to behave in this manner.

Appendix A. List of Banks

Table A.1. List of Banks

Daishi Bank	Mie Bank
Hokuetsu Bank	Hiroshima Bank
Fukuoka Chuo Bank	San-in Godo Bank
Chiba Bank	Chugoku Bank
Bank of Yokohama	Iyo Bank
Joyo Bank	Hyakujushi Bank
Gunma Bank	Shikoku Bank
Musashino Bank	Awa Bank
Chiba Kogyo Bank	Oita Bank
The 77 Bank	Miyazaki Bank
Aomori Bank	Bank of Saga
Akita Bank	The Eighteenth Bank
Yamagata Bank	Bank of Okinawa
Bank of Iwate	Bank of Nagoya
Toho Bank	Aichi Bank
Michinoku Bank	Daisan Bank
Sizuoka Bank	Chukyo Bank
Juroku Bank	Higashi-Nippon Bank
Suruga Bank	Taiko Bank
Hachijuni Bank	Ehime Bank
Yamanashi Chuo Bank	Tomato Bank
Ogaki Kyoritsu Bank	Minato Bank
Fukui Bank	Keiyo Bank
Hokkoku Bank	Tochigi Bank
Shimizu Bank	Kita-Nippon Bank
Toyama Bank	Minami Nippon Bank
Shiga Bank	Towa Bank
Nanto Bank	Fukushima Bank
Hyakugo Bank	Daito Bank
Bank of Kyoto	

Appendix B. Description of Bank-Level Variables

For the definition of bank-level variables, we follow the definition of the Japanese Bankers Association, as well as the Bank of Japan's *Financial System Report* (Bank of Japan 2017). The variables analyzed in this paper are defined as follows:

- Net interest income = interest income – interest expenses
- Fee and commission income = fees and commissions on domestic and foreign exchanges + other fees and commissions + profits on specified transactions + other operating profits – realized gains/losses on bondholdings
- Fee and commission income to interest income (FCtoI) = fee and commission income/net interest income
- Loans to total assets (LtoA) = loans and bill discounted/total assets
- Securities to total assets (StoA) = securities/total assets
- Equity to assets (EtoA) = net assets/total assets
- Deposit-to-debt (DtoD) = retail deposit (deposit excluding current deposit and negotiable certificates of deposit)/total debt (total liability = total assets – net assets)

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