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RESEARCH ARTICLE

Measures of systemic risk and financial fragility in Korea

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Abstract This paper provides a quantitative metric for financial stability of Korean commercial banking system based on the Tsomocos (J Math Econ 39(5–6):619–655, 2003) model, for which we use market data as proxies for probabilities of default and equity valuation of the banking sector. We estimate the effect of the probability of default and the equity valuation of the banking sector on real output using a vector error correction model (VECM). In addition, we estimate the contributions of individual banks to systemic risk using CoVaR and MES (Marginal Expected Shortfall). CoVaR is estimated based on the methodology of Adrian and Brunnermeier (2010), and MES is estimated based on Shapley value methodology which has been introduced by Tarashev et al. (2010).

Keywords Financial stability · Systemic risk · JPoD · CoVaR · MES · Shapley value

JEL Classification E30 · E44 · G01 · G10 · G18 · G20 · G28

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1 Introduction

It has been known that the central bank faces more limitation in achieving financial stability than in achieving price stability when it has both goals. This is attributable mainly to the fact that simple and quantitative metrics to represent the financial stability status have not yet been developed. Specifically, the price stability situation can be evaluated relatively precisely, based on various indicators, e.g., monetary aggregates, interest rates, and inflation, whereas the financial stability situation is difficult to judge given the lack of quantitative indicators for its evaluation (Table 1).

It can be said that the easiest way of explaining financial stability is through the existence of financial instability or the absence of financial crisis. Many conventional studies have focused on identifying common factors behind financial instability based upon the occurrence of financial crises.[1] However, this approach is problematic in that there are many cases in which it is difficult to judge whether a financial crisis has occurred, or if so exactly when it broke out and when it ended. In addition, if the behaviors of the regulatory authorities and depositors change after the financial crisis, then the significance of identifying the causes behind the crisis could be undermined. Lastly, if the analysis is focused only on the crisis period, a lot of effective information can be ignored (Aspachs-Bracons et al. 2012). Accordingly, this study judges that the definition of financial instability presented by Goodhart et al. (2006b), a "combination of high probability of default and low profitability of financial institutions," is useful for grasping the financial stability situation, and evaluates the fragility of the Korean banking system based upon this definition.

Meanwhile, estimation of the risk overarching the entire system closely relates to the implementation of macroprudential policy. Macroprudential policy, differing from microprudential policy, focuses on the stability of the whole financial system rather than that of individual financial institutions. Even though the objective of macroprudential policies is established based from the perspective of the entire system, the financial regulatory instrument and policy intervention is implemented to individual financial institutions. For example, a capital surcharge imposed on a bank depends on its systemic importance so that the systemic risk caused by 'too-big-to-fail' banks can be addressed. Accordingly, accurate measurement of the contributions to systemic risk by individual banks is a key component of macroprudential policy.[2]

Many studies have been conducted on the methodologies of measuring the contributions of individual banks to systemic risk. Tarashev et al. (2009) proposed an approach to estimate the systemic importance of individual financial institutions using the Shapley Value methodology. Acharya et al. (2010) emphasize that the financial system has become vulnerable to macroeconomic shocks due to the lack of systemic risk management in contrast to the adequate handling of risks embedded in individual financial institutions. In order to address this problem, they estimate the individual financial institutions' exposure to the systemic risk through Systemic Expected Shortfall (SES). In a similar manner, Brownless and Engle (2010) develop an estimation

[1] See Berg (1999), Čihák and Schaeck (2007), Dermirguc-Kunt and Detragiache (1998), Disyatat (2001), Kaminsky and Reinhart (1996), Logan (2000), Vallés and Weistroffer (2008), and Vila (2000).

[2] See BCBS (2011).

Table 1 Comparison of price and financial stability (Aspachs-Bracons et al. 2012)

		Price stability	Financial stability
a)	Measurement/definition	Relatively easy	Difficult
b)	Instrument for control	Possible, subject to lags	Limited, difficult to adjust
c)	Accountability	Easy	Difficult
d)	Forecasting structure	Central tendency of distribution	Tails of distribution
e)	Forecasting process	Standard forecasts	Simulations or stress tests
f)	Administrative procedure	Relatively simple	Complicated

methodology of Marginal Expected Shortfall (MES). Adrian and Brunnermeier (2008, 2009, 2010) develop CoVaR that measures the Value at Risk (VaR) of the financial system conditional on an institution being in distress. Using this measure, they estimate the contributions of individual financial institutions to systemic risk ($\triangle$CoVaR).

There is no perfect methodology that precisely measures the contributions of individual financial institutions to systemic risk. Relying on a single approach runs a risk of errors, and therefore, various approaches need to be considered contemporaneously when implementing macroprudential policy. This paper measures the contributions of Korean banks to systemic risk based on two approaches proposed by Tarashev et al. (2010) and Adrian and Brunnermeier (2010), and assesses the usefulness of the systemic risk contribution measurement. The two different approaches were employed because the use of MES, a top-down measure, and CoVaR, a bottom-up measure, allows the systemic risk to be measured from different angles.[3]

Our objective is to offer quantitative metrics of financial stability and contributions of individual banks to systemic risk to be used for the conduct of macroprudential policy. We consider the presence of these measures necessary for the accountability of policy makers regarding the success of regulatory policy.

The remainder of this paper is organized as follows. In Sect. 2, we calculate a single metric, the composite financial stability index for the Korean banking system using the two factors; namely the joint probability of default (JPoD) and the bank equity index of the banking sector. Next, we estimate the contributions of individual banks to the systemic risk of Korea using two approaches, CoVaR and MES. We report the results in Sects. 3 and 4. Finally, our concluding remarks are presented in Sect. 5. "Appendix" contains the VECM estimation results.

2 Composite financial stability index

2.1 Introduction

In this section, we evaluate the level of financial stability of the Korean banking system through the composite financial stability index estimated based on the financial instability definition of Goodhart et al. (2006b). The composite financial stability

[3] See Drehmann and Tarashev (2011).

index, our metric of financial fragility as a weighted two factor model, is derived from the theoretical modeling developed in Goodhart et al. (2005, 2006b,c).[4] Our hypothesis, based on simulations and calibrations of the general equilibrium model, developed in Goodhart et al. (2005, 2006b,c) is that whenever banks' default rates increase and banks' profitability decrease, i.e., when the economy is more *financially fragile*, GDP (our proxy of welfare) falls.[5] This definition has many advantages that can make up for the weakness of other definitions. First, it can be either wholly or partially applied to the system, and can also encompass the perspective of efficient allocation between savings and investment. In addition, the policy authorities can induce financial institutions to maintain their debt (or profitability) below (or above) a certain level that does not destabilize financial system. Moreover, the general equilibrium model is able to measure the impacts of change in regulation on the default probability and welfare level, and can be applied to past cases of financial instability. The results of empirical analysis also show that the impacts on default risk and profitability differ depending upon the form of the external shock. So, in order to measure the financial stability situation properly, using two metrics together rather than using one metric is evaluated to be appropriate.[6]

2.2 Data

We sought variables that would give a good measure of default probabilities and banking profitability. We use the IMF methodology (Segoviano and Goodhart 2009) to estimate a time series for banks' joint probabilities of default, which will be referred to as JPoD. We take the percentage change in equity values of the banking sector as our index of the market's perception of the change in the present value of returns to bank.

The data set to calculate the composite financial stability index includes the CDS spreads, bond spreads, and equity values of Hana Bank (Hana), Industrial Bank of Korea (IBK), Kookmin Bank (KB), Korea Exchange Bank (KEB), Shinhan Bank (Shinhan), and Woori Bank (Woori) (6 banks in total) over the period from 2003 Q1 until 2012 Q1.[7] Bond spread means the difference of the yields between the bank debenture (3 years) and Treasury bond (3 years). Data frequency is 5 week day format.

We calculate the joint probability of distress or default (JPoD) defined as a measure of the probability of all the banks in the system (portfolio) becoming distressed, which represents the tail risk of the system, using PDs of individual banks. We use CDS spreads and bond spreads together to estimate the PDs of individual banks. It is possible to use PDs estimated by either CDS spreads or bond spreads, but as the two data sets

4 See Tsomocos (2003, 2004).

5 In the general version of the model, an increase in default and a decrease in profitability are, typically, associated with a reduction in agents' welfare (see, Goodhart et al. 2006b).

6 See Aspachs-Bracons et al. (2007, 2012).

7 Data of Hana, KB, Shinhan and Woori beyond a specific point (Hana: '05.12.12, KB: '08.10.10, Shinhan: '03.1.1, Woori: '03.1.1) are stock prices of their holding companies. The data for 2012 Q1 are the average of those for 2012 January and February.

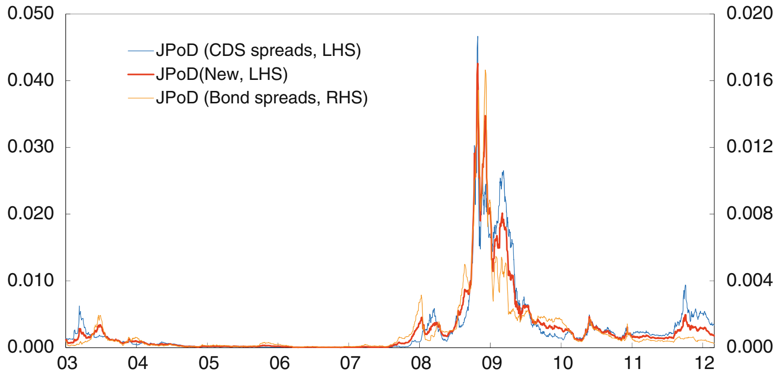

Fig. 1 Joint probability of distress (JPoD) of Korean banking sector

contain different information, we judged use of both data sets to be appropriate.[8] As an alternative, EDF (expected default frequency) provided by Moody's can be considered to measure the PDs of banks. However, it is also often pointed out that the estimation process of EDF is not transparent (Kim et al. 2011). In other words, one cannot know explicitly the model and the parameters used for estimations of EDF (Kim et al. 2011).

We use the CIMDO approach (Segoviano and Goodhart 2009) to estimate a time series for banks' JPoDs. This measure takes into account the impact of individual banks' distress on the rest of the banking sector. Banks' distress dependence is based on the fact that banks are usually linked either directly through the interbank deposit market and exposures in syndicated loans, or indirectly through lending to common sectors and proprietary trades. This distress dependence among banks is also a key feature CIMDO approach. Banks' distress dependence varies across the economic cycle and tends to rise in times of distress since the fortunes of banks decline concurrently through either contagion of idiosyncratic shocks or through negative systemic shocks. Therefore, in such periods, the banking system's joint probability of distress, i.e., the probability that all the banks in the system experience large losses simultaneously, may experience larger—and highly non-linear—increase than those experienced by the probabilities of distress of individual banks.[9]

Figure 1 is the JPoDs of Korean banking sector. It shows that most of the JPoD estimations based on the combination of the CDS spreads and bond spreads data sets lie between the JPoD estimations based on the each data set.[10]

We take the percentage change in equity values of the banking sector as our index of the market's perception of the change in the present value of returns to banks. As

[8] For example, Seo and Lee (2010) argue that CDS spreads of Korea do not represent the unique credit risks of individual banks, as they tend to be highly dependent on macroeconomic and foreign exchange sector variables.

[9] See Segoviano (2009).

[10] Additional analysis will be necessary to discern which JPoD estimation, based either on both data sets or on only one of the data sets, represents the status of the Korea's financial system more appropriately. Meanwhile, according to our estimation for the financial stability index, each using CDS spreads, bond spreads, or both sets of data, the results exhibit no significant difference.

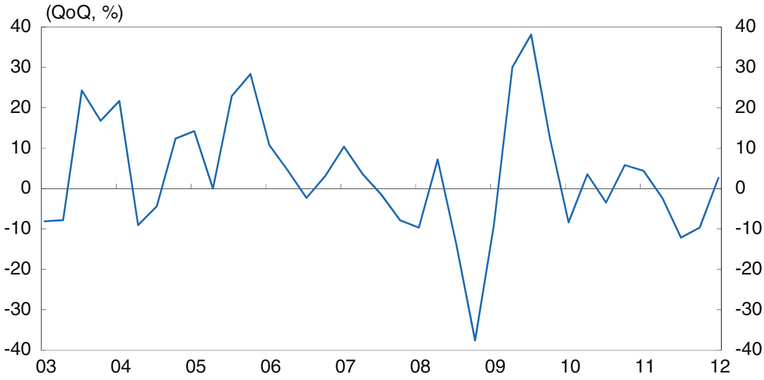

Fig. 2 Equity index growth of Korean banking sector

expected, Fig. 2 shows that the equity growth index deteriorated greatly during the crisis period in 2008.

Considering together Figs. 1 and 2, we observe that although the JPoD dropped precipitously since the 4th quarter of 2008, the continuing deterioration of the bank equity index suggests that financial fragility persists. Hence, we arguably need a composite financial fragility index.

2.3 The empirical model

As already mentioned, our aim is to investigate whether our two indicators of banking sector's distress, namely, JPoD and equity, have the expected impact on output. We thus measure the impact on output (GDP) of the two indicators. We use the VAR (or VECM) methodology, which treats all the variables in the system as endogenous, to derive the weights of two indicators by variance decomposition of the VAR (or VECM).

Our baseline model is a three-variable vector, {*gdp, eq, jpod*}, where *gdp* is the quarter on quarter growth rate of real GDP, *eq* is the quarter on quarter growth rate of the bank equity index, and *jpod* is the measure of the banking sector's default risk which is quarterly average of daily data.

To investigate whether variables are stationary, we conduct unit root tests, Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests. The optimal lags for the ADF test are selected by SIC (Schwarz Information Criterion), and the bandwidth for Phillips–Perron is selected by Newey-West bandwidth. The result of ADF test shows that *jpod* is non-stationary and I(1).

Given that all variables are not stationary, we conduct the Johansen Cointegration Test in order to investigate that these variables are cointegrated. The test results show that there exists at most one cointegrating relationship between these variables.

For these reasons, we derive the weights of two indicators by variance decomposition of the VECM. The ordering of variables is *gdp*, *eq*, and *jpod*, which is determined by the degree of linkage to external factors. Our estimation results using these models are shown in Table 7 and Fig. 8 of "Appendix". They all show that *ceteris paribus*,

Table 2 Statistics of unit root tests

Variables	ADF	PP
gdp	−4.6067***	−4.8180***
eq	−4.7576***	−3.1238**
jpod	−2.5016	−2.5824
Δ*jpod*	−5.3910***	−6.1889***

In the test equation, intercept term is included, and trend term is not included
***, ** indicate that the null hypothesis that the variable has a unit root can be rejected at the 1, 5 % significance level, respectively

Table 3 Results of Johansen cointegration test

Null hyhothesis	Trace statistic	Maximum eigenvalue statistics
None	57.1766 ***	38.9263 ***
At most one	18.2503*	12.3407
At most two	5.9096	5.9096

According to the SIC, we assume that the data have no deterministic trends and the cointegrating equations have intercepts with one lag interval
***, * indicate that the null hypothesis can be rejected at the 1, 10 % significance level, respectively

a positive shock to the banks' probability of default or a negative shock to the banks' equity value has a negative impact on output. These results are consistent with our predictions.

Because the period of estimation is relatively short in Korea, we also estimate the VECM using monthly data.[11] In this case, we use the Industrial Production Index (IPI) as a proxy of GDP due to the difficulty of obtaining monthly GDP data. We check the robustness of the baseline model's result by performing different sets of tests. For example, we conduct additional estimations adding either only *real TB03*, which is the real interest rate (3 year Treasury rate – expected inflation) or both *real TB03* and *CPI*, which means quarterly inflation.[12] In addition, we conduct several estimations based on monthly data, such as {*ipi, eq, jpod*}, {*ipi, real TB03, eq, jpod*}, and {*ipi, cpi, real TB03, eq, jpod*}.[13] The estimation results are shown in Tables 8, 9, 10, 11 and 12 and Figs. 9, 10, 11, 12 and 13 of "Appendix".

We use a two year average of the impact in the variance decomposition to estimate the weights of two indicators. In our baseline model, the effect of JPoD on GDP is always more important than that of equity. Based on a two year average value of variance decomposition, the bank equity index explains 7.8 % of the variation of GDP, while the probability of default of the banking sector explains 11.9 %. Hence,

[11] The monthly average of JPoD is not stationary, and I(1). These monthly data {*ipi*, *eq*, *jpod*} are also cointegrated.

[12] As real interest rate and inflation are representative macroeconomic variables that may have significant effects on GDP, they are frequently used in small macroeconomic VAR models. So we tried to add these variables to our baseline model to check robustness.

[13] The *real TB03* is not stationary, and I(1). All the data sets for robustness check based on both quarterly and monthly are also cointegrated.

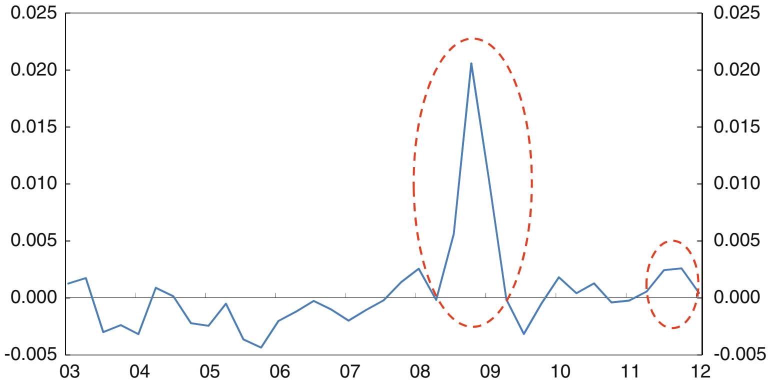

Fig. 3 Financial stability index for Korea

we assign the weight of JPoD as 60 %[11.9/(7.8 + 11.9)], and that of equity as 40 %[7.8/(7.8 + 11.9)]. The results of the variance decompositions for the different specifications show that JPoD explains 4.4–16.2 %, and the bank equity index explains 4–7 %. Accordingly, the relative weights of JPoD and bank equity are respectively 53–70 %, and 30–47 %.[14] The results of our robustness check demonstrate that the predictions of the baseline model are reasonable. Consequently, we assume the relative weights of JPoD and equity to be around 60 and 40 % respectively in the Korean banking system.

2.4 Results

What we have done so far is to test the hypothesis that our two variables of banking sector fragility, JPoD and equity, have a significant effect on welfare as proxied by GDP. Now we want to combine these two factors to obtain a single quantitative metric, an index for financial fragility. We assume the weights of the JPoD and equity for a financial stability index are 60 and 40 % as shown by our empirical analysis above. We construct our financial fragility index by combining the two indicators applying the weights. Before applying the weights, we rescale equity so that its mean absolute value and standard deviation are the same as those of JPoD. The metric is a weighted average of the JPoD and the banking sector equity index. This metric represents GDP losses due to financial instability produced by changes of the JPoD and the equity index:

$$Metric_t = 60\,\% \times JPoD_t - 40\,\% \times \{eq'_t + av(JPoD_t) - av(eq'_t)\}, \tag{1}$$

where $\mathrm{av(JPoD_t)}$ denotes the average of the JPoD, and $\mathrm{av(eq'_t)}$ denotes the average of the transformed equity series ($\mathrm{eq'_t}$).

The financial stability index for Korea is reported in Fig. 3. The increase of the value of the index indicates the intensification of financial instability. It also shows

[14] The relative weights are similar to the results of Aspachs-Bracons et al. (2012) that analyses ten countries, including Belgium, France, Germany, Italy, Japan, Netherlands, Spain, Switzerland, UK and US.

that financial stability of the Korean banking sector declined during the 2008 crisis, and it was improved by the policy response of central banks. In the second half of 2011, financial stability deteriorated within narrow limits due to the European sovereign debt crisis. However, it was improved again by the Longer Term Refinance Operation (LTRO) of ECB in 2012 Q1.

3 CoVaR

3.1 Introduction

CoVaR was developed to assess the systemic risk that reflects externalities and ripple effects of the financial sector, as the problems of microprudential supervision, especially through VaR, had come to light after the 2008 financial crisis.[15] Unlike VaR, which assesses the risk of individual institutions, CoVaR refers to the value of VaR assessed under the condition that a certain financial institution is at risk. Here, Co means conditional, co-movement, contagion, and contribution of individual banks to systemic risk. CoVaR attempts to assess the financial systemic risk when one financial institution realizes low earnings. Through CoVaR, the impact of insolvency of a certain financial institution on systemic risk can be assessed thus enabling the quantification of systemic importance of individual financial institutions. The use of CoVaR could also assess the financial institution's vulnerability to systemic risk or interconnectedness among specific institutions, although this paper focuses on estimating only the contributions of individual financial institutions to systemic risk, ΔCoVaR.[16] This implies that financial supervisory authorities can use ΔCoVaR as a useful macroprudential supervisory tool. For example, the Macroprudential Supervision Group (MPG) of the Basel Committee on Banking Supervision (BCBS) has discussed ways to use ΔCoVaR to complement the indicator-based methodology of assessing systemic importance, in selecting G-SIBs.[17] By using ΔCoVaR, we assess the contributions of domestic banks to systemic risk, and review the usability in terms of macroprudential policy.

3.2 Definition of CoVaR

CoVaR is the Value-at-Risk (VAR) of financial institutions conditional on other institutions being under distress. For a specific financial institution and sector (i), CoVaR refers to VaR of the given financial institution and sector (j) under the condition that

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[15] Co-developed by Adrian and Brunnermeier (2008), Adrian and Brunnermeier (2009) and Adrian and Brunnermeier (2010).

[16] CoVaR means the extent to which banks' returns move together. ΔCoVaR, however, implies a single institution's contribution to the entire systemic risk in the case where j = system, i.e., when the return of the portfolio of all financial institutions is at its VaR level according to Adrian and Brunnermeier (2010). They argue that the measure ΔCoVaR^i quantiles how much an institution adds to overall systemic risk. The measure should capture externalities that arise because an institution is "too big to fail", or "too interconnected to fail", or takes on positions or relies on funding that can lead to crowded trades. For more details, please refer to the pp. 9–10, Adrian and Brunnermeier (2010).

[17] However, BCBS agreed that more review is needed to use ΔCoVaR for the purpose of regulation.

they are under stress. In other words, CoVaR is a conditional VaR, VaR of institution j under the condition that $X^i = VaR_q^i$, that is,

$$\Pr(X^j \leq CoVaR_q^{j|i} | X^i = VaR_q^i) = q, \tag{2}$$

where X^i denotes the return of financial institution i.

Equation (2) states that the probability that losses of financial institution j is greater than CoVaR equal to q when the return of a financial institution i falls below a threshold value.

$\triangle$CoVaR can estimate the contribution of institution i to the risk of institution j through the difference between CoVaR of j when institution i is under stress ($CoVaR_q^{j|X^i=VaR_q^i}$) and CoVaR of j when institution i is under average condition ($CoVaR_q^{j|X^i=Median^i}$):

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_q^{j|X^i=Median^i}. \tag{3}$$

In Eq. (3), if we assume that j is the whole financial system, the degree of specific institution i contributing to systemic risk is as follows:

$$\Delta CoVaR_q^{system|i} = CoVaR_q^{system|X^i=VaR_q^i} - CoVaR_q^{systsem|X^i=Median^i} \tag{4}$$

This paper estimates the impact of individual institution on systemic risk ($\Delta CoVaR_q^{system|i}$), using Eq. (4).[18]

3.3 Estimation procedure and data

3.3.1 Data

We calculate the rate of weekly change in the asset value (market-valued total assets, X_t^i) of individual financial institutions and the entire financial system, using the equity market capitalization and the leverage ratio of ten Korean banks (Jan. 2003–Dec. 2011, weekly data): Busan, Daegu, Hana, IBK, Jeju, Jeonbuk, KB, KEB, Shinhan, and Woori, that is,

$$X_t^i = \frac{ME_t^i \times LEV_t^i - ME_{t-1}^i \times LEV_{t-1}^i}{ME_{t-1}^i \times LEV_{t-1}^i} = \frac{A_t^i - A_{t-1}^i}{A_{t-1}^i}, \tag{5}$$

[18] The initial work of Adrian and Brunnermeier (2008, 2009) on CoVaR defines $\Delta CoVaR_q^{system|i}$ as the difference between CoVaR and VaR (In other words, $\Delta CoVaR_q^{system|i} = CoVaR_q^{system|i} - VaR_q^{system}$), but in 2010 elaborate the definition.

where $LEV_t^i = BA_t^i/BE_t^i$, and $A_t^i = ME_t^i \times LEV_t^i = BA_t^i \times (ME_t^i/BE_t^i)$. Note that ME denotes the equity market capitalization, BE denotes the equity book value, and BA denotes the book value of total assets.

3.3.2 $\Delta CoVaR$

Quantile regression (Koenker 2005) estimates expected value of financial system yield on quantile q of the given institution i:

$$\hat{X}_q^{system,i} = \hat{\alpha}_q^i + \hat{\beta}_q^i X^i, \tag{6}$$

where $\hat{X}_q^{system,i}$ denotes the expected return of the overall system on quantile q, and X^i denotes the return of financial institution i.

In Eq. (6), quantile analysis on quantile q shows that expected value ($\hat{X}_q^{system,i}$) is VaR of the whole system under the condition of return of institution i. Therefore, the expected value of the systemic return under the condition of $X^i = VaR_q^i$ means $CoVaR_q^{system|X^i=VaR_q^i}$. It is conditional VaR_q of the entire system in the event of $\{X^i = VaR_q^i\}$.

$$CoVaR_q^{system|X^i=VaR_q^i} := VaR_q^{system}|VaR_q^i = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i \tag{7}$$

The level of contribution of individual institutions to systemic risk $\left(\Delta CoVaR_q^{system|i}\right)$ is calculated by Eq. (8) below:

$$\begin{aligned}
&\Delta CoVaR_q^{system|i} \\
&= CoVaR_q^{system|X^i=VaR_q^i} - CoVaR_q^{system|X^i=VaR_{50\,\%}^i} \\
&= (\hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i) - (\hat{\alpha}_q^i + \hat{\beta}_q^i VaR_{50\,\%}^i) \\
&= \hat{\beta}_q^i (VaR_q^i - VaR_{50\,\%}^i)
\end{aligned} \tag{8}$$

3.3.3 Time-varying $\Delta CoVaR$

We estimate the trend of changes in joint probability distribution of returns between individual financial institutions and the entire system, by using a function of state variables. The ΔCoVaR explained above produces only one value during a given sample period while the time-varying ΔCoVaR produces results of time-series during the period.

First, we estimate a regression analysis on conditional quantile of a state variable (M):[19]

$$X_t^i = \alpha^i + \gamma^i M_{t-1} + \varepsilon_t^i, \tag{9}$$

$$X_t^{system} = \alpha^{system|i} + \beta^{system|i} X_t^i + \gamma^{system|i} M_{t-1} + \varepsilon_t^{system|i}, \tag{10}$$

where X^i denotes the return of financial institution i, and M_{t-1} denotes the state variable vector.[20]

Next, we estimate time-varying CoVaR and VaR through the predicted value produced by the quantile regression analysis:

$$VaR_t^i = \hat{\alpha}^i + \hat{\gamma}^i M_{t-1}, \tag{11}$$

$$CoVaR_t^i = \hat{\alpha}^{system|i} + \hat{\beta}^{system|i} VaR_t^i + \hat{\gamma}^{system|i} M_{t-1}. \tag{12}$$

Finally, the degree ($\Delta CoVaR_{t,q}^{system|i}$) of an individual institution's contribution to the entire systemic risk is estimated:

$$\begin{aligned} \Delta CoVaR_{t,q}^{system|i} & \\ &= CoVaR_{t,q}^i - CoVaR_{t,50\,\%}^i \\ &= \hat{\beta}^{system|i} (VaR_{t,q}^i - VaR_{t,50\,\%}^i) \end{aligned} \tag{13}$$

3.4 Results

3.4.1 $\triangle CoVaR$

Using △CoVaR and time varying △CoVaR, we estimate a contribution of individual bank on the financial stability of entire banking system. Table 4 below provides the △CoVaRs for individual banks of Korea. It shows △CoVaRs which correspond to the 5th percentile and 1st percentile of the return distribution respectively.

The individual banks that contribute the most to systemic risk are Bank 1, Bank 2 and Bank 3 using 5 % △CoVaR, and Bank 1, Bank 2 and Bank 5 using 1 % △CoVaR.

As shown in Table 2, the correlation between △CoVaR and VaR of individual financial institutions is very high. Accordingly, the scatter plot in Fig. 4 shows a positive correlation between institutions' risk (VaR) and institutions' contribution to systemic risk (△CoVaR). It suggests that bank regulation relying on VaR may be valid in the

[19] Under the assumption that the return of a financial institution is the function of state variables M, we estimate time-varying ΔVaR using quantile regression. We include a set of state variables M that are well known to capture time variation in conditional moments of asset return, and are liquid and easily tradable (Adrian and Brunnermeier 2010).

[20] State variable vector consists of the VIX (KOSPI200 Volatility Index), Short term liquidity spread (CD (91 days)- Government bonds (3-month)), Changes of government bonds (3-month), Changes in yield curve (Difference of Government bonds (10-year)—Government bonds (3-month)), Changes in credit spread (Difference of corporate bonds (BBB-, 3-year)—Government bonds (3-year)), and Stock market return (KOSPI volatility rate).

Table 4 △CoVaRs of Korean banks

Quantile	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Bank 7	Bank 8	Bank 9	Bank 10
5 %	5.86	4.87	4.77	3.97	3.92	3.92	3.73	3.60	2.58	0.91
Ranking	1	2	3	4	5	6	7	8	9	10
1 %	9.82	9.51	9.13	7.48	9.30	8.64	6.40	7.49	5.12	2.61
Ranking	1	2	4	7	3	5	8	6	9	10

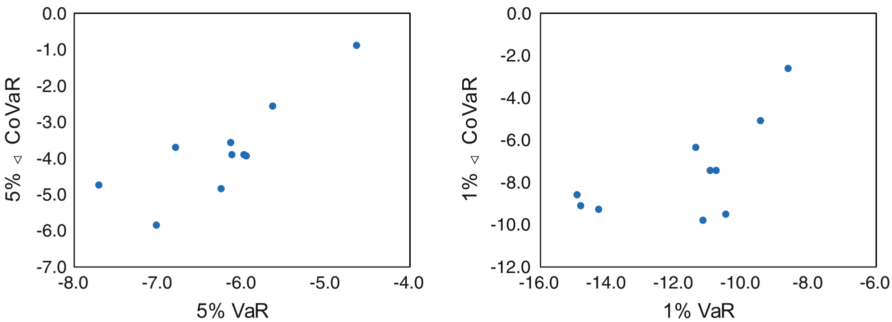

Fig. 4 △CoVaRs versus VaR in Korean banks

case of Korean banks. On the other hand, Adrian and Brunnermeier (2010) analysis showed a very low correlation, and they used this as evidence that the △CoVaR can replace the VaR. The high degree of correlation among financial institutions implies that the applicability of △CoVaR may be limited in Korea.[21]

3.4.2 Time-varying △CoVaR

As a result of estimation of time-varying △CoVaR, we also estimate the contributions of individual banks to the entire financial system. Table 3 below describes the time-varying △CoVaRs for individual banks in Korea. It shows time-varying △CoVaRs which correspond to the 5th percentile and 1st percentile of the return distribution respectively. The estimated results resemble those of the △CoVaR. That is, the individual banks that contribute to the most to the systemic risks are Bank 1, Bank 3 and Bank 2 using 5 % △CoVaR, and Bank 1, Bank 3 and Bank 5 using 1 % △CoVaR. However, the order below the ranking 4 is somewhat different from that of the estimated results of △CoVaR (Table 5).

[21] This seems to be due mainly to the fact that, unlike the relationships among banks in advanced countries such as the US, the interconnectedness among Korean commercial banks, which is captured as the △CoVaR, is low, so that the △CoVaR is not much different from the VaR measuring individual banks' losses. In addition, according to an anonymous referee of this paper, the reason for a high correlation between CoVaR and VaR measures is probably due to the difference of the financial institutions in the samples. That is, the difference can be caused by the fact that the paper is studying commercial banks while Adrian and Brunnermeier (2010) include investment banks and insurance companies.

Table 5 Time series average—△CoVaRs of Korean banks

Quantile	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Bank 7	Bank 8	Bank 9	Bank 10
5 %	5.42	4.30	4.88	3.12	4.17	3.44	2.97	3.12	2.00	0.53
Ranking	1	3	2	7	4	5	8	6	9	10
1 %	8.71	5.65	6.47	4.10	5.84	5.04	5.15	3.59	3.42	1.19
Ranking	1	4	2	7	3	6	5	8	9	10

Average value of time-varying △CoVaR at each period

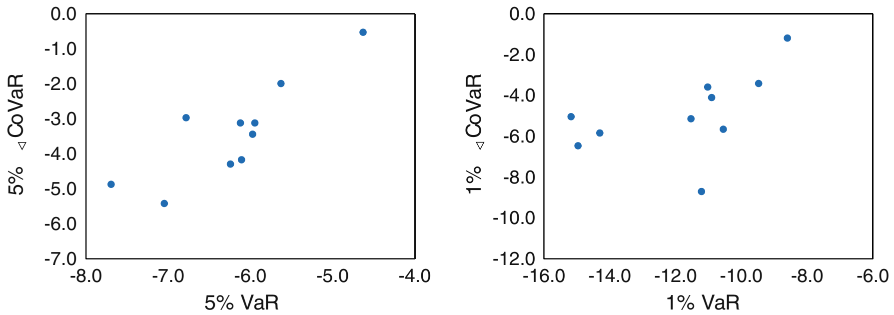

Fig. 5 Time series average—△CoVaRs versus VaR in Korean banks

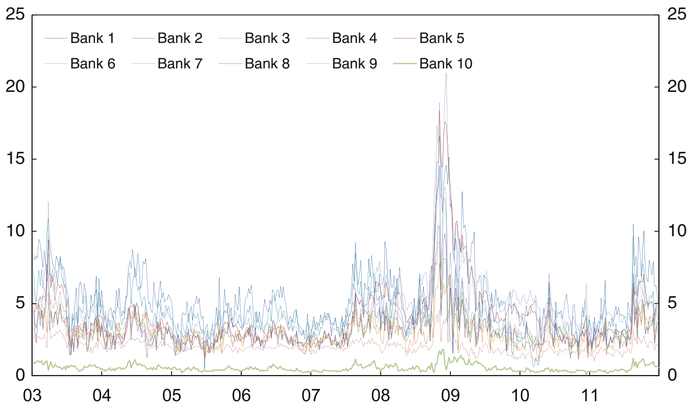

Fig. 6 Time-varying 5 % △CoVaRs of Korean banks

When comparing the estimated results of the time-varying △CoVaR with the VaR of individual financial institutions, there is a positive correlation similar to the △CoVaR case. However, it is somewhat lower than the correlation between the △CoVaR and the VaR (Fig. 5).

Meanwhile, Fig. 6 shows that the contributions of all banks to systemic risk were high during the 2008 financial crisis.

3.4.3 Remarks

CoVaR purports to estimate the contributions of individual banks to the entire financial system's risk. However, we could not calculate the aggregate systemic risk using this approach. From Fig. 6, we can assume that entire systemic risk sharply increased in the late 2008. Yet we cannot directly estimate the level of the systemic risk from CoVaR approach. Despite such disadvantage, CoVaR could be a useful tool to find the risk of individual banks that takes into account its exposure to common factor. Thus, CoVaR measures could be used as an ancillary tool.

We estimate the contributions of individual banks to systemic risk through $\triangle$CoVaR using the quantile regression analysis. It should be noted that the ranking of banks' contribution to the systemic risks change depending on the quantile level. Furthermore, some major Korean banks for which no information on stock prices is available were excluded from the analysis. Meanwhile, the correlation between the $\triangle$CoVaR and the VaR is somewhat high in this study, suggesting that the usefulness of the CoVaR may be limited in the Korean financial system. CoVaR, however, takes into consideration of the interconnections of financial industry sectors that VaR cannot detect, and, hence, is able to identify banks' contribution to systemic risks. In this sense, its usefulness still seems to be valid in Korea. For example, it can be used for checking the systemic importance of domestic banks. Finally, it can be used for measuring the systemic risk changes of individual banks before or after a certain period, sectorial systemic risk, etc.

4 Marginal expected shortfall

4.1 Introduction

Macroprudential policy differs from microprudential policy in that it takes greater interest in the stability of the entire financial system. However, even if macroprudential policy goals are determined from a systemic perspective, financial supervisory tools and policy intervention are implemented on individual financial institutions. For example, a capital surcharge can be imposed on banks depending upon their systemic importance to mitigate systemic risk caused by too-big-to-fail banks. Consequently, it is essential to identify an individual financial institution's contribution to the entire systemic risk to effectively implement macro-prudential policy. From this perspective, MES, the marginal contribution of an individual bank, can be a useful tool for financial supervision for macroprudential policy implementation. Although, various MES estimation methods have been developed, this paper intends to estimate MES of Korean banks based on the methodology introduced by Tarashev et al. (2009)[22] with priority placed upon a fair distribution of contribution to systemic risk. MES refers to an individual bank's loss in the tail of the aggregate sector's loss distribution. In other words, it identifies the marginal contribution of an individual financial institution/firms i to

[22] Acharya et al. (2010) and Brownless and Engle (2010) have also estimated MES.

the systemic risk through expected losses it will be incurred during times of significant slowdown in the entire financial system.

MES is similar to △CoVaR proposed by Adrian and Brunnermeier (2010) in that they both estimate the contribution of an individual financial institution to systemic risk, but differs in following points (Artzner et al. 1999).

First, △CoVaR evaluates an individual bank's contribution separately from the entire systemic risk measurement (bottom-up approach), but MES measures the entire systemic risk first and then evaluates an individual bank's contribution to it (top-down approach). Put differently, if an individual financial institution is in a crisis situation, △CoVaR captures the contribution of any other individual financial institution by estimating risk of the entire system. If the entire system faces crisis, however, MES captures the contribution of an individual financial institution by estimating the extent of losses of an individual financial institution. Second, △CoVaR is calculated based on VaR, while MES is based on ES (Expected shortfall). Finally, the sum of MES is identical to the value of the entire systemic risk. However, the systemic risk cannot be estimated with the sum of △CoVaR.

4.2 Estimation procedure and data

An individual bank's contribution to systemic risk is calculated by estimating the ES of the entire financial system first and then allocating it to each bank.

Expected Shortfall is an average loss that can occur if the loss exceeds VaR (conditional expected loss in the event of losses exceeding VaR):

$$ES_\alpha = E[R|R \leq VaR_\alpha], \tag{14}$$

where α is a confidence level and R is portfolio profits and losses.

Value at Risk is an index of measuring the maximum losses that can occur within a confidence level, while ES takes into account the case where losses exceed VaR. Thus, ES is a more conservative index.

In order to estimate MES, we first calculate ES. Expected shortfall, also known as expected tail loss, is the measure of systemic risk we use in all numerical examples. It is defined as the expectation of default-related losses in the system, conditional on a systemic event. This event occurs when system-wide losses equal or exceed some percentile of their probability distribution. We quantify expected shortfall using Monte Carlo simulations[23] that take as inputs the following parameters for each institution i: s_i (the size of the liabilities of institution i), LGD_i (loss-given-default), PD_i, ρ_i (the loading on the common (or systematic) factor). PD_i is calculated by using CDS spreads. We use the correlation between profitability (equity growth rate) of institution i and entire system as a proxy of common factor (ρ_i), which is an individual financial institution's exposure to the systemic risk.

[23] Monte Carlo simulations are usually used in cases where there is a lack of previous direct time series of variables to be measured, credibility is low due to insufficient information on previous time series or ample noise, and it is impossible to measure time series of variables directly.

Expected shortfall is estimated using the formula presented below using indicators representing the three factors stated previously.

The system-wide losses following a bank's failure can be estimated as follows:

$$\textit{System-wide loss} = \sum_{i=1}^{N} s_i \times LGD_i \times I_i, \tag{15}$$

where s_i denotes the weight of the size of liabilities of bank i relative to the entire system,$\sum_{i=1}^{N} s_i = 1$, LGD_i denotes the system losses following a failure of bank i and it is assumed to be 55 % of liabilities (s_i) of bank i, and $I_i = 1$, if bank i fails, and 0, otherwise.

An individual bank is assumed to fail, when its assets value falls below a specific threshold. In the model, bank i fails, if the indicator representing its assets value (V_i) is lower than the threshold value that is equal to the individual bank's default probability. That is,

$$V_i = \rho_i \times M + \sqrt{1-\rho_i^2} Z_i < \Phi^{-1}(PD_i), \tag{16}$$

where M denotes the risk factor affecting all financial institutions, Z_i denotes the factor affecting financial institution i, M and Z_i follow the normal distribution, PD_i denotes the probability of default of financial institution i, Φ^{-1} denotes the reverse function of standard normal cumulative distribution function, and ρ_i denotes the loadings on the common (or systematic) factor.

Expected shortfall of financial system is calculated with the use of the previous formula and Monte Carlo simulations. Random numbers are created to satisfy statistical characteristics of risk factors, M and Z_i (normal distribution assumed).

Individual bank's contribution to systemic risk is estimated by allocating the entire systemic risk to each bank by calculating its Shapley value. It allocates the total impact to members depending on their respective degree of contribution (Shapley 1953). The total risk is allocated to individual financial institutions in the same manner as the total impact is shared according to the Shapley value calculation. We calculate the Shapley value, ($ShV_i(\sum)$), by evaluating the level of risk of each subsystem:[24]

$$ShV_i\left(\sum\right) = \frac{1}{n} \sum_{n_s=1}^{n} \frac{1}{c(n_s)} \sum_{\substack{S \supset i \\ |s|=n_s}} (v(S) - v(S - \{i\})), \tag{17}$$

where Σ denotes the entire financial system, $S \supset i$ denotes all subgroups of the entire financial system (Σ) including bank i, $|S|$= the number of banks within subgroups, $C(n_s)$ = the number of subgroups (including bank i) when the number of banks is

24 Allocation part using Shapley value methodology in the program for MES estimation is developed by Lee Seung Hwan, Marcroprudential Analysis Department of Bank of Korea. We verified the accuracy of the program. We would like to thank him for his help.

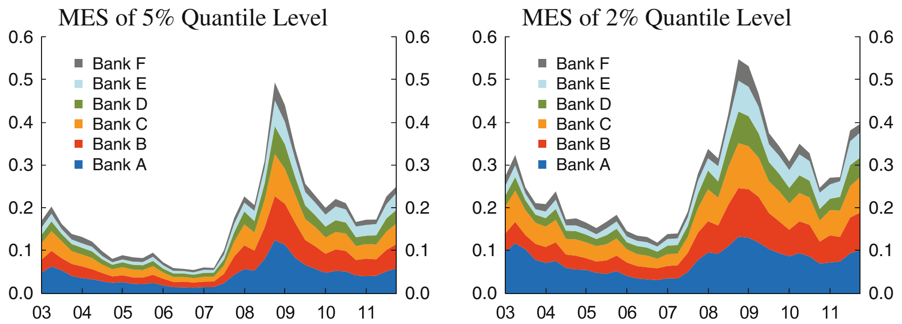

Fig. 7 Estimation of Banks' MES

Table 6 Systemic importance of Korean banks

	Bank A	Bank B	Bank C	Bank D	Bank E	Bank F
MES (5 %)	0.044	0.038	0.035	0.022	0.020	0.014
MES (2 %)	0.076	0.056	0.056	0.032	0.030	0.019

Average MES figure for each time period. MES figures rise as α falls (or confidence level rises)

$n_s (= \frac{(n-1)!}{(n-n_s)!(n_s-1)})$, $\nu(S)$ denotes the systemic risk of the subgroup, and $\nu(\varphi)$ (risk of subgroup which does not include any banks) is zero.[25]

We estimate MES using the data of six Korean banks (2003 Q1–2011 Q4, quarterly data): Hana, IBK, KB, KEB, Shinhan, and Woori. The data set to estimate MES includes the CDS spreads, equity values and liabilities of six banks.

4.3 Results

According to our results, individual banks' contribution to systemic risk varies somewhat depending on the time period. In general, however, Bank A shows the largest contribution followed by Bank B and Bank C, respectively. The ES of the entire system (sum of all MES) has risen since 2007 to peak in the second half of 2008, and has been higher during the post-crisis period than during the pre-crisis period (Table 6; Fig 7).

While the absolute level of marginal contribution to systemic risk varies depending upon the quantile level (or confidence level), the relative level and ranking of each bank's marginal contribution to systemic risk are generally stable during the sample period.

Regardless of the quantile level (5 or 2 %), Bank A shows the largest degree of marginal contribution to systemic risk (systemic importance), followed by Bank B and C. Evaluation of marginal contribution through the Shapley value methodology is effective for fair judgment of each bank's marginal contribution under the assumption that the measurement of systemic risks is accurate. These characteristics can be utilized when assessing the systemic importance of each bank in the course of implementing

[25] If any financial institution does not exist in financial system, the systemic risk is 0.

macroprudential policy. For example, in future discussions on D-SIBs regulation system, the Shapley value may be useful to calculate the systemic importance of individual banks. Efforts should be maintained to enhance the accuracy of the index. This can be achieved by performing sensitivity analysis of basic input variables.

5 Conclusion

We began this paper by stating that there was no obvious framework for measuring financial fragility, though much work is currently being undertaken in this field. It has been our purpose here to demonstrate that such a framework can be obtained. This is clearly a first shot at what has been a difficult problem. We hope and expect others to refine and to improve our methodology, but we contend that it can be done. Our results here suggest that the two variables that we identified in the composite financial stability index are highly significant in determining GDP, and, indeed, the most important factors over longer horizons when they are considered contemporaneously.

A metric for financial stability may contribute towards efficient crisis prevention and management. In addition, policy makers will inevitably be faced with clearly defined objectives and, therefore, be accountable for breaching them. We hasten to add that the component of the composite financial stability index of financial fragility is JPoD, and it is possible to predict its fluctuations (see, Goodhart et al. 2006a). The construction of metrics for financial stability may enable us to adopt the appropriate regulatory policy and implement effective regulatory measures. Ultimately, the aim is to build an evidence-based and analytically rigorous counter-cyclical regulatory structure for prudential regulation to replace the present pro-cyclical one.

6 Appendix

See Tables 7, 8, 9, 10, 11, and 12 and Figs. 8, 9, 10, 11, 12, and 13.

Table 7 Variance decomposition of GDP

Period	GDP	Equity	JPoD
1	100.0000	0.0000	0.0000
2	82.7691	8.4028	8.8282
3	81.9766	8.3010	9.7225
4	80.5439	8.1653	11.2908
5	80.3684	8.0740	11.5576
6	80.0019	7.7111	12.2870
7	79.6720	7.4023	12.9257
8	79.0050	7.1941	13.8008

Table 8 Variance decomposition of GDP

Period	GDP	Real TB03	Equity	JPoD
1	100.0000	0.0000	0.0000	0.0000
2	93.1850	0.2321	0.1700	6.4129
3	86.6390	4.7797	2.3761	6.2052
4	80.8822	4.4534	6.9196	7.7448
5	79.0745	4.4225	8.7788	7.7242
6	78.9196	4.0404	9.0280	8.0120
7	78.8528	3.8755	9.0283	8.2434
8	77.9211	3.8138	9.6167	8.6484

Table 9 Variance decomposition of GDP

Period	GDP	CPI	Real TB03	Equity	JPoD
1	100.0000	0.0000	0.0000	0.0000	0.0000
2	95.1457	0.0077	0.1023	0.3474	4.3969
3	88.8940	1.2381	4.0836	1.6384	4.1459
4	83.5214	2.6974	3.8596	4.7101	5.2115
5	81.4337	3.2268	4.0846	6.0859	5.1690
6	81.2176	3.3469	3.7408	6.3137	5.3810
7	81.3152	3.3348	3.6599	6.2001	5.4901
8	80.6196	3.5658	3.6319	6.4680	5.7148

Table 10 Variance decomposition of IPI

Period	IPI	Equity	JPoD
1	100.0000	0.0000	0.0000
2	88.2632	7.0884	4.6484
3	75.9789	6.7954	17.2257
4	75.7860	7.0368	17.1771
5	76.1319	6.9366	16.9315
6	76.9122	6.7074	16.3804
7	76.5245	7.1585	16.3170
8	75.7580	7.2646	16.9775
9	75.6234	7.2472	17.1294
10	75.5293	7.2896	17.1811
11	75.4641	7.3121	17.2239
12	75.3662	7.3808	17.2531
13	75.1480	7.4509	17.4011
14	74.9940	7.4933	17.5128
15	74.8377	7.5510	17.6113
16	74.6967	7.5943	17.7091

Table 10 continued

Period	IPI	Equity	JPoD
17	74.5738	7.6420	17.7842
18	74.4197	7.7005	17.8798
19	74.2704	7.7512	17.9785
20	74.1247	7.8032	18.0721
21	73.9787	7.8525	18.1688
22	73.8410	7.9016	18.2574
23	73.6977	7.9537	18.3486
24	73.5549	8.0037	18.4414
17	74.5738	7.6420	17.7842
18	74.4197	7.7005	17.8798
19	74.2704	7.7512	17.9785
20	74.1247	7.8032	18.0721
21	73.9787	7.8525	18.1688
22	73.8410	7.9016	18.2574
23	73.6977	7.9537	18.3486
24	73.5549	8.0037	18.4414

Table 11 Variance decomposition of IPI

Period	IPI	Real TB03	Equity	JPoD
1	100.0000	0.0000	0.0000	0.0000
2	88.4442	0.8170	5.6159	5.1229
3	74.1233	5.5543	5.3765	14.9459
4	68.5104	12.5793	5.0457	13.8646
5	68.7661	12.4864	4.9929	13.7545
6	69.6652	12.1828	4.8427	13.3093
7	69.2742	12.1174	5.2296	13.3789
8	68.3371	12.6348	5.1645	13.8637
9	68.2042	12.6688	5.2142	13.9129
10	67.9965	12.6392	5.3264	14.0380
11	67.9086	12.6759	5.3411	14.0743
12	67.8722	12.6582	5.4020	14.0675
13	67.7449	12.6668	5.4563	14.1320
14	67.6049	12.6522	5.5173	14.2257
15	67.4884	12.6304	5.5978	14.2834
16	67.3746	12.6200	5.6410	14.3644
17	67.2962	12.6015	5.6956	14.4067

Table 11 continued

Period	IPI	Real TB03	Equity	JPoD
18	67.1869	12.5878	5.7620	14.4634
19	67.0751	12.5790	5.8193	14.5267
20	66.9719	12.5624	5.8788	14.5869
21	66.8659	12.5474	5.9357	14.6510
22	66.7633	12.5322	5.9934	14.7111
23	66.6620	12.5177	6.0530	14.7674
24	66.5588	12.5045	6.1093	14.8273

Table 12 Variance decomposition of IPI

Period	IPI	CPI	Real TB03	Equity	JPoD
1	100.0000	0.0000	0.0000	0.0000	0.0000
2	87.5458	2.5528	0.3415	5.1387	4.4212
3	74.7336	2.1559	4.2264	4.9947	13.8895
4	68.6723	1.9788	11.9193	4.6174	12.8122
5	68.8998	1.9573	11.8522	4.5769	12.7138
6	69.1909	2.6920	11.4387	4.4490	12.2294
7	68.0768	3.2255	11.2922	4.9464	12.4590
8	67.4245	3.1914	11.7939	4.9010	12.6891
9	67.3807	3.2412	11.7857	4.9202	12.6722
10	67.1628	3.2816	11.7353	5.0291	12.7913
11	66.9303	3.3852	11.7753	5.0339	12.8753
12	66.7878	3.4985	11.7756	5.0867	12.8515
13	66.6573	3.5594	11.7551	5.1436	12.8847
14	66.5707	3.5672	11.7403	5.2014	12.9204
15	66.4761	3.5665	11.7237	5.2952	12.9386
16	66.3599	3.5671	11.7203	5.3396	13.0131
17	66.2702	3.5909	11.6982	5.3898	13.0509
18	66.1551	3.6207	11.6754	5.4563	13.0925
19	66.0490	3.6532	11.6570	5.5109	13.1299
20	65.9600	3.6696	11.6381	5.5729	13.1595
21	65.8624	3.6800	11.6228	5.6326	13.2023
22	65.7642	3.6935	11.6054	5.6906	13.2463
23	65.6643	3.7118	11.5863	5.7512	13.2865
24	65.5649	3.7323	11.5678	5.8067	13.3283

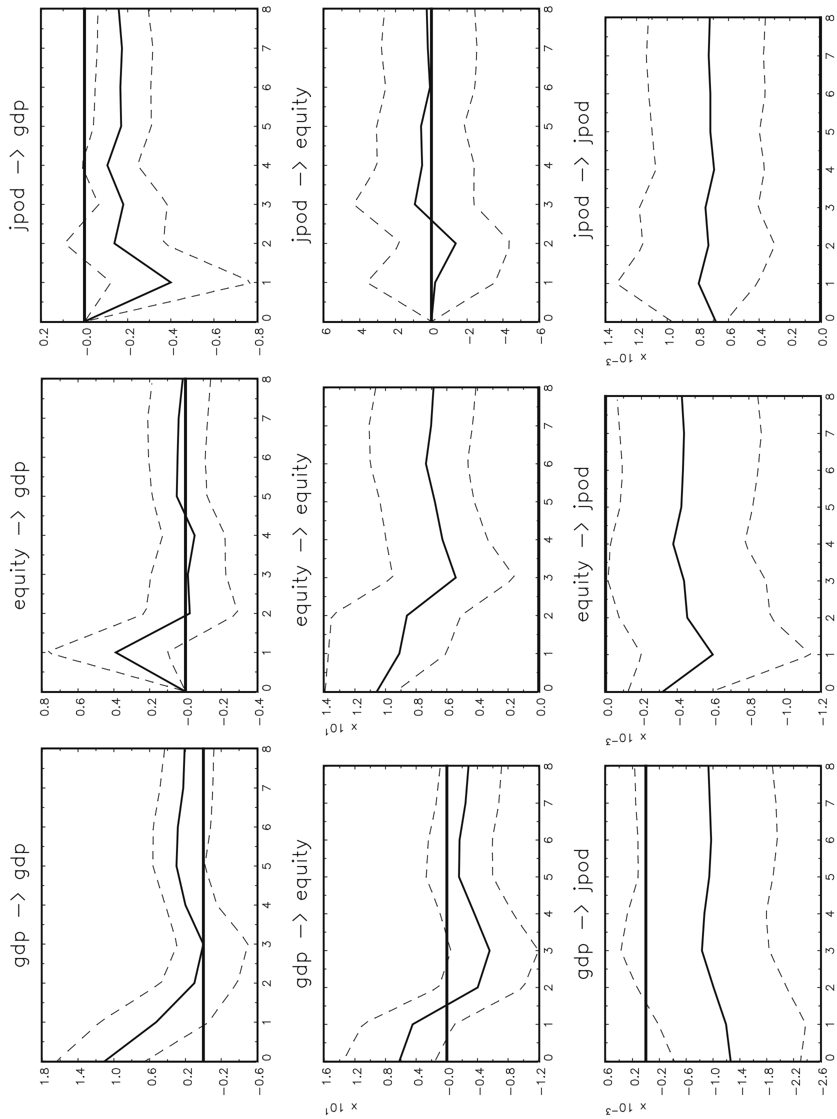

Fig. 8 Impulse response of a VECM with GDP, Equity, JPoD (baseline model). Note: The straight lines indicate the impulse responses based on an innovation of size one standard deviation. The dotted lines indicate the 95 % confidence interval

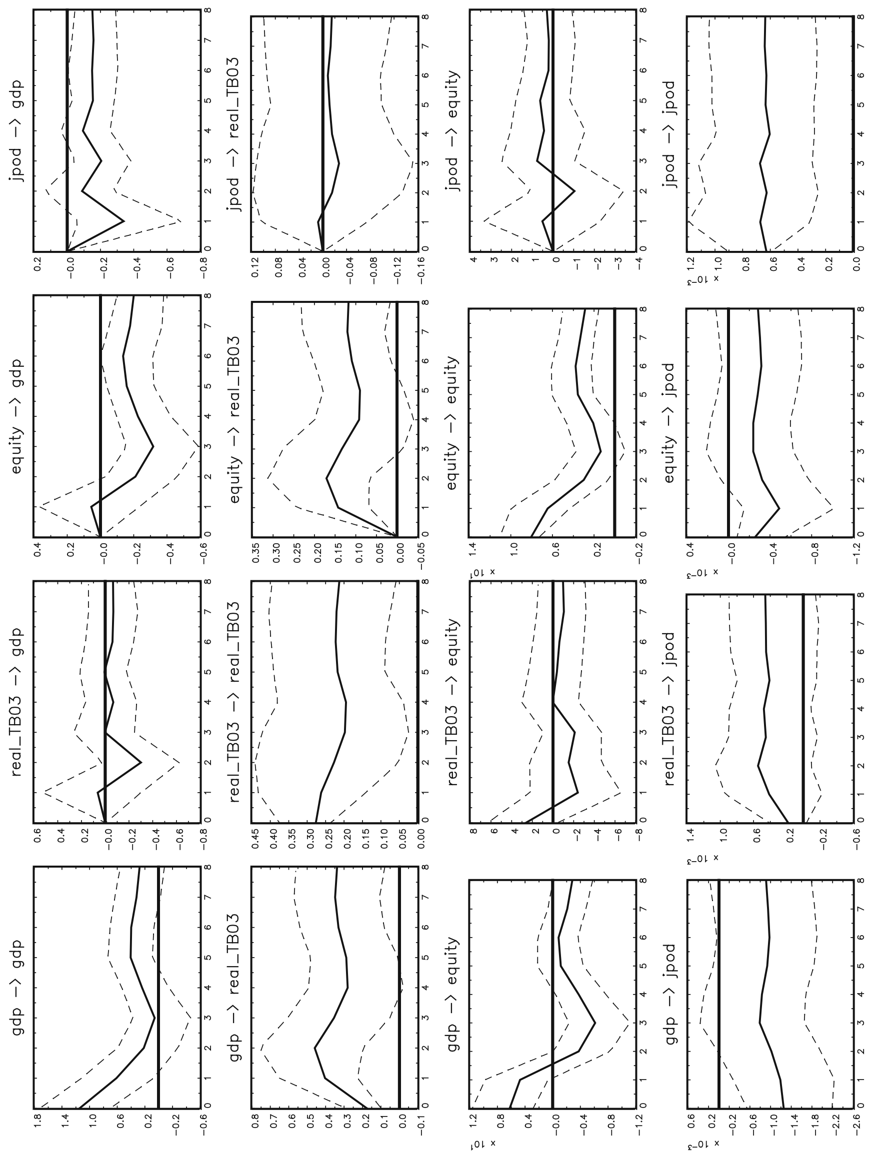

Fig. 9 Impulse response of a VECM with GDP, Real TB03, Equity, JPoD

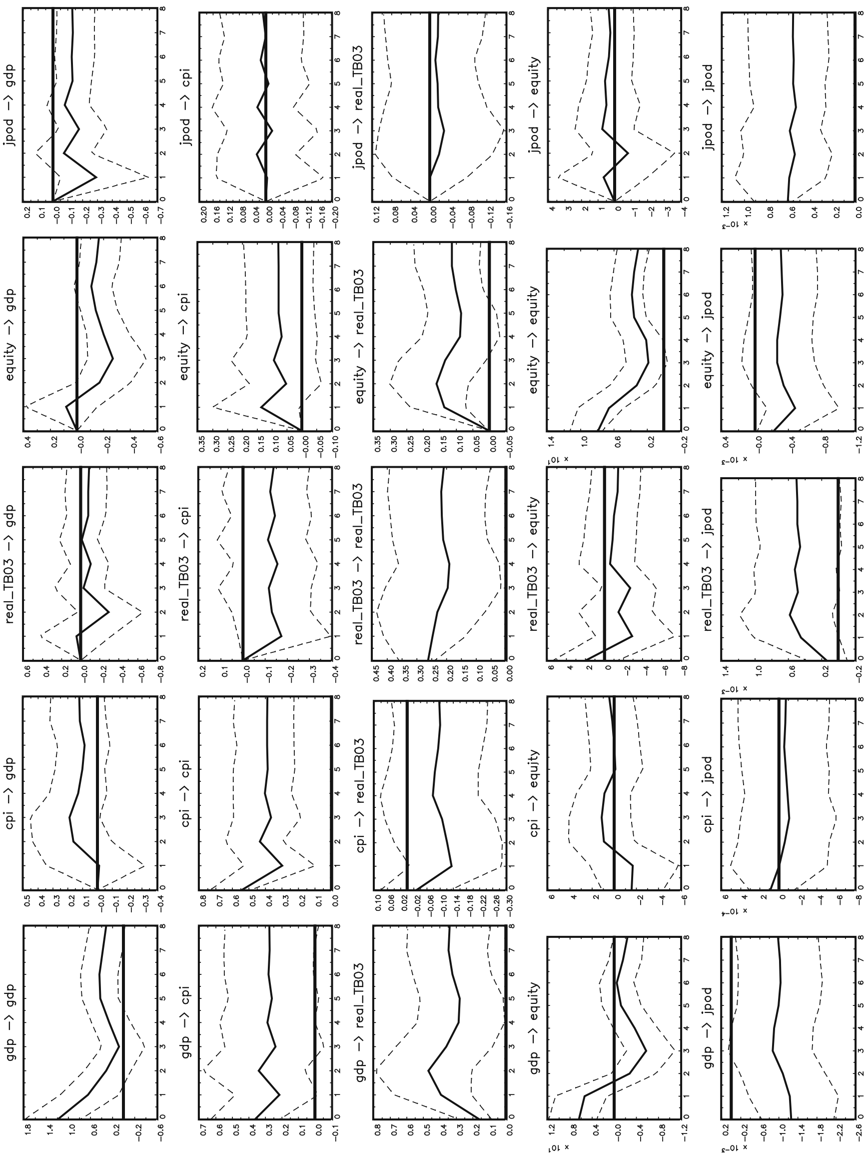

Fig. 10 Impulse response of a VECM with GDP, CPI, Real TB03, Equity, JPoD

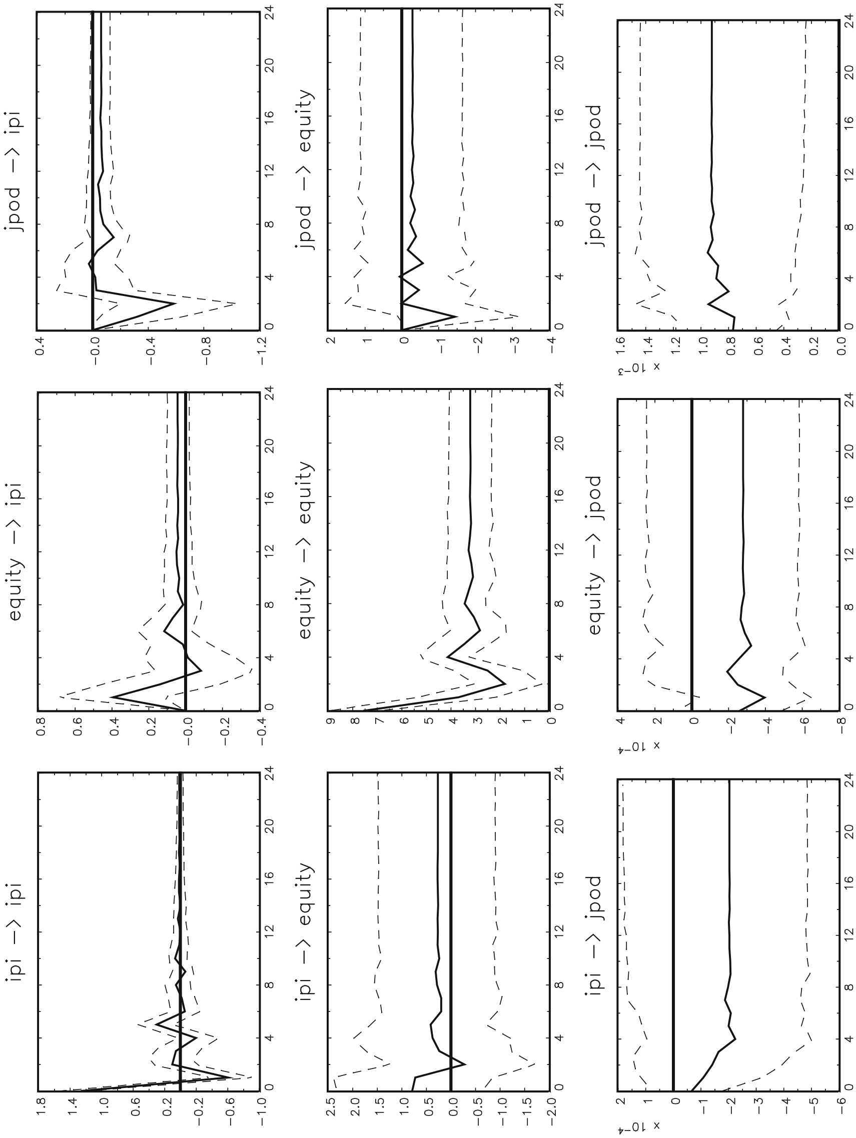

Fig. 11 Impulse response of a VECM with IPI, Equity, JPoD (Monthly data basis)

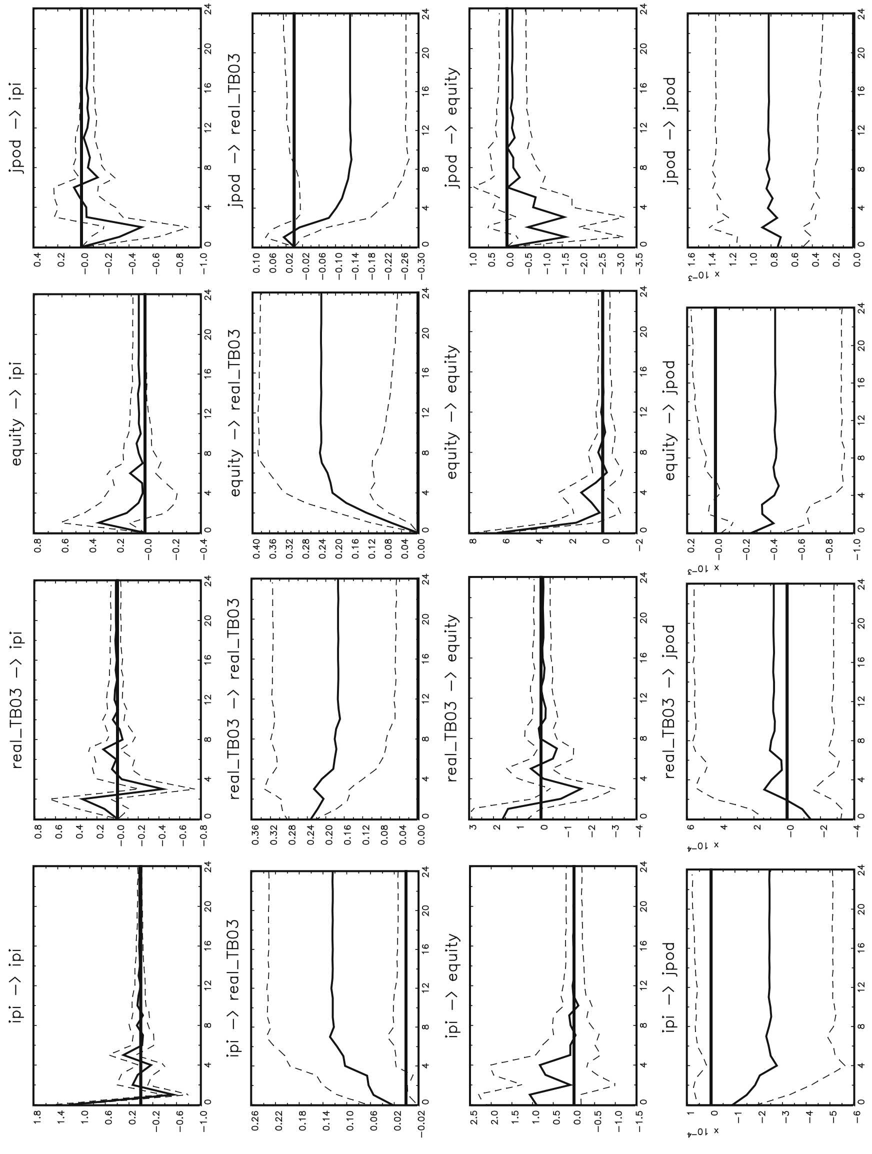

Fig. 12 Impulse response of a VECM with IPI, Real TB03, Equity, JPoD (Monthly data basis)

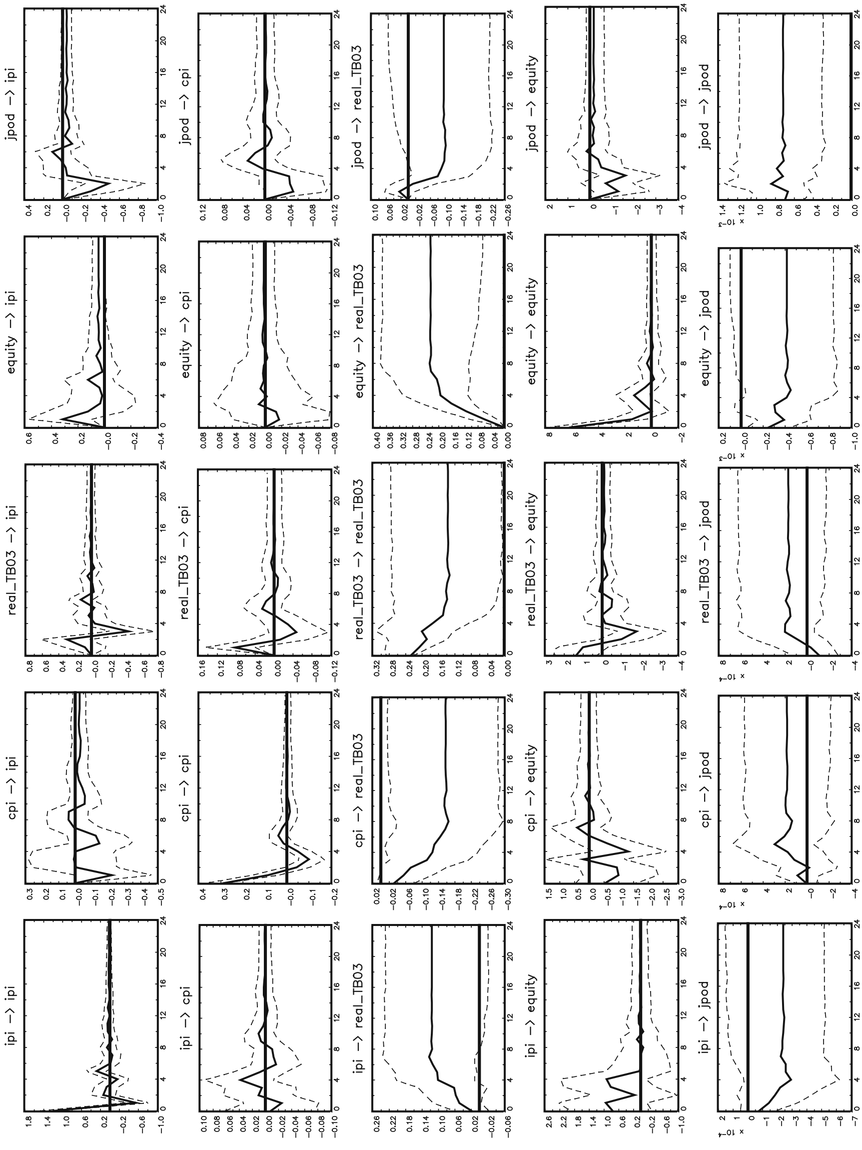

Fig. 13 Impulse response of a VECM with IPI, CPI, Real TB03, Equity, JPoD (Monthly data basis)

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