

Systemic Leverage as a Macroprudential Indicator

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We propose systemic leverage as a macroprudential indicator, which we construct by incorporating into aggregate leverage two systemic risk factors, procyclicality and interconnectedness. We conjecture that these factors are well captured by wholesale funding, off-balance sheet transactions, mark-to-market accounting, and cross-border activities. We determine each factor's weight for the indicator based upon its contribution to the business cycle. We calculate the indicator using the balance sheet data of domestic banks in Korea, and find that it issues warning signals at least one year in advance of financial crises and may complement the credit-to-GDP gap that does not explicitly reflect the systemic risk factors.

Keywords: Systemic Leverage, Macroprudential Indicator, Early Warning

JEL Classification Numbers: E50, G21, G28, G32

I . Introduction

The recent global financial crisis has taught us that initial shocks insignificant in size, for instance from subprime mortgage loans, may evolve into a full-blown financial crisis if they amplify within the financial system. This lesson prompts us to seek better understanding of the mechanism and factors that create systemic risk, and to develop macroprudential policy measures to counter or mitigate this risk. It is therefore crucial to construct indicators that are able to identify incipient systemic risk and provide warning signals of crisis at an early stage.

Although there is no single way of defining systemic risk, a broad agreement has emerged that procyclicality and interconnectedness are the main factors explaining it. Financial institutions build up excess leverage in the business cycle upswing and supply excess liquidity to financial markets and excess credit to households and firms. And in the downturn they then reverse this trend by deleveraging through fire-sales and contracting their credit supply. This procyclical behavior of financial institutions amplifies the financial and business cycle. Through interconnectedness, meanwhile, the other factor explaining systemic risk, shocks may spread within the financial system through direct and indirect financial networks connecting financial institutions. Any well-functioning systemic risk indicator should therefore be able to capture the temporal and cross-sectional factors in systemic risk, i.e. procyclicality and interconnectedness.^{2,3}

2 For the role of financial institutions and the reform of financial regulation in containing systemic risk, refer to Kim & Lee (2009), Noh (2009), Won (2011), Jun (2009) and Choi (2010).

3 The systemic risk indicator should also take into account interactions between the financial system and the macro-economy. For this, refer to Borio (2010).

We then note that two key criteria that a systemic risk indicator should be equipped with are, first, an early warning capacity and, second, the incorporation of procyclicality and interconnectedness. Many studies have focused on market price-based indicators. Lehar (2005), following Merton (1974), uses equity as a call option on a bank's assets. He suggests three main factors affecting systemic risk: the correlation between the values of banks' asset portfolios, their financial soundness in terms of capital adequacy, and the volatility of their assets. Adrian and Brunnermeier (2009) formulate the concept of CoVaR, the value at risk (VaR) of the financial system conditional on institutions being in distress. They construct the indicator using market data such as the yield curve, the aggregate credit spread, and the implied equity market volatility. Giglio (2011) uses a nonparametric approach to derive the bounds of systemic risk from CDS prices. Acharya, Pedersen, Philippon and Richardson (2010) suggest the systemic expected shortfall (SES), its propensity to be undercapitalized when the system as a whole is undercapitalized. They use the market data of equity and CDS spreads as the main components of the SES. Market practitioners meanwhile use market liquidity conditions (e.g., the liquidity risk component of the 3-month LIBOR-OIS spreads). None of these market-based indicators are able to satisfy our two key criteria, however. They are poor at providing early warning signals, behaving more like coincident indicators of financial distress, and they also do not capture the two main components of systemic risk: procyclicality and interconnectedness.

Over the past few years we have seen growing attention paid to quantity-based indicators, particularly using balance sheet data (e.g., of bank credit, liquidity and maturity mismatches, and currency risk) that are able to capture systemic risk in its buildup stage. The gap between the credit-to-GDP ratio and its long-term trend has been proposed as an indicator of systemic risk buildup in the banking system, and hence as a guide to setting the countercyclical capital buffers for banks.⁴ Measures of excess credit growth can provide useful forward-looking indicators of systemic risk.

⁴ See Borio and Drehmann (2009).

However, they cannot capture procyclicality or interconnectedness. They are the simple aggregates of credit supply by individual banks and therefore underestimate systemic risk. Two economies with the same credit-to-GDP gaps, for instance, may exhibit different degrees of systemic risk. The economy whose financial system is more procyclical and interconnected may show deeper deleveraging.⁵

We intend to develop a systemic risk indicator that satisfies both criteria—i.e. that both signals early warnings and incorporates procyclicality and interconnectedness. In order that it satisfies the early warning criterion, we construct it using balance sheet data. We know that the buildup of excess leverage and subsequent deleveraging in the balance sheets of financial institutions are critical to systemic risk, and we may set a threshold for the leverage building up during an upswing. But simple leverage cannot capture procyclicality and interconnectedness and may hence underestimate systemic risk. It therefore needs adjustment with factors that capture ‘hidden leverage’. We come up with a novel concept of ‘systemic leverage’, that incorporates this ‘hidden leverage’ into our simple leverage. We consider four categories of hidden leverage—‘mark-to-market leverage’, ‘interconnectedness leverage’, ‘off-balance sheet leverage’ and ‘FX leverage’. Financial institutions with mark-to-market profits and losses adjust their leverages, in the process of which their supplying of credit fluctuates. Market financing interconnects financial institutions through the financial markets so that external shocks are amplified within the financial system through contagion. Derivative contracts hidden off-balance have embedded leverage, and compound the leveraging and deleveraging process. For emerging market economies, meanwhile, the surge and sudden reversal of FX borrowings is another key systemic risk factor.

Our paper is organized as follows. Chapter 2 discusses the concept of

5 Other measures include metrics of concentration of risk within the system, macro stress-testing, and integrated monitoring systems (e.g., dashboards, heat maps, and composite indicators). See FSB, IMF and BIS (2011).

macroprudential indicators and sets out the key criteria that they should meet. Chapter 3 introduces systemic leverage as a macroprudential indicator and explains the main factors constituting it. Chapter 4, using the method proposed in Chapter 3, calculates systemic leverage for the Korean banking system. Chapter 5 concludes and provides some implications.

II. Macroprudential indicators

This chapter examines macroprudential indicators as systemic risk measures, and the key criteria that they should meet. It points out some limitations of the existing indicators.

2.1 Research background

The global financial crisis of 2008 has shown that initial shocks, even if insignificant in themselves, can cause financial crisis if they amplify within the financial system. This lesson suggests the importance of a macroprudential policy that deals with measuring and containing systemic risk.⁶ The objective of macroprudential policy is thus to identify in advance the potential financial risk existing across the financial system and contain the buildup of systemic risk.⁷ Microprudential regulations targeting the soundness of individual banks are therefore not sufficient for addressing systemic risk, which requires system-wide policies. We need indicators that

6 The Group of Ten (2001) defined systemic risk as “the risk that an event will trigger a loss of economic value or confidence in, and attendant in uncertainty about, a substantial portion of the financial system that is serious enough to quite probably have significant adverse effects on the real economy.”

7 Yoon & Jung (2010) provide an in-depth discussion of systemic risk and the macroprudential policy framework.

are able to capture the risk that evolves endogenously within the system, and to identify it at the buildup stage. We note that optimal decision-making by individual banks does not always lead to financial system stability, owing to the fallacy of composition. Optimal bank lending, for instance, rises in the business cycle upswing when the perceived risk is low, and then falls in the downswing. This procyclical lending exacerbates the business cycle, however. Another case is that of risk diversification, intended to reduce risk, working to instead actually increase systemic risk by making financial institutions more interconnected.

2.2 Criteria for systemic risk indicator

In order for a systemic risk indicator to function properly we suggest that it should satisfy several criteria. First, it should be able to signal warning of a buildup of systemic risk in advance. Systemic risk builds up in the business cycle upswing with financial institutions taking on leverage and churning liquidity out into the financial system. A financial authority may set thresholds to trigger warning signals. According to the recommendations of the BCBS, macroprudential indicators with early warning functions should move at least one year ahead of the real business cycle. Second, the systemic risk indicator should be able to capture the two main components of systemic risk—procyclicality and interconnectedness both within the financial system and between the financial system and the real economy. Third, the indicator should be easily understood by regulators, thus reducing model risk and enhancing transparency, and the data used easily accessible.

2.3 Comparison of existing indicators and their limitations

Many existing indicators are calculated using financial market data. They do not identify potential risk and signal warnings but rather simply reflect the risk already revealed in the markets. They therefore fail to function as early warning indicators. If

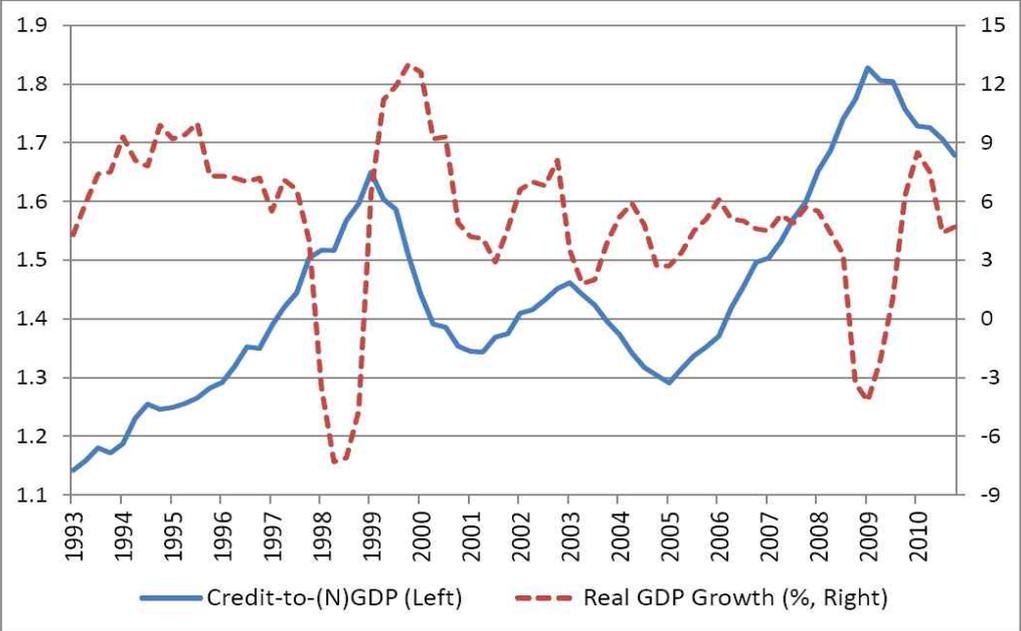
we look at the movements of CDS premiums and stock price indexes one year before the global financial crisis, for instance, none of them send out warning signals. They only signal warnings after the crisis has hit. This means they can only be contemporaneous indicators, and not early warning indicators. Moreover, the information extracted from financial market data contains a psychological risk premium that investors demand. It will therefore tend to underestimate risk in the upswing and overestimate it in the downswing, amplifying the business cycle. Market price-based indicators may send the wrong signals.⁸

In order for macroprudential indicators to effectively signal early warnings we should therefore construct them using balance sheet data, which show the stages of systemic risk buildup. We note that excess market liquidity that creates asset price bubbles is supplied by financial institutions taking on excess leverage. We can look at leverage in the balance sheet from both the liability and the asset sides. For the liability side the ratio of M1 or M2 over GDP can be a good macroprudential indicator showing system-wide liquidity. For the asset side the most frequently used indicator is the credit-to-GDP gap. In this regard, from the fact that systemic liquidity depends more upon assets than liabilities, we consider a credit aggregate superior to a money aggregate. This argument is supported by the empirical analysis of Drehmann, Borio, Gambacorta, Jimenez and Trucharte (2010). Figure 1 shows that the credit-to-GDP gap has some capability as an early warning indicator. It rises steeply before the 1997 and 2008 financial crises in Korea, although also continuing to rise even after the crises owing partly to the government intervention. The credit-to-GDP gap has a limitation, however, in that when the financial and real business cycles differ interpretation becomes ambiguous. If GDP contracts faster than credit in the downswing, for instance, the gap can increase, signaling excess liquidity. More

⁸ Borio (2010) points out problems in market price-based indicators, arguing that asset prices are unusually strong, leverage measured at market prices artificially low, and risk premia and volatilities low precisely when risk is highest. This he terms the “paradox of financial instability”.

importantly, however, this indicator is a simple aggregate of the credit supplied by individual banks, and hence does not incorporate the interactions among economic agents. This is a crucial limitation for macroprudential indicators, considering that systemic risk amplifies through the feedback mechanism. The credit-to-GDP gap thus tends to underestimate systemic risk.

<Figure 1: Credit-to-GDP and real GDP growth rate in Korea>



III. Systemic leverage as a macroprudential indicator

This chapter details the basic concept of systemic leverage that we propose, and the main factors that constitute it.

3.1 Leverage and procyclicality

Financial institutions generally run their businesses by utilizing their own and borrowed capital for loans and investments. Here the ratio of an institution's total assets (or total capital) to its own capital is termed leverage. Institutions use this leverage to maximize their return on equity (ROE), since given the return on assets (ROA) their ROE increases with higher leverage.⁹ Leverage is an easy way of boosting ROE when the ROA is positive, but the opposite holds when the ROA is negative. It is a stylized fact that leverage is procyclical, meaning that it rises in the business cycle upswing when financial risk is perceived to be low and falls in the downswing. And this creates the credit cycle. Importantly, even if leverage remains constant in the upswing this leads financial institutions to increase their credit supply. In the upswing, when profits increase, other things being constant leverage falls.¹⁰ Financial institutions that manage their leverage at target levels may then increase their asset (loan and investment) sizes to adjust leverage to the target levels. Adrian and Shin (2009) show the interactions of leverage with mark-to-market (MTM) profits (losses), leading to excess credit supply in an upswing and credit crunch in a downswing. They argue that leverage should have a negative relationship with asset growth unless it is managed with liabilities.¹¹

They show that leverage behaves very differently for households, commercial banks and investment banks. Leverage for households falls with asset growth, since households do not adjust their leverage to target levels while commercial banks do. Investment banks that actively manage their leverage according to the business cycle raise their target ratios in the upswing, and leverage shows an upward trend against

9 $ROE (R/E) = ROA (R/A) \times \text{Leverage} (A/E)$, where R is the return, E the equity and A the assets.

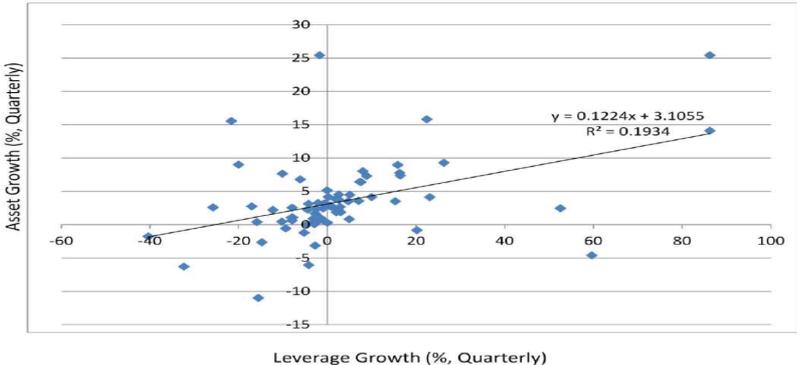
10 $A/E > (A + \alpha) / (E + \alpha)$, where α is the profit.

11 $A/E = 1 + L / (A - L)$ where L is the liabilities. Note that leverage has a negative correlation with assets if liabilities remain constant.

asset growth. In Figure 2 we plot the leverage of Korea’s domestic banks against their asset growth, using quarterly data from between 1993 and 2010. The result is a weakly positive slope, meaning that Korea’s domestic banks do, although weakly, manage the levels of their leverage procyclically. They increase their supply of credit in times of asset growth.

The procyclical behavior of financial institutions is closely linked to their risk management targeting leverage or the risk-weighted capital ratio. First, risk-sensitive capital regulations require banks to hold capital relative to risk-weighted assets that depend upon perception of risk and are hence inherently procyclical. Second, capital varies procyclically because profits, the main driver of capital variation, are strongly influenced by the procyclical movements of loan loss provisions and MTM profits (losses). In the upswing the first factor makes the target leverage rise while the second makes actual leverage fall, causing the gap between leverage and its target level to widen. Banks that adjust their leverage to the target level then increase their supply of credit. In the downswing the opposite occurs. Banks have to cut back their credit supply in downward adjustment of leverage to the target level. Geanakoplos (2010) theoretically demonstrates that this vicious leverage cycle is the key to the asset price bubble and burst, and argues that the leverage cycle should be regulated. Lee (2011) argues that under inflation targeting the effectiveness of monetary policy in controlling liquidity can be weakened if banks manage their leverage actively.

<Figure 2: Leverage management behavior of Korean banks>



3.2 Concept of systemic leverage

During the recent global crisis, the excessive leverage by financial institutions and resulting excess market liquidity were pointed out as the main factors behind the crisis. In this regard, the Basel Committee has introduced a leverage ratio regulation to be implemented from 2018. It focuses on individual banks, however, and so cannot sufficiently capture systemic risk that amplifies through the interactions among financial institutions. A macroprudential indicator to control leverage from the perspective of systemic risk is needed, and for this we propose a systemic leverage that aggregates the individual leverages and incorporates procyclicality and interconnectedness, the components of systemic risk:

$$\text{Systemic leverage} = \sum_i \text{leverage}_i \times (\text{procyclicality} + \text{interconnectedness})$$

It is not easy to capture the systemic risk components, as they are hidden on- and off-balance sheet and can take various forms. The leverage embedded in derivative contracts is hidden off-balance, for instance, and hard work is required to get the data. We can nevertheless take an approach similar to that taken by the Basel Committee in defining the G-SIBs.¹² We also introduce multiple indicators to explain each category. First we notice, following Basel, that interconnectedness can spread through inter-financial assets and liabilities. Second, derivative contracts are to a large extent made among financial institutions, to hedge the risks they are exposed to in their transactions with customers. Losses are also amplified in line with the degree of margin required; the smaller the margin requirement, the higher the embedded leverage. For procyclicality we propose an indicator that captures exposure to MTM valuation. We discussed in Section 3.1 how mark-to-market valuation, together with

12 See “Global systemically important banks: Assessment methodology and the additional loss absorbency requirement,” November 2011. The Basel Committee proposed four categories in defining G-SIBs, and one to three indicators for each category.

leverage adjustment by financial institutions, can intensify procyclicality in credit supply. Finally, we include FX debt, that shows a surge during upswings and a sudden reversal in downswings. This indicator is particularly relevant to emerging market economies.

3.3 Systemic leverage indicators

This section introduces the five components that constitute our systemic risk indicator. The first is ‘borrowing leverage,’ which financial institutions use to increase their returns on equity (ROE). It is the simple aggregate of individual leverages across financial institutions and cannot capture systemic risk, i.e., interconnectedness and procyclicality. We use the other four components that can capture systemic risk to adjust this ‘borrowing leverage. Two of them, termed ‘interconnected leverage’ and ‘off-balance sheet leverage,’ capture interconnectedness. The other two components, which capture procyclicality, are termed ‘MTM leverage’ and ‘FX leverage.’

3.3.1 Borrowing leverage

Borrowing leverage is defined as aggregate assets divided by aggregate equity capital across financial institutions. It is the base leverage on which we construct the systemic leverage indicator by incorporating into it our systemic risk components. It rises with the expansion of assets funded by liabilities, given the same equity capital.

3.3.2 Off-balance sheet leverage

Off-balance-sheet leverage measures the leverage hidden in derivatives and contingent liabilities in the form of off-balance sheet transactions. Financial institutions can increase their leverage without borrowing using derivative contracts. A derivative contract remains off the balance sheet until the case where the counterparty fails to meet its obligations. During the global financial crisis financial institutions

with derivative contracts saw their borrowing leverages rise sharply because of counterparty risk. Other contingent liabilities including guarantees and loan commitments may also increase leverage if they materialize. We define the off-balance leverage as derivatives and contingent liabilities divided by equity capital.

3.3.3 Interconnected leverage

Interconnected leverage captures interconnectedness in the financial system that increases through exposures among financial institutions. We incorporate these exposures using the trading account and available-for-sale securities on the asset side and wholesale funding on the liability side. They include financial bonds, CDs, repos, call loans, interbank lending and deposits. Wholesale funding becomes a readily-available channel through which financial institutions actively increase their leverage during the upswing. But it also becomes the channel through which they undertake deleveraging in response to fire-sales in the wholesale funding markets when their costs of borrowing rise sharply. The interconnected leverage is defined as exposures among financial institutions divided by equity capital.

3.3.4 FX leverage

For emerging market economies, external borrowing through financial institutions has become the major channel of financial distress. The Korean financial system experienced severe disruptions in 1997 and 2008 when massive capital inflows abruptly reversing to outflows.¹³ Before 2008 foreign bank branches in Korea had borrowed heavily from their headquarters to provide FX and currency swaps for domestic banks exposed to overbought forward positions as a result of forward buying contracts with shipbuilders.¹⁴ We calculate FX leverage using external borrowing divided by equity capital.¹⁵

13 FX borrowing peaked during these two crisis episodes. Shin et al. (2011) link both the 1997 and 2008 crises in Korea to excessive FX borrowing.

14 See Ryoo & Park (2008) for more detailed explanation of the external borrowings by Korean banks through the FX and currency swap markets.

15 We can make FX leverage better reflect systemic risk by differentiating among external

3.3.5 MTM leverage

We saw in Section 3.1 that financial institutions increase/decrease their leverages in response to MTM profits/losses in order to meet their target levels. With more assets under MTM accounting, financial institutions are likely to adjust their leverage more sensitively. During the global crisis MTM losses were the main driver behind deleveraging. We may measure MTM leverage as assets under MTM accounting divided by total assets. We do not incorporate the MTM leverage into our indicator here, however, as it is not significant for domestic banks. It might become very significant if we were to measure it for global investment banks in advanced economies.

3.4 Systemic leverage index

The components of systemic leverage that we reviewed in Section 3.3 may be categorized into the basic component of borrowing leverage and three systemic components of off-balance sheet leverage, interconnected leverage and FX leverage. We then propose systemic leverage as a macroprudential indicator as follows:

$$\begin{aligned} I_t &= \log(L_t^{w_1 l_{1t} + w_2 l_{2t} + w_3 l_{3t}}) \\ &= (w_1 l_{1t} + w_2 l_{2t} + w_3 l_{3t}) \log(L_t) \end{aligned} \quad (1)$$

In Equation (1), L_t stands for borrowing leverage and l_{1t} , l_{2t} and l_{3t} respectively off-balance sheet leverage, interconnected leverage and FX leverage, that we use to adjust borrowing leverage, and w_1 , w_2 and w_3 the corresponding coefficients determined by the degrees of contribution to systemic risk. We will explain how we estimate them in Chapter 4.

borrowings in accordance with their maturities.

IV. Empirical analysis

This chapter estimates the parameters for the systemic risk components of systemic leverage w_1 , w_2 , w_3 , and carries out some empirical analyses with the systemic leverage indicator.

4.1 Data

We use balance sheet data for domestic banks provided by the Financial Supervisory Service through the Financial Analysis Information Retrieval System. Our dataset has a monthly frequency and its time span is from January 2001 to December 2010.¹⁶ The domestic banks included are seven commercial banks (KB Kookmin, Shinhan, Woori, Hana, Standard Chartered, Citibank Korea and KEB), six local banks (Kyongnam Bank, Kwangju Bank, Daegu Bank, Busan Bank, Chunbuk Bank and Jeju Bank), four special banks (NH Bank, Suhyup, IBK and KDB), and all foreign bank branches.

Figure 3 shows the plotting of all components of the systemic leverage indicator. In the upper panel borrowing leverage, total assets divided by shareholder's equity, does not show any sign of a build-up of systemic risk before the global crisis. It stays constant for two years before the crisis, after two years of decline. And so by looking at the simple leverage ratio alone we cannot identify any systemic risk build-up. We note, however, that Korea experienced severe financial distress after the Lehman Brothers collapse. The second plot in the same panel shows the trend of off-balance sheet leverage that rises steadily until the global crisis. This demonstrates the necessity of incorporating this component into the indicator. The bottom panel shows two plots:

¹⁶ We exclude data from before 2000 in our analysis in order to avoid inconsistencies arising from changes in the accounting rules and from mergers and acquisitions.

interconnected leverage and FX leverage. Interconnected leverage exhibits a mild rise before the global crisis, followed by a sharp decline after it. This seems to suggest this component to have been at an unsustainable level before the crisis. The most dramatic component is FX leverage, which displays a steep upward trend before the crisis and a sharp reversal afterward. Overall, we may identify the buildup of systemic risk through looking at all systemic components.

<Figure 3: Components of systemic leverage>

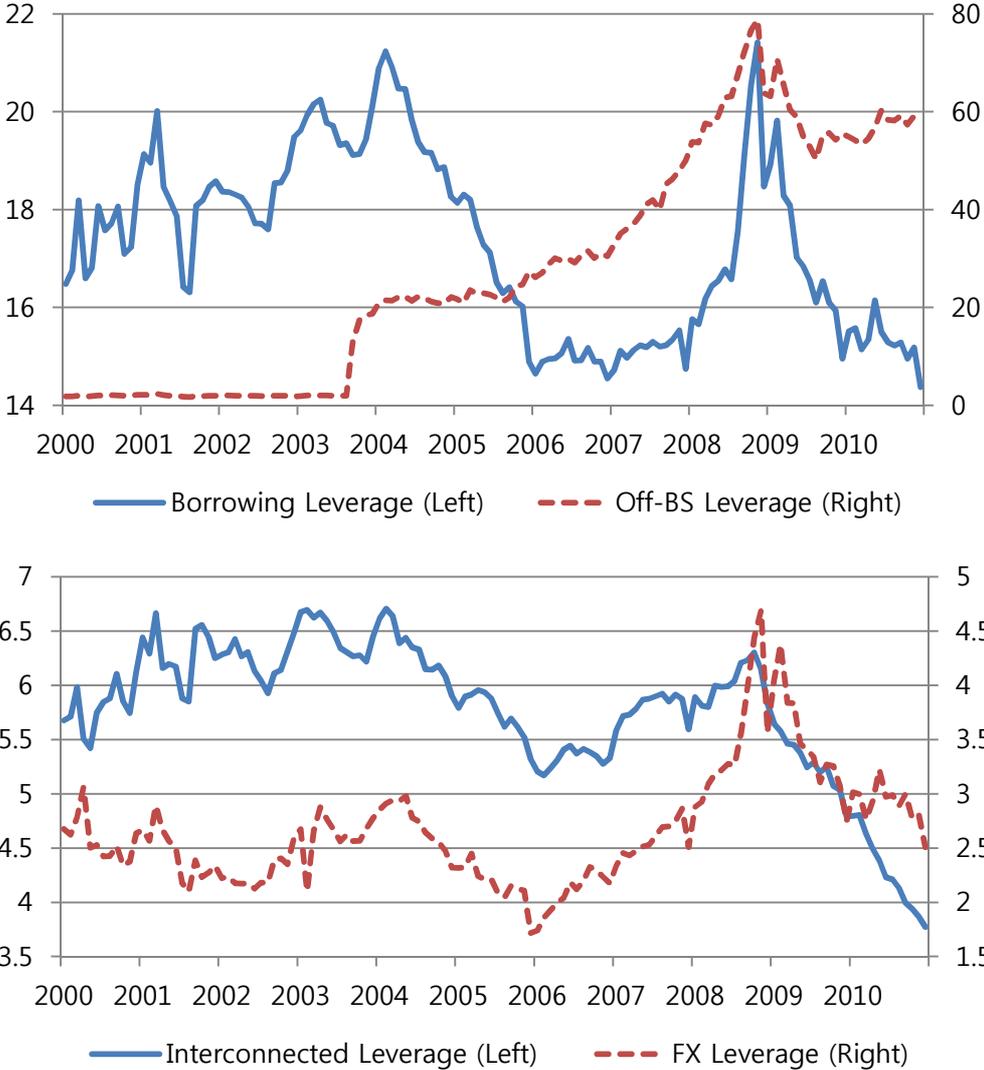


Table 1 gives the basic statistics for each component of systemic leverage.¹⁷ We notice that off-balance sheet assets and FX liabilities are very volatile in terms of their relative standard deviations.

<Table 1: Basic statistics for systemic leverage>

(Billion won)

	Assets	OBS	Inter. Assets	FX Liab.	Equity Cap.
mean	1323416	2840251	438629	216756	77835
median	1182980	1556524	408907	157636	70806
S.D.	444576	2846790	136441	114479	30484
kurtosis	0.499	0.606	0.255	0.838	0.321
skewness	-1.073	-1.239	-1.418	-0.751	-1.392
min	694023	75757	239068	103680	34293
max	2265143	8334678	663544	495793	131798
observation	132	132	132	132	132

4.2 Methodology

We can estimate parameters in Equation (1) $w = (w_1, w_2, w_3)$, with their sensitivities to procyclicality measured from their contribution to the business cycle. Our empirical analysis consists of two parts: we first measure the business cycle, and then estimate the parameters.

¹⁷ Equity capital data show irregularity because banks reflect bad debt expenses only at the end of each quarter. We thus smooth it with the ‘RLOESS’ (a robust version of local regression using weighted linear least squares and a first degree polynomial model) technique.

4.2.1 Measurement of business cycle

We might consider using the GDP growth rate to measure the business cycle. Its frequency is quarterly, however, while our analysis requires monthly data. And it also lags behind the business cycle. We therefore use the KOSPI stock index and the won/dollar exchange rate instead, because they have monthly data and move closely along with the business cycle.

We construct a Markov regime-switching model with two variables and two states. $S_t = \{1, 2\}$, where $S_t=1$ for normal times (i.e., low volatility) and $S_t=2$ for crisis times (i.e., high volatility):

$$Z_t^{(1)} = \mu_{S_t}^{(1)} + b_1^{(1)} Z_{t-1}^{(1)} + b_2^{(1)} Z_{t-1}^{(2)} + \sigma_{S_t}^{(1)} \epsilon_t^{(1)} \quad (2)$$

$$Z_t^{(2)} = \mu_{S_t}^{(2)} + b_1^{(2)} Z_{t-1}^{(1)} + b_2^{(2)} Z_{t-1}^{(2)} + \sigma_{S_t}^{(2)} \epsilon_t^{(2)} \quad (3)$$

We assume that the states evolve over time in accord with the first order Markov chain, $P[S_t | s_1, s_2, \dots, s_{t-1}] = P[S_t | s_{t-1}]$, and that the transition probability is time-invariant. We estimate the Markov regime switching model by the maximum log-likelihood estimation method.¹⁸ We then infer the filtered probabilities $\pi_{1,t} = P[S_t = 1 | y_1, y_2, \dots, y_t]$ and $\pi_{2,t} = P[S_t = 2 | y_1, y_2, \dots, y_t] = 1 - \pi_{1,t}$.

Table 2 shows our estimation results. Volatility for both the KOSPI and the won/dollar exchange rate is lower in State 1 (normal state) than in State 2 (crisis state). The returns of the KOSPI and the won/dollar exchange rate, $\mu_{S_t}^{(1)}$ and $\mu_{S_t}^{(2)}$, are positive and negative respectively in State 1, and the opposites hold in State 2. We can therefore claim State 1 as the normal state and State 2 as the crisis state. Figure 4

¹⁸ Refer to Hamilton (1989) and Kim & Kim (2010) for maximum likelihood estimation in a regime switching model.

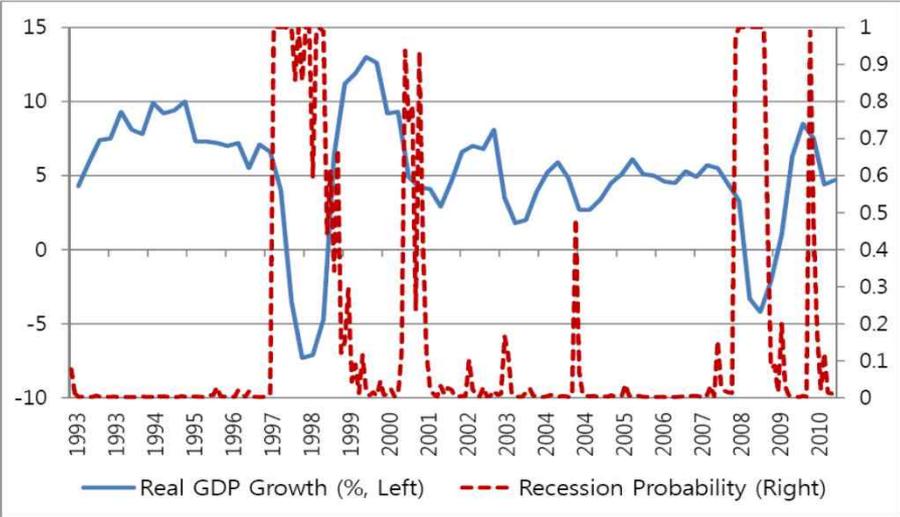
shows the filtered probabilities¹⁹ and the quarterly GDP growth rates. We notice that they move in the same direction:

<Table 2: Results of the maximum likelihood estimation for the regime-switching model of two variables and two states>

	$\mu_1^{(.)}$	$\mu_2^{(.)}$	$\beta_1^{(.)}$	$\beta_2^{(.)}$	$\sigma_1^{(.)}$	$\sigma_2^{(.)}$	P_{11}	P_{22}	LLH
$Z_t^{(1)}$	0.007 (1.333)	-0.011 (-0.350)	0.091 (0.829)	-0.165 (-0.433)	0.005 (3.351)	0.023 (1.273)	0.98 (3.50)	0.89 (0.83)	738.95
$Z_t^{(2)}$	-0.002 (-0.348)	0.020 (0.904)	0.050 (0.734)	0.065 (0.248)	0.000 (1.253)	0.012 (0.766)			

Numbers in parentheses are t-test statistics; P_j is the transition probability from state i to state j; LLH is the value of the log-likelihood function.

<Figure 4: Real GDP growth rate and filtered probabilities of business cycle>



19 With the result of maximum likelihood estimation we can express the state at each point of time in a probability. The probability has two types: filtered probability, $p_t = \Pr(S_t = i | \varphi_{t-1})$, and smoothed probability, $q_t = \Pr(S_t = i | \varphi_T)$. We choose filtered probability, putting priority on real-time analysis from the policy perspective. We however find both probability types produce similar results for the regime-switching times and overall pattern.

4.2.2 Parameter estimation through sensitivity analysis

Given the financial cycle constructed by the process of filtered probabilities, we estimate parameters showing the sensitivity to the cycle of each factor i of systemic leverage as follows:

$$Y_{t+h} = \alpha_i + \beta_i^h X_t + e_t, \quad (4)$$

where $Y_t = \Phi^{-h}(p_{2t})$ and $p_{2t} = \Pr(S_t = 2 | \Psi_{t-1})$, which is the filtered probability at time t of State 2, and $\Phi(\cdot)$ is the standard cumulative normal distribution function and Ψ_{t-1} denotes the set of observations obtained as of $t-1$. The X_i represents each factor of systemic leverage—borrowing leverage, off-balance sheet leverage, interconnected leverage and foreign exchange leverage. Note that we exclude mark-to-market leverage due to data constraints.

The coefficient β_i^h shows the sensitivity of each factor i of systemic leverage to the financial cycle. In other words, it represents the contribution of each factor to the buildup of systemic risk. The upper case h is the lead time between the systemic indicators and the financial cycle. We incorporate it to see how early each factor sends out a warning signal. This should make sense, because changes in the balance sheets of financial institutions affect the financial markets with time lags. We set the lead time h at 3, 6, 9 and 12 months. Note that the coefficient β_i^h of each factor is the average over the lead time h . We expect its sign to be positive if it has a positive contribution to the financial cycle.

Equation (4) appears to be identical to the modified probit regression analysis since it uses the linear regression method, applying the probit inverse function $\Phi^{-n}(\cdot)$ to the monthly probability of State 2. It however differs from the probit regression in that State 2 takes probabilities between 0 and 1 each time, while for the probit regression it takes either 0 or 1.

We use the repeated simple regression analysis, not the multiple regression analysis, in order to avoid multicollinearity among our explanatory factors. We also do not aim to improve forecastability of the financial cycle by incorporating the systemic risk factors, but rather to consistently measure the contribution of each component to procyclicality. Therefore, if we use a multiple regression we only make it more difficult to interpret the sensitivity of each component, because of their differences in explanatory power. Finally, as Rodriguez Moreno and Pena (2010) argue, a more intuitive and simpler model is necessary because it makes economic interpretation easier.

<Table 3: Sensitivity of systemic risk factors to the business cycle>

β_1^h	OBS leverage	Inter. leverage	FX leverage
h=3	0.021*** (10.986)	0.242*** (5.989)	0.317*** (8.449)
h=6	0.020*** (9.363)	0.309*** (7.357)	0.229*** (5.303)
h=9	0.015*** (5.980)	0.329*** (7.418)	0.124*** (2.634)
h=12	0.009*** (3.534)	0.323*** (7.209)	0.075 (1.559)

***, **, * indicate statistical significances of 1%, 5%, 10% respectively, and the values in parentheses are t-test statistics.

Table 3 gives the regression results for each component showing its sensitivity to procyclicality. For all components, the sensitivity coefficient β_1^h shows a positive sign and is significant for all values of h, meaning that they all contribute to systemic risk and should be incorporated into the systemic leverage indicator as adjustment coefficients.

We get a parameter of each factor w_i from the simple average of the sensitivity coefficient β_1^h for the horizon $h = 3, 6, 9, 12$. By plugging the parameters into Equation (1), we derive the systemic leverage indicator for the Korean banking system as follows:

$$I_t = (0.01062l_{1t} + 0.3008l_{2t} + 0.1863l_{3t})\log(L_t) \tag{5}$$

4.3 Evaluation of systemic leverage as an early warning indicator

<Figure 5-1: Systemic leverage as an early warning indicator>

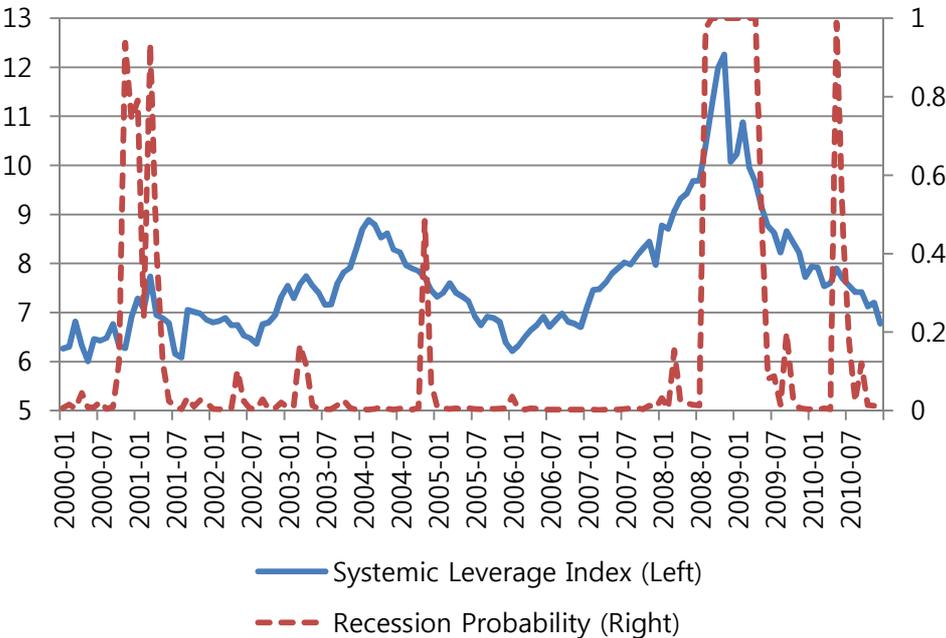


Figure 5 shows systemic leverage calculated using the monthly time-series data of all components. In order to evaluate its capability to issue early warnings we compare it with the business cycle that we derived in the previous section. Systemic leverage is for more than one year prior to the global crisis above its 7.70 average for the period as whole, showing that it can effectively issue an early warning. In particular, if we look at the year-on-year trend of systemic leverage growth, it reaches

15% in January 2007 and remains at around 20% for about the next two years, far exceeding the average of 5.20% for the whole period. Its early warning capability hence becomes more clearly noticeable. Using the systemic leverage indicator we can identify the buildup of systemic risk above the threshold and implement macroprudential policies to contain its further buildup.

<Figure 5-2: Systemic leverage as an early warning indicator>
(year-on-year growth rate)

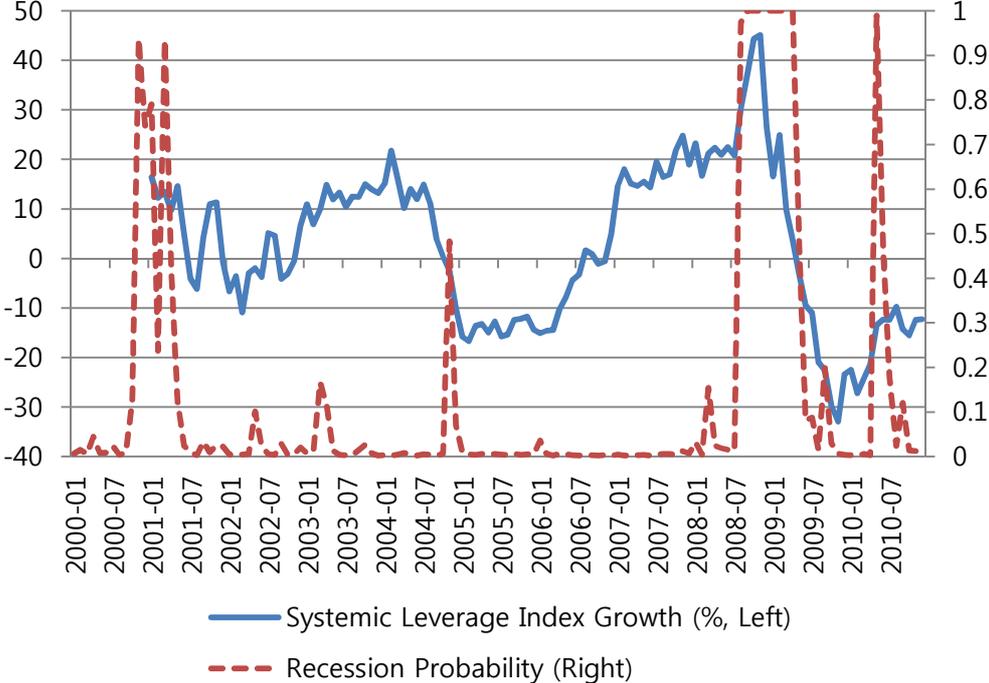
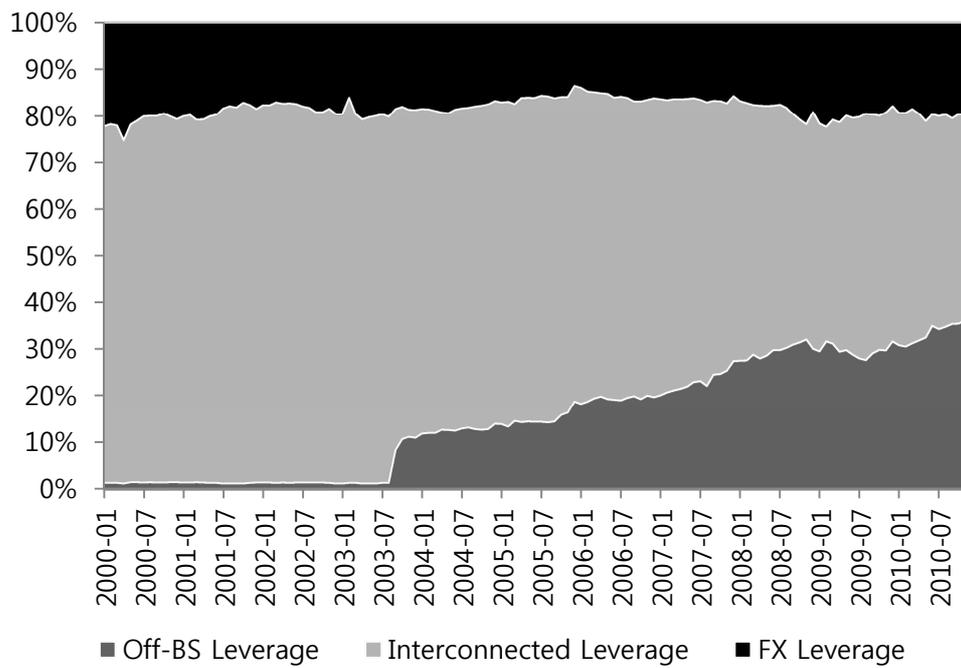
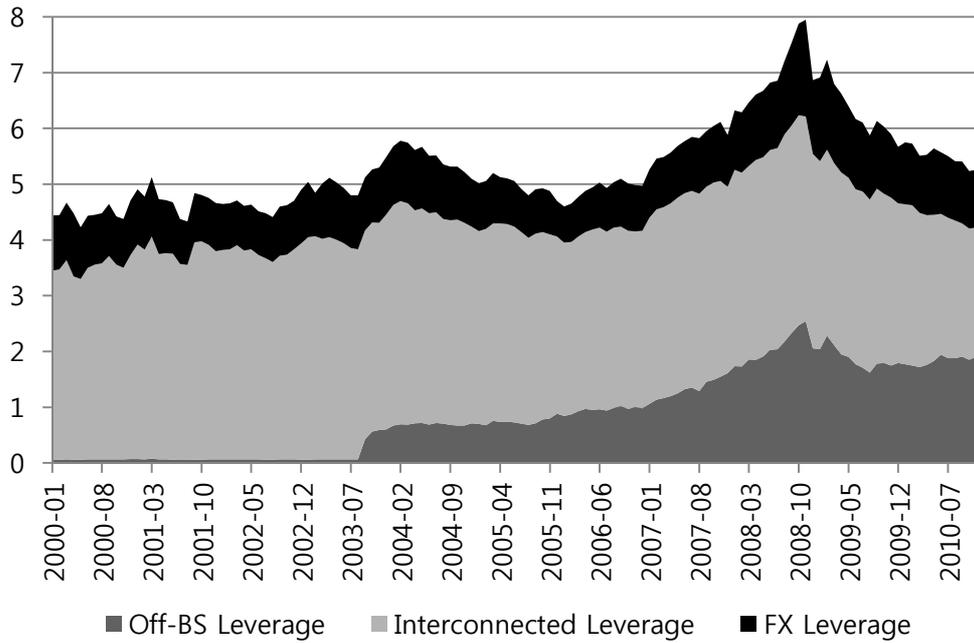


Figure 6 illustrates the trend of each component of systemic leverage, and its contribution to overall systemic risk. In the upper panel we can see FX leverage growing most rapidly before the global crisis, while interconnected leverage makes the largest contribution. With this kind of information we can make granular analysis and pinpoint the problem areas, and apply surgical tools and policies in response. This is one of the merits that our methodology brings. Moreover, its simplicity and transparency help regulators to better communicate with the markets.

<Figure 6: Systemic risk components of systemic leverage>



For more in-depth analysis of systemic leverage concerning its early warning function, we estimate the Markov regime-switching model with three states and one variable as follows:

$$\Delta I_t = \mu_{S_t} + \beta_{S_t} \Delta I_{t-1} + \sigma_{S_t} \varepsilon_t \quad (6)$$

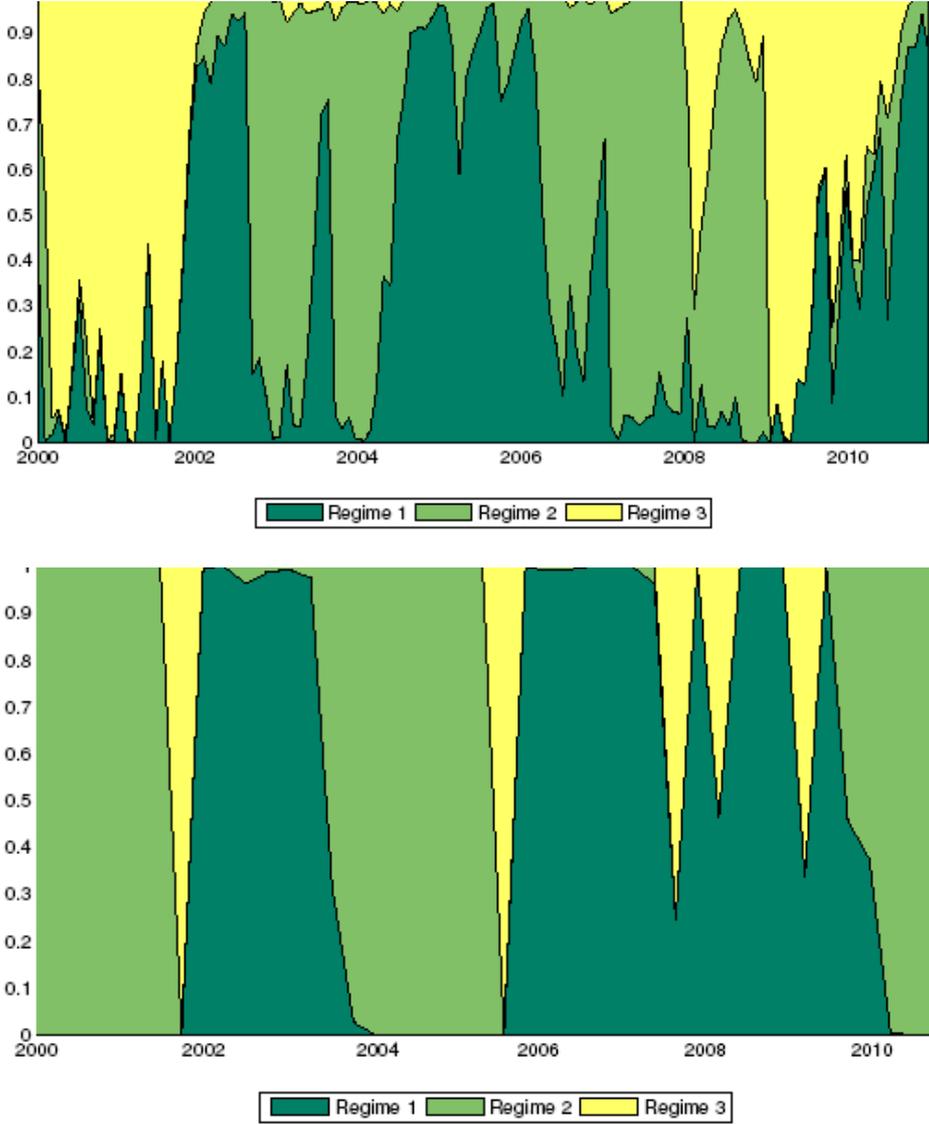
Note that ΔI_t is the log difference of systemic leverage in Equation (5), and that $S_t \in \{1,2,3\}$ is the state variable where $S_t = 1$ represents a stable state (low volatility), $S_t = 2$ a weakly stable state (medium volatility), and $S_t = 3$ an unstable state (high volatility). It is plausible that the volatility of ΔI_t rises during the period of systemic leverage accumulation because the growth rate of I_t would increase. We estimate parameters μ, β, σ with the maximum likelihood estimation method, and find them to have different values for the different states. We assume ε_t follows a normal distribution. We also estimate Equation (6) for the credit-to-GDP gap and compare it with systemic leverage in terms of their capabilities of issuing early warnings.²⁰

Figure 7 shows the state-dependent filtered probabilities for systemic leverage and the credit-to-GDP gap. Table 4 provides the results of estimation for both indicators. The systemic leverage indicator issues warning signals one year ahead of both the 2003-04 credit card crisis and the 2008 global financial crisis. More specifically, in the case of the global financial crisis, triggered by external factors, it issues a warning signal of a $S_t = 2$ probability above 0.5 from March 2006. And for the credit card crisis, triggered by misguided domestic policy and lack of regulation, it issues a very strong warning signal above 0.9 from 2001 to early 2002 that belongs to the $S_t = 3$ regime. Carrying out the same estimation for the credit-to-GDP gap and comparing the results with those for systemic leverage, we find it to issue much

²⁰ For the credit-to-GDP gap, for which we have only quarterly data, we compile data from 1993 in order to have sufficient observations.

weaker warning signals for both crises. This demonstrates that for the early warning function systemic leverage may complement the credit-to-GDP gap that does not incorporate the two main systemic risk factors, procyclicality and interconnectedness.

<Figure 7: Filtered probabilities of systemic leverage (upper) and credit-to-GDP gap (lower), estimated from regime-switching model of 3 states and 3 variables>



<Table 4: Estimation results for the systemic leverage indicator and the credit-to-GDP indicator, estimated from the Markov regime switching model of 3 states and 3 variables>

	Systemic Leverage	Credit-to-GDP
μ_1	-0.013 (-3.150)	0.017 (8.350)
μ_2	0.017 (3.035)	-0.017 (-6.107)
μ_3	-0.002 (-0.131)	0.019 (93.500)
σ_1	0.001 (5.270)	0.000 (0.000)
σ_2	0.001 (4.375)	0.000 (1.730)
σ_3	0.005 (4.702)	0.000 (0.000)
P_{11}	0.93 (13.29)	0.82 (4.82)
P_{12}	0.07 (1.17)	0.07 (1.75)
P_{13}	0.00 (0.00)	0.10 (1.43)
P_{21}	0.04 (0.80)	0.00 (0.00)
P_{22}	0.93 (0.00)	0.91 (4.33)
P_{23}	0.03 (1.00)	0.09 (1.29)
P_{31}	0.06 (1.50)	1.00 (1.96)
P_{32}	0.00 (0.00)	0.00 (0.00)
P_{33}	0.94 (31.33)	0.00 (0.00)
Log-likelihood	237.95	199.85

V. Conclusion and implications

Our paper proposes systemic leverage as a macroprudential indicator, incorporating the systemic risk factors, procyclicality and interconnectedness, into the simple borrowing leverage. We conjecture external borrowings and wholesale funding and off-balance sheet items to be the main sources of systemic risk in Korea. We reckon these systemic risk factors as hidden leverage that cannot be captured by a simple aggregate indicator, e.g. the credit-to-GDP gap. We coin names for each type of hidden leverage—FX leverage, off-balance sheet leverage, and interconnected leverage.

We calculate our systemic leverage indicator using balance-sheet data for domestic banks in Korea, and find that it can issue warning signals in advance of financial distress. We argue that it is capable of issuing early warnings because of two characteristics. First, it uses balance-sheet data that show the accumulation of systemic risk. We note that this is unlike the case with market price-based indicators, which only reflect already revealed risk. Second, our systemic leverage indicator incorporates systemic risk components that the credit-to-GDP gap lacks. Moreover, the systemic leverage indicator enables us to identify the contributions of different components to systemic risk.

Of course, systemic leverage cannot by itself explain all aspects of systemic risk in the financial system. For instance, it may not provide sufficient information on credit supply relative to the real economy. To resolve this problem it should be supplemented by the credit-to-GDP gap. And measures of leverage can be further complemented by market data, for example concerning the rate of asset-price growth.

For further research we may carry out some cross-country analyses, in particular incorporating the MTM leverage that we conjecture to have been crucial to

the global crisis in advanced economies. We can also use the systemic leverage indicator to determine the macroprudential levy when implemented, which can be variably applied depending upon the degree of deviation from a target level.

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<Abstract in Korean>

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2008년 글로벌 금융위기는 시스템적 리스크(systemic risk)와 이를 사전에 억제하기 위한 거시건전성정책(macprudential policy)의 중요성이 부각되는 계기가 되었다. 특히, 금융의 경기순응성(procyclicality)이 높고 금융기관들이 금융시장을 통해 밀접하게 연계(interconnected)되어 있는 경우 최초의 미시적 충격이 시스템적 피드백 과정을 통해 거시적인 수준으로 증폭되기 때문에 작은 충격에도 금융위기가 발생할 수 있다는 것을 보여주었다. 이에 따라 시스템적 취약성이 높은 경우 선제적으로 대응할 필요성이 있다는 인식을 배경으로 시스템적 리스크 정도의 측정에 관한 관심이 증대되었다. 본 연구는 금융위기의 근본 요인으로 지목되는 금융기관의 레버리지를 시스템적 리스크 관점에서 포착하는 “시스템적 레버리지(systemic leverage)”를 거시건전성 조기경보지표(early warning indicator)로 제안한다.

본 연구에서 시스템적 레버리지는 금융기관의 레버리지를 단순히 합한 것이 아니라 대차대조표의 자산, 부채 및 자본에 숨어 있는(hidden) 경기순응성과 연계성을 찾아내어 반영한다. 먼저, 부채에서 시장성수신(wholesale funding)의 비중이 높을수록 시스템적 리스크는 증가하는데, 이는 금융시장이 불안정하면 특히 시장성수신의 조달금리가 크게 상승하면서 시장성수신 비중이 높은 금융기관의 펀딩리스크가 높아지기 때문이다. 또한 해당 자산을 보유하고 있는 모든 금융기관의 평가손실을 유발한다. 신흥시장국의 경우 외화차입금이 주요 시스템적 리스크 요인으로 작용한다. 외화차입금은 국내 상황 뿐 아니라 해외 상황에도 민감하게 반응하면서 환리스크를 수반하기 때문에 충격이 경제 전반으로 확산되는 경향이 있다. 다음으로 파생상품은 기초자산의 가치변동에 따라 가격이 결정되기 때문에 금융시스템의 연계성을 증충적으로 높인다. 또한 상품에 내재된(embedded) 레버리지를 활용하기 때문에 손실을 증폭시킨다. 이러한 파생거래는 대부분 부외(off balance)에 숨겨져 있다가 위기시 부내(on balance)로 이전되어 레버리지를 급격히 증가시킨다. 그리고 시가평가 대상 자산의 비중이 높을수록 호황기에 레버리지가 과도하게 확대되고 불황기에 급격히 축소된다.

본 연구는 대차대조표 난·내외 숨어 있는 다양한 형태의 레버리지를 우발채무나 파생상품 등의 난외 항목에 내재된 “부외 레버리지,” 시장성수신 비중을 고려한 “연계 레버리지,” 국내 금융시스템 특성상 외화 차입 의존도를 반영한 “외화 레버리지,” 시가평가제도로 인해 확대될 수 있는 “시가평가 레버리지”로 구분하고, 이들 각 레버리지 요소들을 금융기관의 레버리지를 합한 “차입 레버리지”에 반영함으로써 단일지수화 한 시스템적 레버리지 지표를 도출한다. 단일지수 내 각 레버리지 요소의 가중치는 경기순응성에 대한 기여도를 기준으로 산출하였다. 그리고 동 지표를 국내은행의 대차대조표 자료를 이용하여 직접 시산하고 조기경보지표로서의 유효성을 평가해 보았다. 지표의 조기 경보 기능을 분석해 본 결과, 시산된 지표가 금융위기 발생 시점보다 최소 1년 전에 조기 경보 기능을 제공함을 실증적으로 확인하였으며, 기존의 거시건전성지표로 주로 사용되던 credit-to-GDP gap 지표의 한계점을 보완할 수 있을 것으로 기대된다. Credit-to-GDP gap은 금융기관을 통해 공급된 신용총량을 나타내며 시스템적 리스크의 핵심 요소인 금융의 경기순응성과 연계성을 효과적으로 포착하지 못하는 한계점이 있다.

글로벌 금융위기를 통해 올바른 시스템적 리스크의 측정 및 거시건전성 감독 관리 방안의 필요성이 제기되고 있는 시점에서 본 연구를 통해 제안하는 시스템적 레버리지 지표는 국내 금융시스템의 특성에 기반하여 경기순응성과 상호연계성을 모두 고려하였고, 대차대조표의 자산과 부채 측면을 종합적으로 포함함으로써 금융시스템의 자금조달과 자산운용 측면을 동시에 반영한다는 점에서 기존의 통화량 지표나 신용총량 관련 지표와 비교하여 우월성을 가지고 있다. 또한, 지나치게 복잡하지 않은 형태의 모델을 사용하여 정책 당국과의 의사소통에 용이성을 도모하였으며, 각 레버리지 요소들의 값과 기여도를 대차대조표를 통해 즉시 산출하는 것이 가능하므로 빠르고 투명성 있는 공시효과를 도모할 수 있다는 장점이 있다. 물론, 시스템적 레버리지 지표만으로 금융시스템에 내재된 위험의 모든 측면을 완벽하게 설명할 수는 없기 때문에, 보조 지표로서 타 경제 지표들의 추이와 함께 상호보완적으로 분석할 필요가 있으며, 이를 통해 금융당국의 종합적이고 효과적인 거시건전성 감독 관리가 이루어질 것을 기대한다.

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