Systemic Leverage and Homogeneity: Assessing Multifaceted Amplifying Mechanism of Systemic Risk

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Abstract

This paper examines the amplifying mechanism of systemic risk propagation within a nonlinear framework. We focus on the hidden leverage-induced asset value dynamics in the financial markets, intertwined with balance-sheet components of the banking system. We propose a *systemic leverage* index by estimating smooth transition regression models based on the intrinsic element of the financial system, off-balance-sheet transaction, and cross-border activities of the Korean commercial banking system. We find strong evidence that the amplification is more pronounced with the cross-sectional homogeneity in managing systemic leverage as a whole. This observation provides the important policy-oriented implication that an individual bank's systemic importance can be gauged by its marginal contribution to system-wide homogeneity.

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1 Introduction

A system-wide leverage expansion generally entails common exposures to hidden risk factors. For instance, the Japanese asset bubble crisis of 1991 and the 2008 global financial crisis have similar systemic-risk propagation mechanisms leading to severe economic recessions: the stacking up of balance-sheet vulnerabilities combined with a run-up of asset prices causes more severe economic downturns (Elekdag, Kose & Cardarelli 2009), and leverage build-up is inseparable from an accumulation of excessive risks. Excessive growth of credit tends to be followed by a crisis (Gourinchas & Obstfeld 2011), as prevailing financial risk is underestimated in the business cycle upswing. As a result, financial crises commonly occur when too much debt is combined with a sharp fall in asset price; see Reinhart & Rogoff (2008), Adrian & Shin (2010), Greenlaw, Hatzius, Kashyap & Shin (2008), and Schularick & Taylor (2012). Speculative asset price bubbles along with their sharp correction frequently generate instability in the financial system; thus, an economic boom watered *systemically* by a leverage-induced asset price bubble is a harbinger of financial crisis.[1]

Overall, financial cycles are typically more than proportional to the dynamics of economic activity through a mutually amplifying feedback loop in an asymmetric manner. Brunnermeier & Sannikov (2014) point out that financial frictions lead to the amplifying shocks, directly through leverage and indirectly through asset prices. Hence, we highlight the interaction between the business and financial cycles in terms of their bilateral transmission of systemic shocks through credit channels, of which an example is the balance-sheet channel providing a logical link between the financial system and the real economy; see Bernanke & Gertler (1995), Kiyotaki & Moore (1997), Bernanke, Gertler

[1] Extensive financial distress stems from the unwinding of financial imbalances cloaked by optimistic economic conditions (Borio & Lowe 2002). This phenomenon is coined as *volatility paradox*, which has attracted policy makers' attention to the failure of micro-prudential regulations. Kim & Kim (2014) argue that such macro-financial vulnerabilities are rooted in a procyclical interaction between market-wide risk perception and system-wide asset management behavior.

& Gilchrist (1999) for similar arguments.[2] Another channel of credit flow is through the banks' lending activities. This bank lending channel delivers a theoretical framework for the existence of bank-originated systemic shocks. This channel indicates that factors impacting a lender's balance sheet can magnify economic downturns, as banks with weak capital become more reluctant to provide additional credits to the real economic sectors or can even be forced to deleverage by selling non-toxic loans; see Bernanke & Lown (1991) and Kiyotaki & Moore (1997).

More direct transmission channels of the systemic risk are related to the interconnectedness among financial institutions. Interconnected channels can appear either within the financial system or between the real and financial sectors in the economy (Borio 2014). Numerous studies suggest that the degree of interconnectedness depends on the commonality of asset holdings, as banks holding similar asset portfolios tend to make similar risk-taking decisions. Allen, Babus & Carletti (2012) focus on asset commonality as a source of systemic risk in the presence of information externalities. Consequently, a decline in the asset prices can significantly affect the entire banking system via an adverse feedback loop through the interconnected financial network caused by fire sales and market freeze (Shleifer & Vishny 2011). Therefore, the concept of *herding*, equivalently *homogeneity* among economic agents, applied to the systemic risk analysis emerges along with the commonality of banks' asset portfolio composition. Furthermore, wholesale funding of the liability becomes an easy channel through which financial institutions actively increase their leverage during the upswing. However, it also becomes a destructive channel through deleveraging processes in response to fire-sales. Thus, it contains information on the liquidity hoarding and counterparty risk hidden in the interbank loan and the wholesale funding market.

Based on these arguments above, this paper examines two important dimensions

[2] The concept of financial frictions in the banking sector was introduced by Kehoe & Levine (1993), Jermann & Quadrini (2012), Alvarez & Jermann (2000), and Miao & Wang (2015) under endogenous borrowing constraints. An amplifying mechanism referring to financial institutions is examined by Brunnermeier & Sannikov (2014) and Adrian, Moench & Shin (2010).

of systemic risk: (i) procyclicality in the time-series dimension and (ii) the nonlinear amplification mechanism in the cross-sectional dimension. In this context, we emphasize that the term *leverage* can be misguiding in the sense that leverage as such contains no direct connection to asset prices. We propose a concept of *systemic leverage* in the sense that building up leverage entails the lurking systemic risks at the aggregate level. We construct a systemic leverage index from commercial banks' balance-sheet information with market-wide risk factors based on the theoretical foundation in Adrian & Shin (2010) to capture the source of macro-financial vulnerability.[3] Specifically, we employ a set of systemic leverage components, as the information set contained in systemic leverage components is closely connected to system-wide risk perceptions. We use sub-components of the systemic leverage in that different types of leverage, such as economic and embedded leverages, should be considered simultaneously, as no single measure can capture the multiple dimensions of a financial crisis (D'Hulster 2009).

We also demystify the multifaceted nonlinear amplification mechanism based on the monetary transmission channels between the financial and business cycles. We explore two important dimensions of the systemic risk propagation, including marking-to-market (MtM) valuation for procyclicality (from the time-series perspective) and the nonlinear feedback mechanism (from the cross-sectional perspective) by focusing on the balance-sheet expansion at both aggregate and individual bank levels. For analyzing the first dimension, we construct a systemic leverage index by aggregating balance-sheet information in the banking system along with herding (or, equivalently, homogeneity) measures by employing the bank-specific balance-sheet data. At the aggregate level, we propose a model-induced systemic leverage index to investigate how this systemic leverage propagates to the business cycle corresponding to various exogenous shocks implied by a reduced-form vector autoregressive (VAR) model. We employ policy rate, land price, equity and exchange rate based on economic arguments as measures of exogenous shocks.

[3] Adrian & Shin (2010) stress out that the intertwined role of the two channels (i.e., through the balance-sheet and market channels) effectively captures the degree of a bank's risk-taking.

Then, we examine how these outer shocks propagate to the systemic leverage index and, in turn, from the systemic leverage index to the economic fluctuations using an impulse response analysis.[4]

For analyzing the second dimension, we examine cross-sectional amplifying effects in terms of interconnectedness, as the realization of a nonlinear amplification mechanism is strongly associated with the degree of interdependence in the system. For this task, we first conjecture that the amplification mechanism is well-captured by measuring systemic leverage based on the intrinsic elements of the financial system, off-balance sheet transaction, and cross-border activities. We then motivate this decomposition to extract an information set regarding various systemic risk sources from the commercial banks' financial statements. Furthermore, we consider the degree of homogeneity at the individual level. Our conjecture is that the entire system has the same exposure to common shocks, when banks make similar asset holding and risk-taking decisions.[5] Based on the asset commonality argument in Allen et al. (2012), we propose component-wise herding (homogeneity) measures. By associating the degree of homogeneity with the degree of interconnectedness, we analyze whether the ex-ante homogeneity exacerbates ex-post crisis induced damages.[6] Accordingly, we suggest a novel measure of the marginal contribution of each individual institution to the overall systemic leverage management. Finally, we emphasize that this decomposition is compatible with a framework for dealing with domestic systemically important banks, as suggested by the Basel Committee on Banking Supervision (BCBS 2012).

Our approach deviates from that of the traditional banking literature, which often

[4]It is noteworthy that bank credit expansion can predict increased *crash risk* in the bank equity index and equity market index (Baron & Xiong 2014). Similarly, Hirshleifer, Hou, Teoh & Zhang (2004) find that the level of net operating assets is a strong negative predictor of future stock returns.

[5]Acharya & Yorulmazer (2008) generalize this view to posit that the likelihood of joint failures increases with the correlation of banks' asset portfolios. This viewpoint is also related to Rampini (2004), Calmès & Théoret (2010), and Christiano, Motto & Rostagno (2014) in that cross-sectional heterogeneity can be countercyclical.

[6]In line with our proposed concept of systemic leverages, two new liquidity measures among the Basel Committee's key reforms to promote a more resilient banking sector (the Liquidity Coverage Ratio [LCR] and the Net Stable Funding Ratio [NSFR]) are suggested in the Basel III regulation scheme.

treats banks as passive intermediaries that channel money from ultimate lenders to borrowers. Departing from the view of banks as passive functional devices for channeling, we interpret ex-ante homogeneity as the aggregate result of individual bank's proactive asset management behavior. An optimistic perception of the systemic risk in the commercial banking sector lowers the lending standard and prompts banks to lend excessively to a real estate sector, which can lead to an asset price boom and bust (Asea & Blomberg 1998). A collectively pessimistic banking system not only fetters economic growth, but also renders monetary policy ineffective (Asanuma 2013).[7]

This paper makes several contributions both to the literature on systemic risk and the literature on systemic risk measures, including the financial stability index, by identifying lurking systemic risk factors from balance-sheet information. As our proposed systemic leverage index directly incorporates the quality of asset/liability in the balance sheet, our approach is preferable to the mere leverage regulation for complementing the existing risk-sensitive capital requirements, as Kalemli-Ozcan, Sorensen & Yesiltas (2012) show that excessive risk taking tendencies before a crisis are hard to detect due to the lack of information about the quality of assets. In this regard, this paper attempts to identify systemic risk factors and each bank's marginal contribution directly from balance-sheet data based on a structural modeling approach. As central regulators have access to the monthly balance-sheet data with detailed components, our proposed methodology can be used as a practical macroprudential toolkit for regulating systemic leverage at the macro level.[8] By associating four systemic leverage components with hidden system-wide risks, we propose a macro-framework for regulating systemic leverages under the Basel III framework. Several countries are going through a new wave of surging housing prices; our approach offers a theoretical background for building better macroprudential policy tools, especially effective for the central bankers of emerging countries. For example, empirical

[7]Lee (2011) argues that under inflation targeting the effectiveness of monetary policy in controlling liquidity can be weakened if the Korean banks manage their leverage actively

[8]For an extensive review of macroprudential policies see Hanson, Kashyap & Stein (2011) and Crowe, DellAriccia, Igan & Rabanal (2011) on the pros and cons of various policy options.

success stories about the effects of loan-to-value (LTV) and debt-to-income (DTI) during the financial crisis in several nations such as Korea, Brazil, Hong Kong and Malaysia have surfaced recently.[9]

The rest of this paper is organized as follows. Section 2 introduces our systemic leverages and its components. Section 3 describes the modeling specification and data. Section 4 presents the empirical results at both the aggregate and individual levels. Section 5 provides concluding remarks.

2 Systemic Leverages and its Components

This section develops the concept of systemic leverage and its components. We discuss the economic implication of systemic leverage by decomposing it into its components with a special focus on the amplifying mechanism from both time-series and cross-sectional perspectives.

2.1 Economic Implication of Systemic Leverage

It is well-documented that systemic risk can be gauged from the fluctuation of aggregate financial cycle over the economic cycle. Borio (2014) and Borio & Drehmann (2009) argue that a larger discrepancy between the two cycles is associated with more calamitous outcomes in the economy, as exemplified by the dotcom bubble-burst around 2000 when the financial and business cycles hit the off-beat. A myopic policy response appears to unnecessarily amplify the adverse feedback loop by incurring the vicious circle of interactions between the financial and business cycles. Hence, it is legitimate to connect those policy

[9] There are numerous studies for regulating aggregate systemic leverages. The vicious leverage cycle shown by Geanakoplos (2009) is the key to the asset-price bubble and burst. Kapan & Minoiu (2013) proves that strong bank balance sheets are one of the crucial factors in the recovery of credit-induced crises. Another stream of literature advocates incorporating LTV and DTI as macroprudential toolkits. Christiano & Ikeda (2014) show that leverage restrictions on banks generate a very substantial welfare gain in the steady state and Sgherri & Zoli (2009) study the role of LTV limits in reducing credit cycle volatility in a small open economy.

responses to our proposed systemic leverages, as the system-wide leverage is related to the business cycle through the loan and lease components along with the financial cycle through the liability components in the balance sheet.

We postulate that policy makers implement macroprudential policies based on their system-wide risk appetite $\alpha \in (0,1)$. Let $L(\cdot)$ denote the expected loss incurred by the realization of systemic risk and SL denote the level of systemic leverage. Based on α, policy makers devise and implement a macroprudential policy in the form of $\Omega(\alpha)$. Then, the expected loss implied by systemic leverages can be expressed as $L\big(\Omega(\alpha) \cdot \mathrm{SL}\big)$ in which the level of systemic leverages are adjusted by the systemic policy function. As Borio (2014) proposes, this expected loss is associated with the deviation between the financial (F_t) and business (B_t) cycles. We assume that α determines a certain optimal point between the financial and business cycles in terms of the macroprudential policy perspective and the optimality takes a functional form of $f\big(\alpha F_t + (1-\alpha)B_t\big)$. As we observe that the expected losses implied by the two approaches converges ex-post, the equivalence between the two approaches is assumed to hold ex-ante. Then, after inverting the function L, we obtain

$$\Omega(\alpha) \cdot \mathrm{SL} = h\big(\alpha(F_t - B_t) + B_t\big),$$

where $h = L^{-1}f$. This derivation enables us to interpret the systemic leverages as macroprudential policy responses to the deviation between the financial and business cycles after controlling for the distinctive business-cycle effect.

2.2 Systemic Leverage Components

We further decompose the systemic leverage into its components based on different balance-sheet items so that each component has a different macroprudential implication. In this way, systemic leverage has a close connection to diverse transmission channels. Different systemic leverages can imply different risks intertwined systemically. We thus decompose the systemic leverage into three components−intrinsic element of the financial system, off-balance-sheet transaction, and foreign exchange leverage−from the Korean commercial bank financial statements. This decomposition is compatible with a framework for dealing with domestic systemically important banks, as recently suggested by the Basel Committee on Banking Supervision (BCBS 2012).[10]

The first systemic leverage component is the intrinsic (INT) leverage within the financial system, as interbank loans in the bank's balance sheet contains information about the degree of interconnection with the exposure to potential contagion effect or adverse feedback loop in the banking system. The intrinsic leverage captures the interdependence within 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. The intrinsic leverage is defined as exposures among financial institutions divided by equity capital.[11] Most of exposures among financial institutions are inherently illiquid assets; without abilities to withstand large losses, they usually work as the source of the increased level of systemic risk.

The second systemic leverage component is the off-balance-sheet leverage (OBS), which measures the leverage hidden in derivatives and contingent liabilities. Financial institutions can increase their leverage using derivative contracts, which are usually not obliged to report or to materialize until the counterparty fails to meet its obligations. Financial institutions with lots of off-balance-sheet components witnessed their leverages rise sharply because of counterparty default risk during the financial crisis. In this regard,

[10]As the core business of the commercial banking system is channeling leverages for other agents, we naturally consider the *borrowing* (BOR) leverage as a total leverage at the aggregate level. Specifically, the BOR leverage is defined as traditional on-balance sheet banking assets (including loans and securities, and other forms of security assets) over the aggregate equity capital. Note that the BOR leverage encompasses the systemic leverage components as we introduce in the following paragraphs.

[11]Billio, Getmansky, Lo & Pelizzon (2012) investigate the level of interconnectedness within the financial system and find the banking and insurance sector to be important contributors.

Zawadowski (2011) argues that banks in a web of hedging contracts fail to internalize the negative externality caused by their own failure. Other contingent liabilities include guarantees and loan commitments and these hidden debts also increase leverage if they are realized. We define the off-balance leverage as derivatives and contingent liabilities divided by equity capital to imply accounting (i.e., information opaqueness) risk due to uncertain assets or liabilities and hidden spillover. Also noteworthy that OBS activities reduce total risk but do not affect systematic risk (Hassan 1993).

We should not neglect the foreign borrowing (FX) leverage in emerging economies, where external borrowing through foreign financial institutions can serve as the major channel of financial distress. For example, the Korean financial system experienced severe financial turmoils in 1997 and 2008 when massive capital outflows incur. FX borrowing peaked right before these two crisis episodes. The main reason is that since FX borrowing positions of domestic banks were closely intertwined with forward buying contracts with shipbuilders, foreign bank branches operating in Korea utilized their advantages in funding cost by heavily borrowing from their headquarters to provide currency swaps before the 2008 global crisis.[12] Furthermore, as Kaminsky & Reinhart (1999) point out, a currency crisis deepens a banking crisis, activating a vicious spiral. We calculate the FX leverage ratio as external borrowing divided by equity capital to capture the rollover and currency risk of FX nominated debts.

2.3 Amplifying Mechanism and Homogeneity

A small shock can be amplified when the financial intermediation arrives in a constrained state.[13] Both academic researchers and practitioners have pointed out that at least two

[12] See Ryoo & S. (2008) for more detailed explanation.

[13] This argument is supported by empirical observations of the financial markets and nonlinear dynamics across different economic variables. For instance, Huang, Zhou & Zhu (2012) suggest that a bank's contribution to the systemic risk is roughly linear in its default probability, but highly nonlinear with respect to its size and asset correlation. He & Krishnamurthy (2012) build a theoretical model that not only qualitatively delivers the nonlinearity observed in the data but also quantitatively matches the differential co-movements in distress and non-distress periods.

difficult and critical questions emerge in terms of systemic risk analysis: (i) when to capture the *procyclicality* in a proactive manner and (ii) how to model the *nonlinear* realization of the systemic risk. Subsequently, we associate the *nonlinearity* with an *amplifying mechanism* to capture the asymmetric risk spillover that can occur in an increasingly complex financial network or the entire economy by extending Kim & Kim (2014). The fundamental question on the source of the nonlinear dynamics has not yet been answered explicitly, though several potential answers have been suggested by utilizing what financial statements of the banking industry describe. Therefore, it is essential to associate the existence of nonlinearities with these homogeneous activities among financial institutions.[14]

Numerous studies analyzed the role of homogeneity and heterogeneity. The rationale behind this viewpoint is that a system-wide homogenization increases the likelihood of systemic joint failure along with greater negative externalities to the real economy. For example, Rampini (2004) analyzed a model in which the risk associated with entrepreneurial activity implies that such activity is procyclical and results in the amplification and intertemporal propagation of productivity shocks and that cross-sectional homogeneity among agents can be procyclical. In addition, Calmès & Théoret (2010) confirm that banks tend to behave more homogeneously vis-à-vis macroeconomic uncertainty. In particular, they find that both the cross-sectional dispersion of loans-to-assets and the cross-sectional dispersion of non-interest income share shrink, particularly during financial crises, when the resilience of the banking system is weakest. Based on the above arguments, we establish the connection with the nonlinearity to homogeneity, the degree of *herding* among commercial banks. Our approach is closely related to that in Calmès & Théoret (2010), and De Jonghe (2010).

[14]Several papers focus on the role of debt. Dasgupta (2004) and Castiglionesi & Navarro (2007) attribute banks' interlinkage in the form of deposit crossholdings and an agency problem between bank shareholders and debtholders to a source of contagion, accordingly.

3 Methodology and Data

This section describes our modeling approach used to construct the systemic leverage index and the homogeneity-based marginal contribution of individual banks to the systemic vulnerability. Then, we describe our data and sample for the empirical analyses.

3.1 Model Specification

Let A^i be the i-th aggregate asset value component, assumed to follow the Geometric Brownian Motion given by[15]

$$\frac{dA_t^i}{A_t^i} = (r_t + \lambda_t^i + u_t^i)dt + \sigma_A^i dW_t^i, \tag{1}$$

where λ_t^i is the market-wide risk premium, u_t^i is the system-wide asset management, and σ^i is the volatility of the i-th asset component value, respectively.[16] We further postulate the following assumptions:

(i) $\lambda_t^i = \beta_A^i \xi_t$ captures the CAPM-based systematic risk premium, where ξ_t is the systematic (market) risk factor.

(ii) u_t^i denotes the system-wide leverage management whose functional form is given by $u_t^i = g^i(Y_{t-d})X_t$, where $g^i(Y_{t-d})$ captures the nonlinearity causing the boom/burst sentiment by measuring how much the financial risk appetite is deviated from the economic fundamental, and $X_t = (F_t - B_t)$ measures the deviation between financial and business cycles.

We take the vector of systemic leverage components as the transition variable Y_{t-d} with one-quarter lag, and the credit-to-GDP gap as our measure of the deviation between

[15]The intuition behind the expression comes from the definition of the value, which is a multiplicative form of price and quantity.

[16]We also apply this equation to the dynamics of individual asset value components in Section 4.

financial and business cycles. We let $\ell^i = A^i/E$ be the i-th systemic leverage component, where E represents the system-wide aggregate equity value whose dynamics can be expressed as

$$\frac{dE_t}{E_t} = (r_t + \beta_E \xi_t + u_t^E)dt + \sigma_E dB_t,$$

where β_E is the CAPM-based equity risk premium, and $E(dW_t^i dB_t) = \rho_t^i dt$.[17] Applying Ito's lemma yields the dynamics of the systemic leverage component given by

$$d\log \ell_t^i = \alpha^i dt + \left(\beta_A^i - \beta_E\right)\xi_t dt + g^i(Y_{t-d})X_t dt + \Sigma_t^i d\hat{z}_t, \tag{2}$$

where $\alpha^i = -\frac{1}{2}\left\{(\sigma_A^i)^2 - (\sigma_E)^2\right\}, \Sigma_t^i = \sqrt{(\sigma_A^i)^2 + (\sigma_E)^2 - 2\rho_t^i\sigma_A^i\sigma_E}$.

3.2 Smooth Transition Regression Model

For estimation purposes, we adopt the smooth transition regression (STR) model for specifying a *continuum* of regime shifts. The STR model presumes the transition dynamics based on continuous transition functions that allow smooth regime changes.[18] Thus, the STR model shows a rich dynamics, limit cycles, asymmetric behavior and jumps and naturally lends itself to modeling institutional structural breaks. In addition, defining a threshold based on exogenous variables is easy and has many applications including exchange rates, industrial production, Okun's Law, and the Phillips curve estimations.[19]

[17]Here, we assume $u_t^E \approx 0$ grounded in the argument of Adrian and Shin (2010) and empirical evidence from the banking and corporate finance literature.

[18]A regime-switching model that allows for two regimes with extreme values of 0 or 1 is nested in the STR model specification.

[19]A general specification of the STR model is given by

$$y_t = G(x_t, s_{t-d}, \psi) + \varepsilon_t = \beta_0^{'} x_t + \Sigma_{m=1}^M \beta_m^{'} x_t h(x_t, s_{t-d}, \psi) + \varepsilon_t,$$

where G is a nonlinear function of x_t, s_{t-d} and parameters ψ. M denotes a number of different regimes. The STR model specification allows the changing of the parameters in the model according to the value of an exogenous threshold variable s_{t-d}, where d is a delay parameter. A widely used transition function is a logistic function given by

$$h(x_t, s_{t-d}, \psi) = \frac{1}{1 + \exp(-c_m(s_{t-d} - \delta_m))}.$$

In the following analysis, we adopt the specification of logistic function as our transition functional form for parsimony. A logistic function is attractive in that it maps real values into a bounded interval, leading to a probabilistic interpretation. In this context, we model the leverage-induced systemic risk amplification by incorporating potentially nonlinear business fluctuation and financial market response as

$$g^i(Y_{t-d}) = \kappa^i + \frac{\delta^i}{1 + \exp(-c^i(Y_{t-d} - \zeta^i))},$$

where Y_{t-d} is a transition variable to determine the nonlinear impact of δ^i coefficient, and c^i and ζ^i are shape and location parameters, respectively. By discretizing (2), we derive a version of the STR equation given by

$$\Delta \log \ell_t^i = \hat{\alpha}^i + \hat{\beta}^i \xi_t + \hat{g}^i(Y_{t-d}) X_t + \hat{\Sigma}_t^i \epsilon_t^i, \tag{3}$$

where $\hat{\alpha}^i = \alpha^i \Delta t$ denotes the intercept, and $\hat{\beta}^i = (\beta_A^i - \beta_E)\,\Delta t$ captures the systematic risk factor loading. Hence, we can re-arrange the expression as

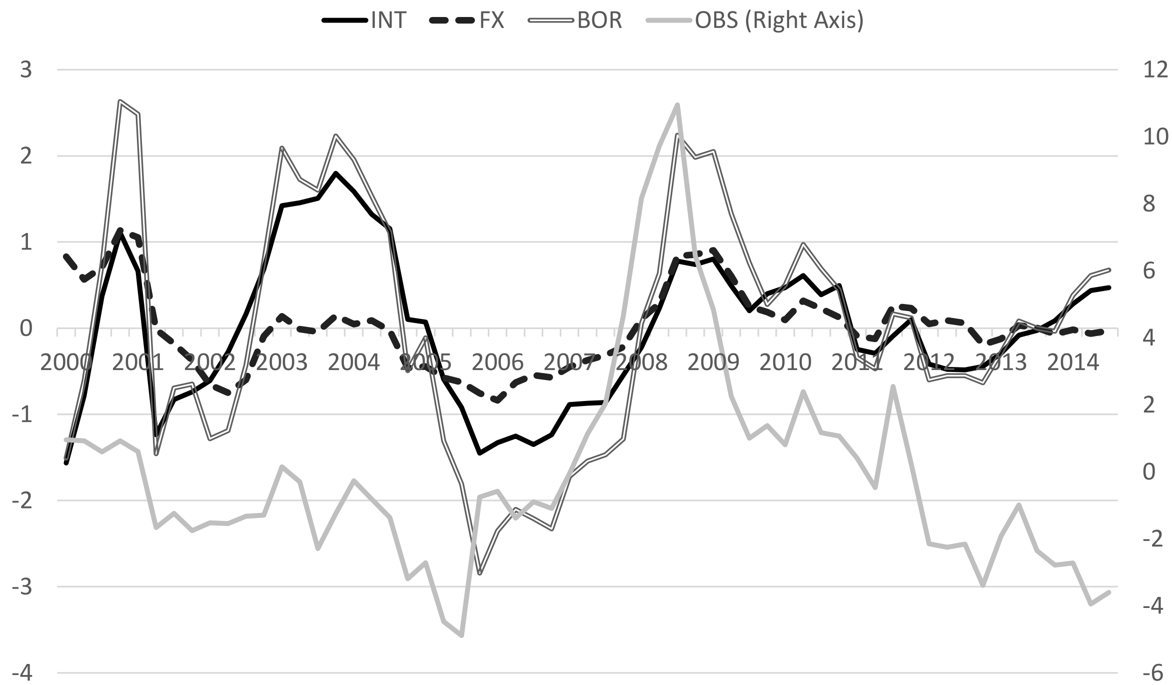
$$\hat{g}^i(Y_{t-d}) = \kappa^i \Delta t + \frac{\delta^i \Delta t}{1 + \exp(-c^i(Y_{t-d} - \zeta^i))} = \hat{\kappa^i} + \frac{\hat{\delta}^i}{1 + \exp(-c^i(Y_{t-d} - \zeta^i))}$$

denotes a nonlinear function of Y_{t-d} for the i-th systemic leverage component.[20]

Intuitively, we postulate that the deviation between financial and business cycles (X_t) has a nonlinear elasticity on the management of each component of systemic leverage according to the transition variable Y_{t-d}. Put differently, the transition function in the form of $\hat{g}^i(Y_{t-d})$ can be interpreted as the nonlinear and gradual macroprudential policy impacts of the credit-to-GDP gap on the system-wide management of the i-th systemic leverage component. It should be highlighted that the logistic functional form of the transition function allows us to investigate if the nonlinear and asymmetric amplification

[20] To estimate logistic smooth transition regression models (3), we use a set of Matlab codes, implemented by McAleer & Medeiros (2008)

Figure 1: Time-series dynamics of the filtered systemic leverage components



Note. Time-series dynamics of the HP-filtered systemic leverage components of the borrowing leverage (BOR), intrinsic element of the financial system (INT), off-the-balance-sheet transaction (OBS), and foreign exchange leverage (FX) from the Korean commercial banks' financial statements. A value for the smoothing parameter is 1600, a norm for quarterly data.

in the elasticity is associated with the dynamics of the transition variable.

Note that the estimable equation (3) matches the stylized fact (see Figure 1) that systemic leverages show a smooth transition dynamics due to the existence of many different agents and different degrees of institutional investing inertia with time lags.

3.3 Data and Sample

We use balance-sheet data for Korean domestic banks provided by the Financial Supervisory Service through the Financial Analysis Information Retrieval System.[21] Table 1 reports the descriptive statistics of our full data set. Our dataset has a quarterly frequency and its time-span is ranging from the first quarter of 2000 to the third quarter of 2014. The domestic banks included are seven commercial banks (KB Kookmin, Shinhan, Woori,

[21]http://fisis.fss.or.kr/fss/fsi/id/fssmain.jsp

Hana, Standard Chartered, Citibank Korea and KEB), and six local banks (Kyongnam Bank, Kwangju Bank, Daegu Bank, Busan Bank, Chunbuk Bank and Jeju Bank).

Presumably, the credit-to-GDP gap is the most relevant proxy for the deviation between the financial and business cycles. For example, Borio & Drehmann (2009) find that the credit-to-GDP gap is the best performing one across various variables considered by the authors. We construct the credit-to-GDP following the BCBS guide 187. We obtain credit and domestic GDP series for the empirical analysis from the bank of Korea (BOK) website.[22] Then, we apply the Hodrick-Prescott (HP) filter to detrend the gap. The smoothing parameter, generally referred to as λ in the literature, is typically set to 1600 for quarterly data to capture the long-term trend in the behavior of the credit-to-GDP ratio in each jurisdiction.

To incorporate the systematic (market) risk factor, ξ_t, we consider the interest rate differential between the yield on the commercial paper (CP) for non-financial firms and the yield on the certificate of deposit (CD). Ra & Yan (2000) show that the excessive use of commercial paper by financial institutions and corporations contributed to the vulnerability of the Korean economy to external shocks; we thus focus on the economic role of the commercial paper during the financial crisis. Loosely speaking, the CP is a price proxy for the business cycle measured by the yield, as commercial paper issuers tend to use the proceeds from issuance to cover their short-term financing needs for working capital and inventory, which are directly related to the economic fluctuations. Therefore, the spread between the CP and CD is a price differential proxy for the deviation between the financial and business cycles. We obtain both yield series from the BOK.

4 Empirical Results

This section presents our empirical results to examine the amplifying mechanism of systemic risk propagation within a nonlinear framework. We conjecture that a logistic tran-

[22]http://www.bok.or.kr

sition function represents the asymmetric and nonlinear transition from one regime to the other. Viewed in this vein, we focus on the coefficients on the amplification and asymmetry components in the fitted model to the balance-sheet information of the banking system.

4.1 Nonlinear Systemic Risk Propagation

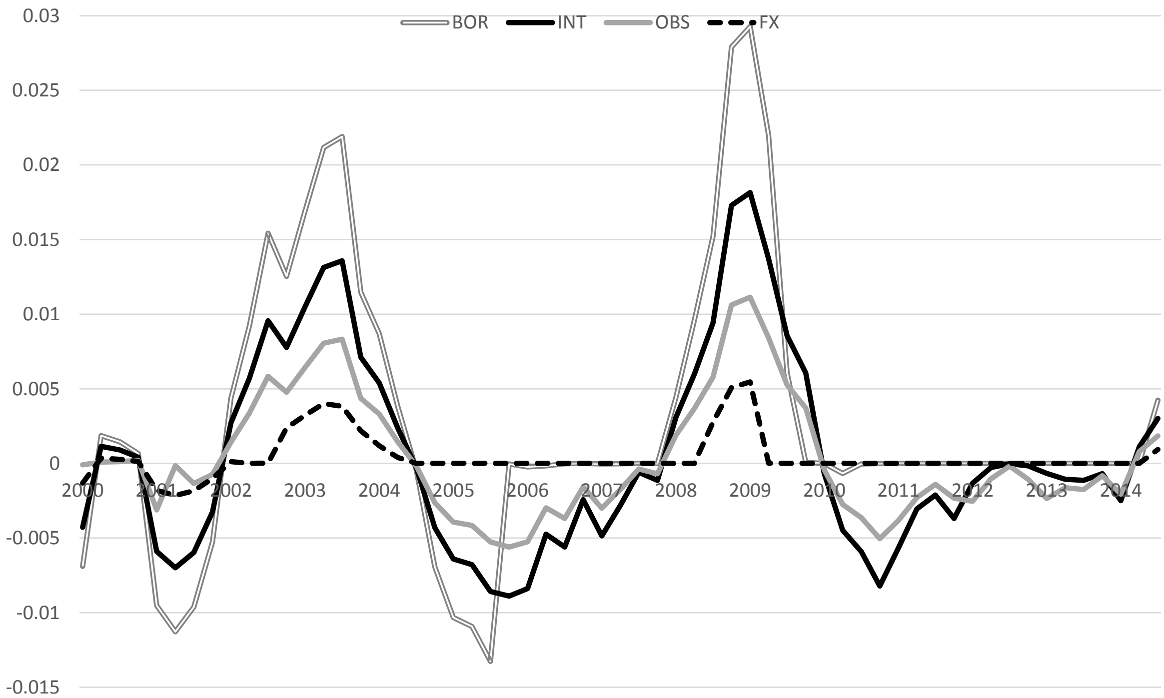
We first test for linearity to detect the potential nonlinear amplifying mechanism in the systemic leverage management in an asymmetric manner. Motivated by van Dijk & Paap (2002), the linearity test is based on the third-order Taylor series expansion of the logic function around the null hypothesis against our logistic STR model specification. The results indicate that the linearity in the elasticity of the deviation between financial and business cycles on the systemic leverage management can be rejected at the 5% significance level except for the intrinsic leverage.[23] This observation highlights the importance of the nonlinearity in our proposed STR model specification, if we consider the potential amplifying mechanism beyond the domestic financial system.

We next estimate the nonlinear equation (3) with three contemporaneous systemic-leverage components by maximum likelihood estimation. Table 2 reports the estimation results based on the aggregate balance-sheet data. We find strong evidence that the nonlinear amplifying effects show strong statistical significances across different systemic leverage components. Moreover, the estimated coefficients ($\hat{\beta}^i$) on the systematic risk factor (CP-CD) capturing the sensitivity to the market-wide risk perception are significantly negative for BOR and INT leverage components. The negative coefficients on the systematic factor indicate that the aggregate commercial banks deleverage their market positions, when the systematic risk increases and vice versa.[24]

[23] The p-values of the linearity test for BOR, INT, OBS, FX leverage components are $0.0200, 0.1416, 3.119 \times 10^{-7}, 4.382 \times 10^{-4}$, respectively.

[24] The smooth transition regression model suffers from a technical difficulty in the joint estimation of the shape and location parameters. Specifically, a large number of observations in the neighborhood of the location parameter is necessary when the slope of the transition function is steep as the shape parameter increases. As pointed out by Terasvirta (1994), this technical issue is associated with the

Figure 2: Time-series of systemic leverage management specific to each component



Note. This figure plots the time series of u_t^i's procyclical dynamics for all systemic leverage components with different magnitudes. u_t^i is constructed based on estimation results from the nonlinear equation (2) and u_t^i denotes the system-wide leverage management whose dynamics is composed by combining the nonlinearity causing the boom/burst sentiment with the deviation between financial and business cycles. A detailed description of u_t^i is given in Section 3.

One notable finding is that the negative relationship between the estimated coefficients on the price- and quantity-proxy variables. Specifically, the BOR and FX leverages share the same patterns to include negative signs for beta and positive signs for amplification coefficients. This finding has an important policy-oriented implication from the macroprudential perspective: a key prerequisite for policy makers is to capture the procyclicality at the right time. Then, the policy priority should be arranged by decomposing the systemic leverage into sub-components so that one can differentiate the degree of the procyclical and countercyclical effects of each component. Different systemic leverage components can have different cyclicalities, leading to the policy implication that the role of the nonlinear amplifying effect should be curbed according to the degree of procycli-

statistical insignificance of the estimated shape parameters in Table 2. Refer to Terasvirta (1994) for more details.

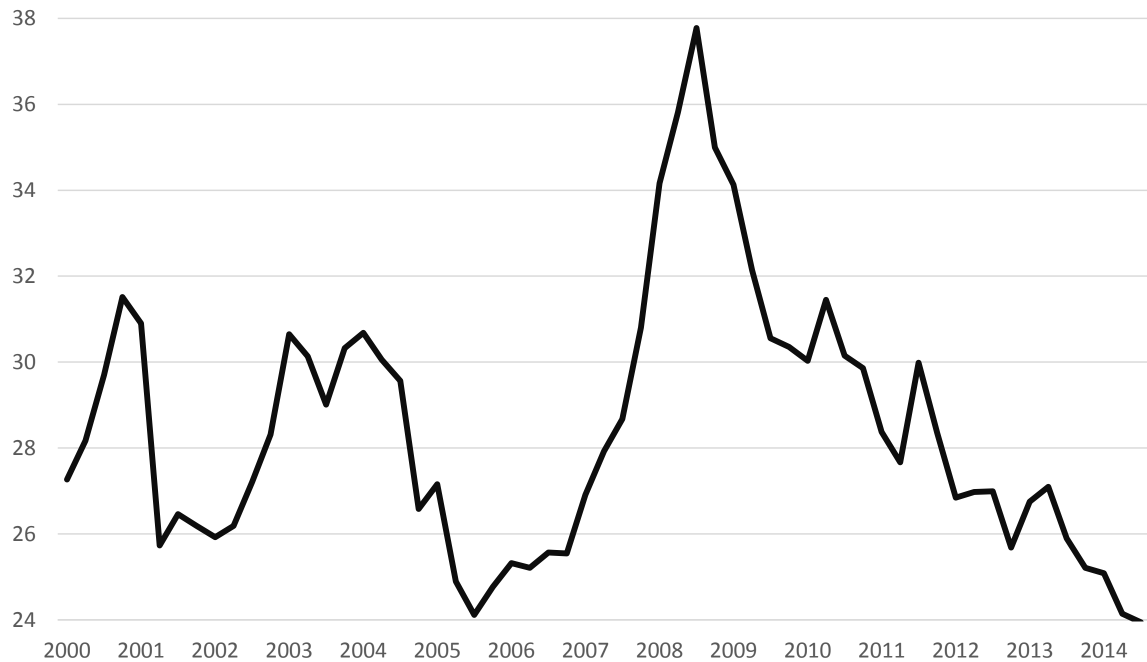
cality. As the negative sign of $\hat{\beta}^i$ implies the procyclical relationship between systemic leverages and systematic risk factor ξ_t, it is particularly nontrivial to observe the evidence that the borrowing, intrinsic, and FX leverages show a strong procyclicality with systematic risk factor. However, we find no procyclical evidence for the off-balance sheet leverage.

By the macroprudential nature of procyclicality, constructing a systemic leverage index requires employing aggregate balance-sheet data. Based on equation (2), we estimate a nonlinear function $\hat{g}^i(Y_{t-d})$. Figure 2 exhibits the time-series behavior of systemic leverage management, denoted by $u_t^i = \hat{g}^i(Y_{t-d})X_t$, specific to each component. The economic implication of u_t^i is the aggregate asset management behavior for individual systemic leverage components. We observe a significant degree of difference among nonlinear amplifying effects and strong procylical asset management behavior across different systemic leverage components. It certainly captures a sensitivity to procyclicality measured from its contribution to the deviation between the financial and business cycles in that all the destructive economic activities including a fire-sale or a market freeze are related to the nonlinearity. It is also directly connected to the macroprudential policy responses to the deviation in a nonlinear way as represented by the transition function $\hat{g}^i(Y_{t-d})$. In this regard, we construct an aggregate systemic leverage index using the information of $\hat{g}^i(Y_{t-d})$. We propose a simple weighting scheme of the amplifying effects given by

$$\mathrm{SLI}_t = \Sigma_i w_t^i \ell_t^i, \tag{4}$$

where $w_i = \Phi(\hat{u}^i(X_t))$ for i={BOR, INT, OBS, FX}, $\Phi(\cdot)$ denotes the cumulative distribution function of a standard normal variable, and $\hat{u}^i(X_t)$ is the standardized value of $u^i(X_t)$ so that it has zero mean and unit variance. The time-series behavior of the systemic leverage index implies how the macroprudential policy responses to the deviation between the financial and business cycles manifest themselves in a nonlinear way, which we refer to as *the systemic leverage propagation mechanism*.

Figure 3: The Systemic Leverage Index



Note. This figure illustrates the time-series behavior of the aggregate systemic leverage index defined as (4).

Figure 3 depicts the time-series dynamics of the aggregate systemic leverage index. One particular feature is that the systemic leverage index exhibits a procyclical dynamics. Note that the systemic leverage index is constructed by using the information from both the systemic leverage components and market risk perception. The procycality implies that the interaction between the system-wide portfolio management behavior and the market-wide risk perception is procyclical, as Korean commercial banks are actively adjusting their asset portfolios in a procyclical manner. Unlike the continuing boom period when other countries enjoyed the appreciation of housing prices, the Korean economy experienced a period of hardship from 2004 to 2006 owing to a credit-card crisis with a significant impact on both the financial system and the real economy. Later, the Korean banking system expanded its balance sheet rapidly until late 2008, mostly by increasing mortgage loans. Although the credit expansion measured by our calculation was similar to the housing market booms of the U.S., the Korean economy was relatively resilient to the 2008 global shock. From Table 2, we verify that the amplification coefficient for the OBS leverage is not statistically significant. The strict application of macroprudential policies such as DTI and LTV combined with the non-existence of the OBS leverage effect is recognized as a potential explanation for why the Korean economy was relatively resilient to the 2008 global shock. Interestingly, after the global financial crisis, the Korean commercial banking system kept shrinking their balance sheet aggressively until the third quarter of 2014.

Next, we investigate how this systemic leverage propagates to the business cycle corresponding to various exogenous shocks implied by a reduced-form vector autoregressive (VAR) model given by

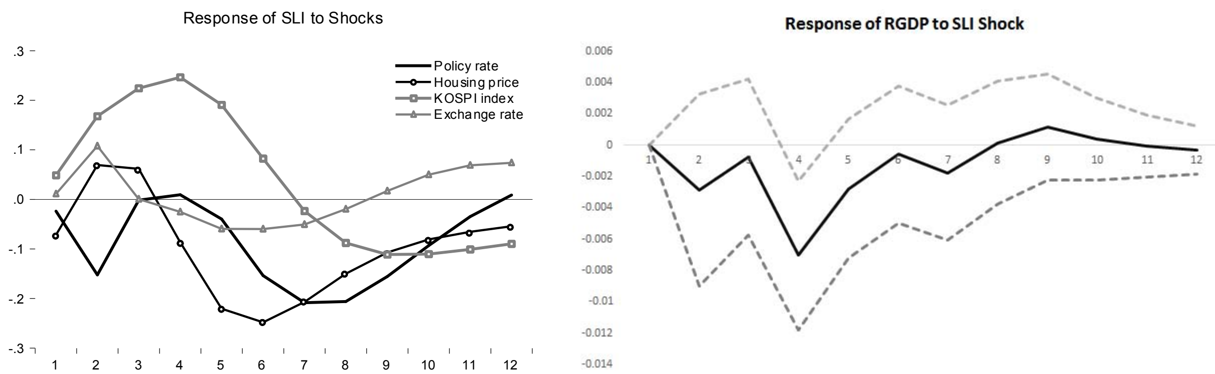
$$Z_t = a + \sum_{i=1}^{p} A_i Z_{t-i} + W_t, \tag{5}$$

where $\mathrm{W}_t \sim N(0, Q)$ and $Z_t = [\mathrm{PR}_t, \mathrm{HOUSING}_t, \mathrm{KOSPI}_t, \mathrm{EX}_t, \mathrm{SLI}_t, \mathrm{RGDP}_t]'$ is a vector of five variables juxtaposed corresponding to the degree of being exogenous. PR_t represents a policy rate; $\mathrm{HOUSING}_t$ is a year-over-year growth rate of the housing price; KOSPI_t is a year-over-year growth rate of the Korean stock index; SLI_t represents the aggregate systemic leverage; and RGDP_t is the Korean real gross domestic product. All variables are observed on a quarterly basis and seasonally adjusted. In this framework, we employ a set of macroeconomic variables including policy rate, land price, equity and exchange rate as a proxy of exogenous shocks based on the literature. We first examine how these shocks propagate to the systemic leverage index (SLI) and in turn, from the systemic leverage index to the economic fluctuations both using an impulse-response analysis. The optimal number of autoregressive terms with lag 1 is determined as based on data availability and parsimony. [25]

The left panel in Figure 4 exhibits how the systemic leverage index responds over time to a one-unit increase of exogenous shocks and the right panel shows how the macroecon-

[25] In a similar vein, Semmler & Mittnik (2012) estimated the banking and macroeconomic linkages using a multi-regime VAR. Hubrich & Tetlow (2015) investigated the interaction between a practical financial stress index and real activity, inflation and monetary policy using a Markov-switching VAR model.

Figure 4: Impluse-response dynamics of the systemic leverage index



Note. The left panel plots an impulse-response dynamics of policy rate, land price, equity and exchange rate shocks to the systemic leverage index and the right panel shows the impulse-response dynamics of the systemic leverage index to the real gross domestic product (RGDP). Response periods are 12 quarters.

omy reacts over time to a one-unit increase of exogenous shock by the systemic leverage index. The impulse response dynamics of the left panel are the estimated change in the systemic leverage index following a one-standard-deviation shock to a set of macroeconomic variables. The magnitude of the systemic leverage index response to the year-over-year growth rate of the KOSPI index is the biggest, followed by the exchange rate and the growth rate of the housing price. The results are as expected via a univariate reasoning. The impulse response dynamics of the right panel is the estimated change in the real gross domestic product (RGDP) provided by the BOK following a one-standard-deviation shock to the systemic leverage index. Two dotted grey lines represent the one-standard error confidence band for the estimate.[26] As indicated by the solid line, the shock to the SLI leads to a decline in the real gross domestic product within the first three quarters. After that point, the real gross domestic product gradually returns to its initial value. The decline in the real gross domestic product is significantly different from zero, as indicated by the fact that the confidence band lies entirely below zero. This result is comparable to Hakkio & Keeton (2009), who employed the Chicago Fed National Activity

[26]We report 68% confidence bands estimated for the impulse-response functions using the asymptotic calculation, which is common in the VAR literature (Stock & Watson 2002)

Index (CFNAI) and the Kansas City Financial Stability Index (KSFSI). They found that the shock to the KCFSI led to a decline in CFNAI within the first six months, whereas the shock to the systemic leverage index yielded similar but short-lived effects on the real gross domestic product after the three quarters.

4.2 Marginal Contributions to the Systemic Vulnerability

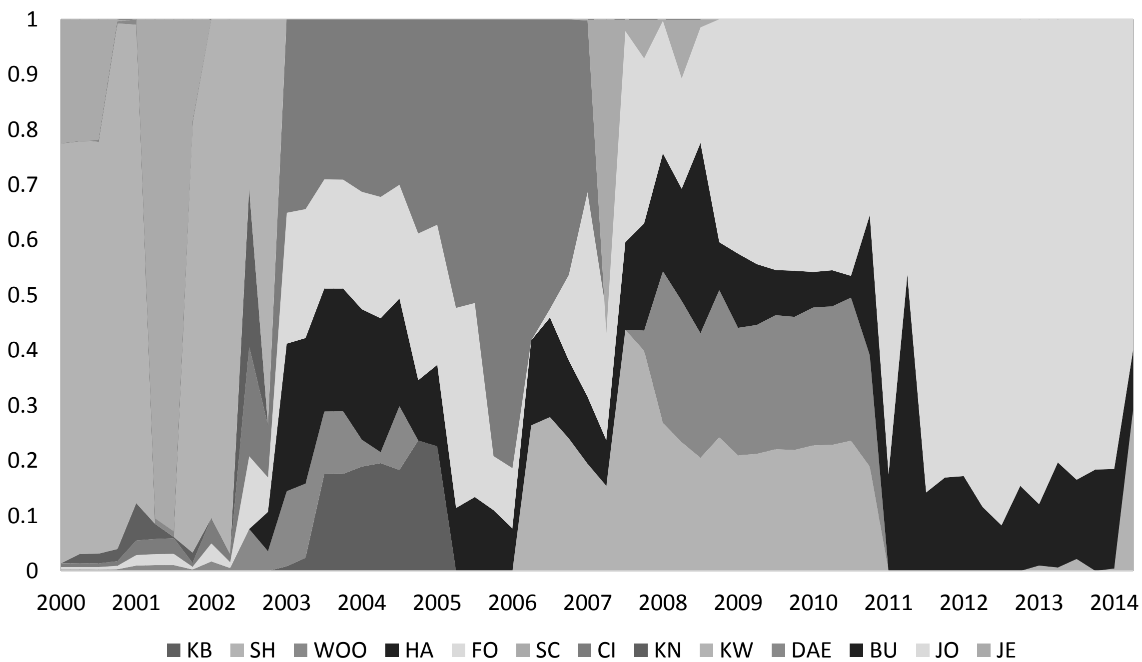
We infer that homogeneous banks contribute more to the systemic vulnerability. The Financial Stability Board's interim report in June 2010 claims that *"Financial institutions should be subject to requirements commensurate with the risks they pose to the financial system."* This statement emphasizes that macroprudential policies should be complemented by micro-manageable policies with respect to systemic risk contributions. There are two insoluble questions in the systemic risk literature: (i) how can the systemic risk in financial systems be measured as a whole, and (ii) how should the contributions of individual banks to the systemic risk be measured? These two questions are directly linked to both macro and micro-prudential tools for simultaneously regulating procyclicality in the time-series perspective and nonlinearity in the cross-sectional perspective. To calculate each banks' marginal contributions to systemic risk propagation, we decompose the function $g^i(\cdot)$ as

$$g^i(Y_{t-d}) = h^i(Y_{t-d}, \Theta)\delta^i,$$

where Y_{t-d} is a transition variable and $h(Y_{t-d}, \Theta)$ is a logistic function with $\Theta = \{c^i, \zeta^i\}$ capturing shape and location parameters, respectively. As the value of the logistic function is bounded to 0 to 1, we can interpret $h^i(Y_{t-d}, \Theta)$ as a probability of falling into the strong nonlinear effect or otherwise. Since the magnitude and signs of δ^i can amplify the nonlinear effects, we stress the role of the signs of δ^i as well. For example, most of the signs of the coefficients for the INT leverage are negative, whereas most of the signs of the coefficients for the OBS and FX leverages are positive during the crisis periods.

To compare individual banks' contributions to the systemic risk, we propose the

Figure 5: Marginal contributions of individual banks for the INT leverage



Note. This figure illustrates the time series behavior of individual banks' normalized $u^i_j(Y_t)$ for the INT leverage component, and its contribution to overall systemic risk. The subscript i and j denote {BOR, INT, OBS, FX} and the domestic banks, accordingly. The banks are seven commercial banks (Kookmin [KB], Shinhan [SH], Woori [WOO], Hana [HA], Standard Chartered [SC], Citibank Korea [CI] and KEB [FO]), and six regional banks (Kyongnam Bank [KN], Kwangju Bank [KW], Daegu Bank [DAE], Busan Bank [BU], Chunbuk Bank [JO] and Jeju Bank [JE]). The total number of individual banks is 13, with seven being a group of larger banks, and the rest being a group of local banks.

time-t marginal contribution of the j-th individual bank to the i-th systemic leverage component given by

$$\omega^i_{j,t} = \frac{u^i_j(X_t)}{\Sigma_j u^i_j(X_t)}, \tag{6}$$

where i={BOR, INT, OBS, FX}. Within the same framework, the systemic importance of each bank can be measured by its marginal contribution to the hypothetical systemic leverage index of the entire banking system. In addition, the marginal contribution of each bank adds up to the aggregate systemic risk both in terms of nonlinearity. As Tarashev, Borio & Tsatsaronis (2010) argued, an operational macroprudential approach to financial stability requires tools that allot system-wide risk to individual financial institutions. Given the homogeneity of the systemic importance across financial institutions, this additivity property is desirable from an operational perspective because it allows the macroprudential tools to be implemented at individual bank levels. Note that the systemic leverage index at the aggregate level and the homogeneity measures are constructed based on the fitted nonlinear amplifying functions; thus, one can decompose the macro measure of systemic leverage into sub-components across different economic channels. Figure 5 illustrates the time-series behavior of individual banks' normalized $u^i_j(Y_t)$ for the INT leverage component, and its contribution to overall systemic risk. Citi (CI) bank made the largest contribution to the interconnectedness risk before the financial crisis, while Shinhan (SH), Woori (WOO), and Korean Foreign Exchange (FO) bank made the biggest contributions during the crisis. Interestingly, the Korean Foreign Exchange (FO) bank has the largest and persistent proportion in the marginal contribution since the global financial crisis. Figures 8 and 9 show the other largest contributors for each OBS and FX leverages. Figure 8 shows that HANA(HA) bank became a major player before the financial crisis, which might have amplified the shocks during the crisis. An intriguing finding in Figure 9 is that Korean Foreign Exchange(FO), a major player in the foreign exchange market made the largest contribution to systemic risk for the FX leverage. With this information, we can make a granular analysis and pinpoint the problem areas, and then apply surgical tools and policies in response. This is one of the benefits of our methodology. Moreover, its simplicity and transparency help regulators to better communicate with the markets.

4.3 Homogeneity at the Individual Level

Having captured the nonlinear and asymmetric amplifying mechanism, we construct a degree of homogeneity based on macroeconomics research that cross-sectional homogeneity can be procyclical, or equivalently that cross-sectional heterogeneity can be countercyclical. The cross-sectional homogeneity is in line with diversification behavior; see Wagner (2010), Ibragimov, Jaffee & Walden (2011), and Acharya & Thakor (2015). In this regard, Calmès & Théoret (2010) confirm that both the cross-sectional dispersion of loans-to-assets and the cross-sectional dispersion of non-interest income share shrink during slow growth episodes, and particularly during financial crises, when the resilience of the banking system is most vulnerable. Our approach lends an additional weight to this negative externality theory by proposing a direct relationship between negative externality and nonlinearity. The systemic leverage propagation mechanism combined with a homogeneity is given by

$$\mathrm{HERD}_t^i = \frac{1}{\Sigma_{j=1}^{N}\{(\omega_{j,t}^i)^2\}}, \tag{7}$$

where the meaning of $\omega_{j,t}^i$ is described in the previous section. The argument for employing squared sum of the values of $\omega_{j,t}^i$ is as follows. As we normalize the cross-sectional sum of $\omega_{j,t}^i$ to one, the sum of squared values $\Sigma_{j=1}^{N}\{(\omega_{j,t}^i)^2\} \geq 1$ holds. Thus, the equality holds only if all values of $\omega_{j,t}^i$ are same as in the case when all banks are perfectly homogeneous. The value of HERD_t^i becomes larger when commercial banks become more homogeneous, and vice versa.[27] Therefore, the HERD_t^i measure captures a cross-sectional homogeneity implied by nonlinear amplifying responses of the Korean commercial banks to the system-wide risk perception. If the homogeneity among banks becomes larger, the nonlinear amplifying effect implied by the systemic leverage$_t^i$ also becomes bigger; thereby, HERD_t^i measure becomes larger. In turn, this homogeneity leads to the radical and asymmetric response to the financial crisis.

Our homogeneity measures are comparable to the herding measures proposed by Lakonishok, Shleifer & Vishny (1992) and Frey, Herbst & Walter (2014).[28] Although the abovementioned two herding measures fail to consider the degree of intensity, our homogeneity measures focusing on the amplification effect capture how the Korean com-

[27]For a robustness check, we also consider an alternative definition of the homogeneity measure as a sum of the absolute distance from the average of $u_j^i(X_t)$, and the results are intact.

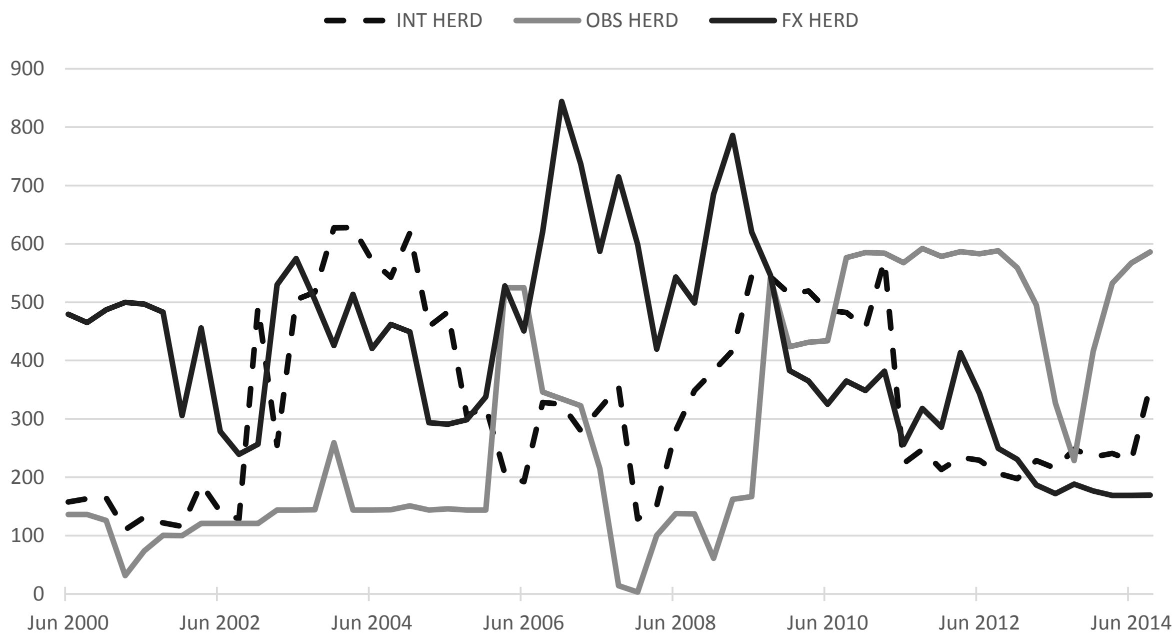
[28]Note that Lakonishok et al. (1992) employ portfolio data to measure herding as an excessive concentration of transactions of fund managers on the same side of the market, whereas Frey et al. (2014) have shown that the methodology proposed by Lakonishok et al. (1992) is biased. Specifically, the herding measure proposed by Lakonishok et al. (1992) should be adjusted.

mercial banks interact each other along with systematic risk factors. Put differently, our homogeneity measure is based on the systemic risk theory and can capture the degree of homogeneity among commercial banks. In addition, it is hard to detect the herding effect because of the difficulties in data collection, particularly when herding is associated with hiding relevant private information. Our proposed measures try to overcome this technical difficulty by focusing on the interactions between the market-wide risk perception and the system-wide balance sheet adjustment in an economically interpretable manner.

To construct the homogeneity measure, we run the smooth transition regression (3) by using a set of balance-sheet data specific to individual banks. The domestic banks included are seven commercial banks (Kookmin [KB], Shinhan [SH], Woori [WOO], Hana [HA], Standard Chartered [SC], Citibank Korea [CI] and KEB [FO]), and six local banks (Kyongnam Bank [KN], Kwangju Bank [KW], Daegu Bank [DAE], Busan Bank [BU], Chunbuk Bank [JO] and Jeju Bank [JE]). Table 3 reports a set of estimation results for beta(CP-CD), amplification(Amp), shape, and asymmetry(Asy) coefficients of using individual banks' INT leverages.[29] Tables 4 and 5 report the estimation results for OBS and FX leverages, respectively. The main finding is that Korean banks show a strongly homogeneous behavior, as the signs of almost all $u_j^i(X_t)$ coefficients exhibit the same direction with different magnitude. Notable exceptions are the magnitude of amplification function $u_j^i(X_t)$ coefficients shown by KW and JE bank in the intrinsic leverage. The size of $u_j^i(X_t)$ coefficients in KW bank is nine times larger than the cross-sectional average and that of JE coefficients is three times larger than the cross-sectional average. These findings may support the micro-perspective policy implication of regulating systemically important risk-takers. Another finding is that the signs of the amplification coefficients of the large and small banks in the off-balance-sheet leverages are opposite. Banks whose statistical significance of amplification coefficients with at least two ** are HA and FO

[29]Negative adjusted R^2 appears when the residual sum of squares approaches to the total sum of squares, implying that the explanation of the response is very low or negligible. Hence, negative adjusted R^2 implies the insignificance of the explanatory variables. The results may be improved with a larger size. In the tables, we have changed negative adjusted R^2s to zeros.

Figure 6: Homogeneity (HERD) measures for INT, OBS, and FX leverages



Note. This figure illustrates the time series behavior of the homogeneity measure HERD_t^i for $i =$ [INT, OBS, and FX] in equation (7). Since the homogeneity measure HERD_t^i is defined as the distance of each homogeneity measures from the X-axis captures the degree of homogeneity among all banks; wider divergence from the X-axis indicates larger herding tendency.

among the large banks and KN, DAE, and JO among the small ones. The signs of HA and FO are positive and those of KN, DAE, and JO are negative. Hence, larger banks procyclically adjust their portfolios, whereas smaller banks countercyclically adjust their portfolios. These results are not observed at the aggregate level. The reasons for the homogeneity preference vary.[30] Rajan (2005), for example, argues that compensation schemes at many financial firms may induce herding behavior as managers seek insurance against under-performing their peers.

Figure 6 confirms that cross-sectional heterogeneity can be countercyclical. Recalling the definition of the homogeneity measure HERD_t^i, the distance of each homogeneity measure from the X-axis captures the degree of being homogeneous among all banks.

[30] The theory offers some reasons why banks tend to herd: performance-based reward structures for managers (Scharfstein & Stein 1990), protection against liquidity shocks (Kahn & Santos 2010), lack of information (Liu 2011), decreasing deposit rates (Acharya, Santos & Yorulmazer 2010) and too-many-to-fail regulation (Acharya & Yorulmazer 2007).

Banks become homogeneous when financial institutions make similar or even the same asset holdings and risk-taking decisions. After the dotcom bubble-burst and before the Korean credit card crisis hit around the end of 2004, the INT and FX homogeneity indices exhibit the countercyclicality, meaning that the Korean commercial banks tend to be increasingly homogeneous. During the 2008 global crisis, most Korean banks struggled to fund US dollars for their own survival. The homogeneous behavior among banks measured by the FX herd measure captures the clearer pattern where the peak of the FX herd measure was hovering during the crisis period.

Another intriguing pattern in Figure 6 is that the homogeneity measures show different directions, especially during the financial crisis period. The direction of the homogeneity measure based on the FX increases rapidly and stays at the higher level during the financial crisis, whereas the homogeneity measure based on the off-balance-sheet and interconnectedness exhibits opposite directions. In the post-crisis period, the HERD measure specific to FX keeps decreasing, whereas the same measure with respect to OBS reveals a jump-type movement. This result is a sharp contrast to our aggregate level finding. This result is matched with the stylized fact that the Korean banks tend to hold similar positions, facing the same exposures, and pursuing similar strategies.

Therefore, employing various systemic leverages enables policy makers to differentiate between the procyclical and countercyclical effects at the individual level based on the homogeneity tendency. This lead to the crucial policy implication that policy makers must wield a surgical instrument rather than a blunt sword in implementing macroprudential policies because different systemic leverages have different cyclicalities.

4.4 Homogeneity measure as a macroprudential toolkit

We further study whether the proposed homogeneity measures have the ability to predict the asset price fluctuations (Borgy, Clerc & Renne 2014) and the real GDP growth cycles (Buch & Neugebauer 2011). Accordingly, we take the Korea composite Stock Price

Index (KOSPI_t) for an asset-price proxy, and the real GDP growth rates (RGDP_t) as the prediction target variables.[31] Following Borgy et al. (2014), we construct asset-boom proxy by extracting a trend from the time-series using the HP filter so that our dependent variables are inherently cyclical.[32] As monthly data of the KOSPI variable is available, we apply the HP filter to the monthly time-series, and then we extract the quarterly points to match the available data points of the RGDP variable. Specifically, we set up the predictive regression model with forecasting horizons ranging from zero to 4 quarters given by

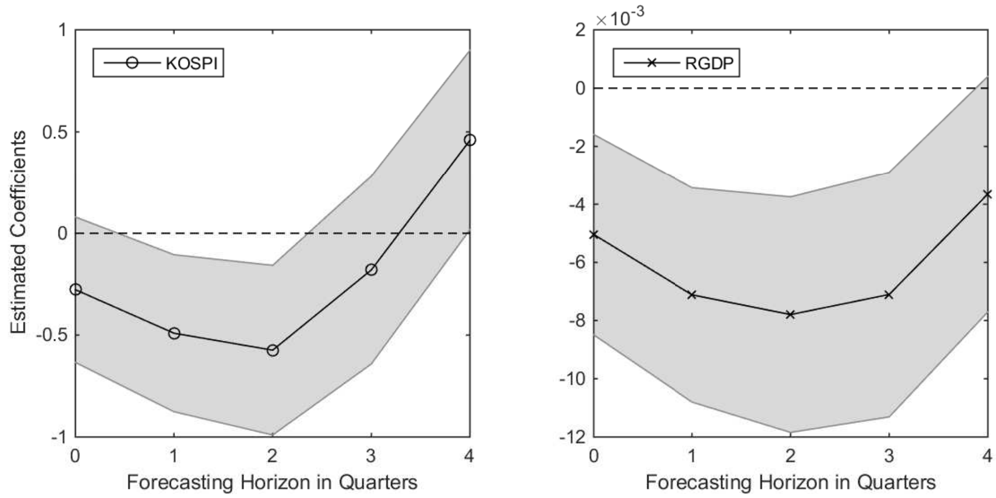
$$y_{i,t+q} = a_i + A_j \mathrm{HERD}_{j,t} + B_i V_t + \varepsilon_{i,t+q}, \tag{8}$$

where i and j denotes $[\mathrm{KOSPI}_t, \mathrm{RGDP}_t]$, and [INT, OBS, and FX], respectively, and the forecasting horizon q takes intergers from 0 to 4. Moreover, we postulate that $\varepsilon_t \sim N(0, Q)$, and $V_t = [\mathrm{CREDIT}_t, \mathrm{PR}_t, \mathrm{EX}_t, \mathrm{IP}_t]'$ is a vector of four control variables, where CREDIT_t is a HP-filtered bank credit to the private sector, PR_t represents a policy rate, and EX_t is a year-over-year growth rate of the exchange rate. All variables are observed on a quarterly basis and seasonally adjusted. Figure 7 exhibits the statistical significances of the representative HERD measure on $[\mathrm{KOSPI}_t, \mathrm{RGDP}_t]$ dependent variables, where we construct the representative HERD measure by taking the first principal component of the component-specific HERD measures for INT, OBS, and FX leverages. Notice that the dependent variables in our predictive regression model, $[\mathrm{KOSPI}_t, \mathrm{RGDP}_t]$, are inherently aggregate macro variable for which capturing the nonlinear amplification mechanism is worthwhile from the macroprudential perspective.

Figure 7 summarizes key findings from our predictive regression analysis, as both panels exhibit a distictive pattern in common. The estimated coefficients A_j on the representative HERD measure are mostly negative with strong statisical significance for each dependent variable up to fourth quarters of forecasting horizons. Those signifi-

[31] The KOSPI is a capitalization-weighted index of all common shares on the Korean Stock Exchanges.
[32] We find similar results by employing year-over-year growth rates.

Figure 7: Predictive powers of the representative HERD measure



Note. This figure plots the estimated coefficients A_j on the representative HERD measure for forecasting horizon from 0 to 4 quarters based on the equation (8) along with their 95% confidence intervals. The representative HERD measure is the first principal component of the HERD measures for [INT, OBS, and FX]. The dependent variables are KOSPI_t (left panel) and RGDP_t (right panel), respectively. All variables are constructed on a quarterly basis and seasonally adjusted.

cantly negative coefficients indicate that the proposed homogeneity measure can serve as a countercyclical regulation toolkit for macroprudential supervision. In particular, the representative HERD measure provides a meaningful early warning signal for the first and second quarters ahead on the KOSPI variable, whereas the same measure exhibits even stronger prediction power up to the next four quarters on the real GDP growth. It is noteworthy to mention that the prediction power on the real GDP growth rate (RGDP_t)is more pronounced than that on the stock price index (KOSPI_t). This finding fortifies the implication that our proposed HERD measure is better suited to work as a macroprudential policy instrument, considering the nonlinear externalities incured by the commercial banking system with financial markets. Our empirical finding justifies the policy-oriented implication of our proposed systemic leverage measures.[33]

[33]We also performed a similar predictive regression analysis by employing the component-specific homogeneity (HERD) measures for INT, OBS, and FX leverages, respectively. The HERD measure for FX leverage shows strong statistical significances for the first, second, and third quarters ahead on the KOSPI variable, whereas the HERD measure for OBS leverage shows strong statistical significances for relatively longer horizons such as four and five quarters ahead. This pattern is reversed when the RGDP is taken as a dependent variable. The detailed results are available upon requests.

5 Conclusion

This paper proposes a battery of systemic leverage measures for assessing multifaceted amplifying mechanism of systemic risk propagation. We decompose the systemic leverage into three balance-sheet components of intrinsic leverage, off-balance-sheet leverage, and FX leverage to capture two important dimensions of the systemic risk propagation: (i) the mark-to-market (MtM) valuation for procyclicality from the time-series perspective as a whole, and (ii) the nonlinear feedback mechanism from cross-sectional perspective at the individual bank level. Based on a simple model specification, we define the nonlinear amplifying mechanism in an economically interpretable way and connect the systemic risk realization in a nonlinear way to the homogeneity among commercial banks.

Our empirical results confirm that nonlinear amplification effects show economic and statistical significance across all systemic leverage components. We further verify that cross-sectional homogeneity can be employed as a measure of marginal contribution of each bank to the systemic risk propagation as a whole. These findings provide a variety of important implications for policy makers for the purpose of macroprudential supervision. As our proposed systemic leverage index, homogeneity measures, and marginal contribution calculation are constructed by directly incorporating the quality of asset/liability in the balance sheet, the proposed systemic leverage index can complement existing risk-sensitive capital requirement and bank-specific leverage regulation by reflecting the degree of system-wide vulnerability from both time-series and cross-sectional perspectives simultaneously.

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Table 1: Summary Statistics

Panel A: Summary statistics of the systemic leverage components

	INT	**OBS**	**FX**	**CP-CD**	**C to G**
Mean	9.6767	16.4577	2.8322	0.2564	0.0040
Median	9.3482	17.1660	2.5259	0.1700	-0.0243
Maximum	12.5839	31.6244	5.3648	1.6700	0.2620
Minimum	7.7896	5.3576	1.9009	0.0500	-0.1319
Std. Dev.	1.4507	6.9640	0.9019	0.2615	0.0977
Skewness	0.5920	0.0387	1.4235	3.5194	0.8972
Kurtosis	2.1212	2.0637	4.4340	17.6861	3.0176
Jarque-Bera	5.3443	2.1698	24.9819	652.0094	7.9158
Probability	0.0691	0.3379	0.0000	0.0000	0.0191
Obs.			59		

Panel B: Summary statistics of the macro-economic and financial variables

	PRATE	**HP**	**KOSPI**	**EX**	**RGDP**
Mean	3.5975	0.0180	0.0260	-0.3610	0.0276
Median	3.7500	0.0131	0.0401	-3.1000	0.0279
Maximum	5.2500	0.0700	0.2334	39.7000	0.0549
Minimum	2.0000	-0.0091	-0.3091	-18.2000	0.0077
Std. Dev.	1.0107	0.0197	0.1154	11.4253	0.0112
Skewness	-0.0166	1.1101	-0.7477	1.7213	0.2885
Kurtosis	1.8377	3.7141	3.3529	6.1698	2.4632
Jarque-Bera	3.3240	13.3724	5.8039	53.8352	1.5266
Probability	0.1898	0.0012	0.0549	0.0000	0.4661
Obs.				59	

Note. Descriptive statistics. This table reports the indicated summary statistics of the selected variables at quarterly frequencies from 2000 to 2014. Panel A reports summary statistics of three systemic leverage components and two risk factors considered in the equation (2). CP-CD denotes the interest rate differential between the yield on the commercial paper (CP) for non-financial firms and the yield on the certificate of deposit (CD). C to G denotes the credit-to-GDP constructed by following the BCBS guide 187. Panel B reports the summary statistics of macro-economic and financial variables for the Vector Autoregressive Regression. PRATE represents a policy rate; HP is a yoy growth rate of the housing price; KOSPI is a yoy growth rate of the Korean stock index; EX represents a yoy growth rate of exchange rate; RGDP is the Korean real gross domestic product.

Table 2: Estimation results for aggregate systemic leverage components

Components	CP-CD	Amplification	Shape	Asymmetry	Adj.R^2	DW	Obs.
BOR	-0.0100**	0.1118***	26.98	4.1438***	0.3971	0.6776	
	(0.0052)	(0.0175)	(91.51)	(0.0843)			
INT	-0.0081***	0.0693***	10.80	5.5733***	0.5565	0.6541	
	(0.0030)	(0.0083)	(33.4)	(0.4980)			58
OBS	0.0189*	0.0425	25.24	0.9239***	0.0343	0.5822	
	(0.0125)	(0.0357)	(125.72)	(0.2955)			
FX	0.0001	0.0213***	27.08	3.5363***	0.1878	0.5438	
	(0.0016)	(0.0084)	(84.74)	(0.1606)			

Note. Estimation results for the systematic beta (CP-CD), amplification, shape, and asymmetry coefficients using aggregate BOR, INT, OBS, and FX leverages. Standard errors are reported and *, ** and *** indicate two-tailed statistical significance at the 10%, 5% and 1% levels, respectively.

Table 3: Estimation results for individual banks' INT leverage

Banks	Type	CP-CD	Amplification	Shape	Asymmetry	Adj.R^2	DW	Obs.
KB		-0.0017	0.0940**	24.08	7.0898***			
		(0.003)	(0.0329)	(125.42)	(0.4749)	0.48	0.29	51
SH		-0.0037	0.0553***	28.95	6.4268**			
		(0.0049)	(0.0167)	(804.65)	(3.6679)	0.27	0.68	33
WOO		-0.0049	0.0608***	23.02	6.399***			
		(0.0044)	(0.0149)	(108.42)	(0.1861)	0.24	0.67	58
HA	**Large**	0.0005	0.1195***	2.72*	5.1155***			
		(0.0034)	(0.0413)	(1.88)	(0.4397)	0.30	1.23	47
FO		-0.022***	0.1161***	38.93	1.6351***			
		(0.0063)	(0.0177)	(156.14)	(0.1185)	0.38	1.14	58
SC		-0.0111**	-0.0103	25.00	3.1345			
		(0.0049)	(0.0217)	(59.38)	(0.0951)	0.09	0.63	58
CI		-0.0023	0.1591***	29.97	1.8046***			
		(0.0035)	(0.0167)	(64.14)	(0.1144)	0.58	1.14	58
KN		-0.0038	0.4125*	63.01	4.0285***			
		(0.0088)	(0.2632)	(446.29)	(0.0318)	0.03	2.49	58
KW		0.0299	17.8380**	340.91	0.2049			
		(0.286)	(10.4703)	(467.7)	(0.0054)	0.00	2.20	58
DAE		-0.0008	0.125*	21.23	7.0879***			
	Small	(0.0027)	(0.0855)	(961.4)	(7.4268)	0.19	1.13	58
BU		-0.0063**	-0.0621**	19.97	5.2692***			
		(0.0037)	(0.0343)	(26.7)	(0.0942)	0.25	0.69	58
JO		-0.0094**	-0.004	7.79	7.4567***			
		(0.0041)	(0.0134)	(18.81)	(0.3419)	0.05	1.32	58
JE		-0.01263	5.2572***	135.46	0.8817***			
		(0.0466)	(1.1133)	(491.69)	(0.0765)	0.22	2.70	58

Note. Estimation results for systematic beta (CP-CD), amplification, shape, and asymmetry coefficients using individual banks' INT leverages. The domestic banks included are seven commercial banks (Kookmin [KB], Shinhan [SH], Woori [WOO], Hana [HA], Standard Chartered [SC], Citibank Korea [CI] and KEB [FO]), and six local banks (Kyongnam Bank [KN], Kwangju Bank [KW], Daegu Bank [DAE], Busan Bank [BU], Chunbuk Bank [JO] and Jeju Bank [JE]). The total number of individual banks is 13, with seven being a group of larger banks and the rest being a group of local banks. Standard errors are reported and *, ** and *** indicate two-tailed statistical significance at the 10%, 5% and 1% levels, respectively.

Table 4: Estimation results for individual banks' OBS leverage

Banks	**Type**	**CP-CD**	**Amplification**	**Shape**	**Asymmetry**	**Adj.** R^2	**DW**	**Obs.**
KB		-0.0120	0.0390	22.97	2.3123			
		(0.0102)	(0.0329)	(787.36)	(3.6692)	0.00	1.01	51
SH		-0.0069	-1.2169*	4.26**	3.8386***			
		(0.0139)	(0.775)	(2.22)	(0.2743)	0.40	0.54	33
WOO		0.0023	0.0647*	22.95	1.5682			
		(0.0119)	(0.048)	(3242.53)	(26.8993)	0.00	0.57	58
HA	**Large**	0.0008	0.2172***	42.12	1.3857***			
		(0.0202)	(0.0763)	(259.98)	(0.0992)	0.19	0.60	47
FO		-0.03***	0.1204***	4.1149e5	4.8622***			
		(0.0119)	(0.0438)	(1.1526e-17)	(0.0000)	0.38	1.14	58
SC		0.0156	0.2022	2.2520e7	1.2005***			
		(0.0705)	(0.3058)	(7.4179e-18)	(0.0000)	0.00	1.05	58
CI		-0.0724***	-0.2501	5.8997***	2.9119***			
		(0.0301)	(0.8198)	(3.08)	(0.1727)	0.46	1.02	58
KN		-0.0072*	-0.2507**	4.0475**	2.7862***			
		(0.0044)	(0.1083)	(2.03)	(0.1517)	0.57	0.57	58
KW		0.0003	0.0035	8.9499e5	0.9004***			
		(0.0052)	(0.0203)	(7.9652e-17)	(0.0000)	0.00	1.68	58
DAE		-0.0135*	-0.1517***	76.64	2.0540			
	Small	(0.0082)	(0.0571)	(3607.)	(2.3475)	0.54	1.06	58
BU		-0.014**	0.0199	21.16	2.4912***			
		(0.0061)	(0.0323)	(29.98)	(0.0652)	0.31	1.02	58
JO		0.0006	-0.0235**	21.00	1.1355			
		(0.0031)	(0.0127)	(434.62)	(15522.)	0.02	0.67	58
JE		-0.0182***	0.0187	121.79	1.1672***			
		(0.0074)	(0.0384)	(268.39)	(0.0208)	0.20	2.50	58

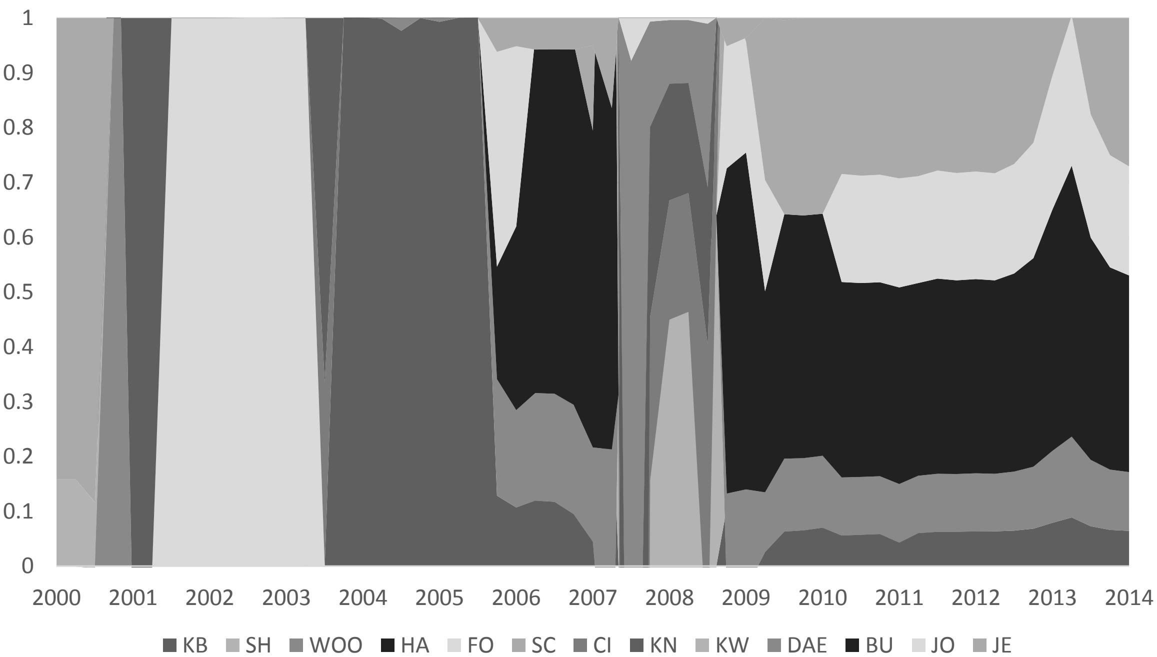
Note. Estimation results for systematic beta (CP-CD), amplification, shape, and asymmetry coefficients using individual banks' INT leverages. The domestic banks included are seven commercial banks (Kookmin [KB], Shinhan [SH], Woori [WOO], Hana [HA], Standard Chartered [SC], Citibank Korea [CI] and KEB [FO]), and six local banks (Kyongnam Bank [KN], Kwangju Bank [KW], Daegu Bank [DAE], Busan Bank [BU], Chunbuk Bank [JO] and Jeju Bank [JE]). The total number of individual banks is 13, with seven being a group of larger banks and the rest being a group of local banks. Standard errors are reported and *, ** and *** indicate two-tailed statistical significance at the 10%, 5% and 1% levels, respectively.

Table 5: Estimation results for individual banks' FX leverage

Banks	**Type**	**CP-CD**	**Amplification**	**Shape**	**Asymmetry**	**Adj.** R^2	**DW**	**Obs.**
KB	**Large**	-0.0006	0.0033	19.12	6.9475***			
		(0.0007)	(0.0037)	(78.36)	(0.0902)	0.23	1.11	51
SH		0.0034**	0.0085**	37.92	2.3796***			
		(0.0014)	(0.0049)	(83.43)	(0.0738)	0.49	1.03	33
WOO		0.0032***	0.0896***	17.31	3.5083			
		(0.0013)	(0.0369)	(2477.82)	(27.5983)	0.30	0.49	58
HA		-0.0018	0.0157**	14.01	4.9252***			
		(0.0017)	(0.0073)	(50.86)	(0.4155)	0.12	0.84	47
FO		-0.0006	0.0605***	18.83	0.9391***			
		(0.0042)	(0.0126)	(51.14)	(0.135)	0.34	1.15	58
SC		-0.001	0.012*	10.28	4.389***			
		(0.0016)	(0.0087)	(27.47)	(0.2311)	0.02	1.32	58
CI		-0.0031*	0.0231***	14.10	3.291***			
		(0.0019)	(0.007)	(19.47)	(0.1699)	0.16	1.02	58
KN	**Small**	0.0011***	0.019**	22.12	2.2322			
		(0.0016)	(0.0109)	(401.03)	(0.3658)	0.00	2.00	58
KW		0.0001	0.0537*	8.73	3.2524***			
		(0.0019)	(0.0345)	(18.87)	(0.291)	0.00	1.12	58
DAE		0.001**	0.0028*	20.95	3.9431**			
		(0.0006)	(0.0017)	(332.68)	(2.1696)	0.54	1.06	58
BU		0.0005	0.0152***	17.97	2.4154***			
		(0.0018)	(0.006)	(121.65)	(0.6262)	0.16	0.44	58
JO		-0.0014*	0.0058**	24.03	3.5192***			
		(0.0009)	(0.0027)	(90.04)	(0.1485)	0.02	0.77	58
JE		-0.0007*	-0.0034*	12.95	1.1595***			
		(0.0004)	(0.0027)	(15.59)	(0.0962)	0.21	1.94	58

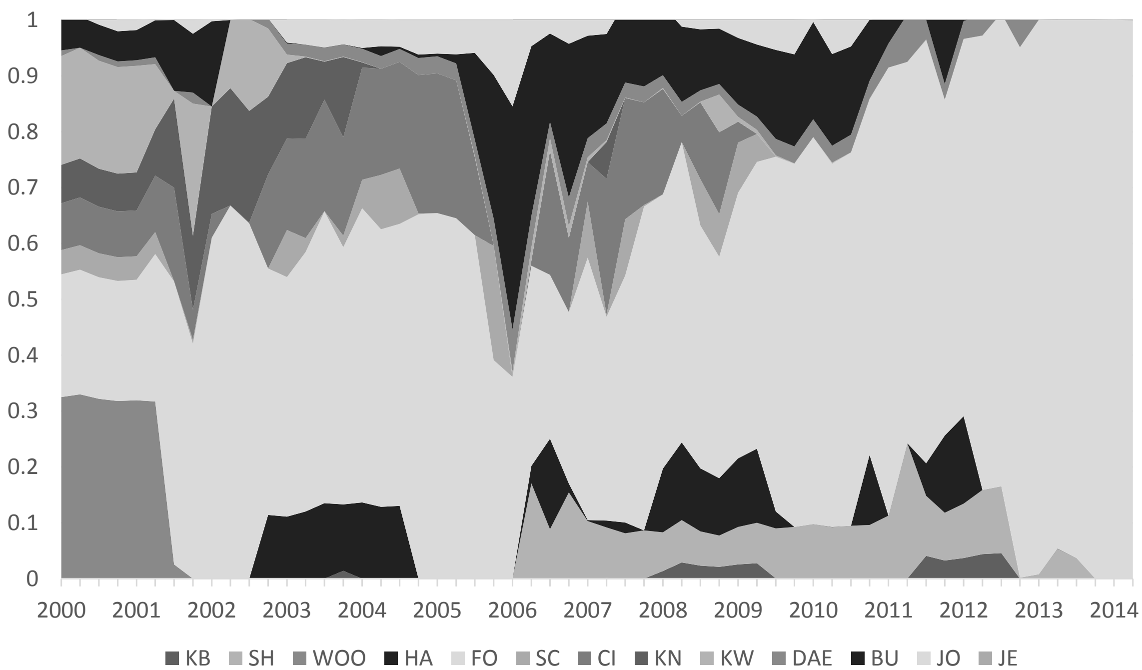
Note. Estimation results for systematic beta (CP-CD), amplification, shape, and asymmetry coefficients using individual banks' INT leverages. The domestic banks included are seven commercial banks (Kookmin [KB], Shinhan [SH], Woori [WOO], Hana [HA], Standard Chartered [SC], Citibank Korea [CI] and KEB [FO]), and six local banks (Kyongnam Bank [KN], Kwangju Bank [KW], Daegu Bank [DAE], Busan Bank [BU], Chunbuk Bank [JO] and Jeju Bank [JE]). The total number of individual banks is 13, with seven being a group of larger banks and the rest being a group of local banks. Standard errors are reported and *, ** and *** indicate two-tailed statistical significance at the 10%, 5% and 1% levels, respectively.

Figure 8: Marginal contributions of individual banks for the OBS leverage component



Note. This figure illustrates the time series behavior of individual banks' normalized $u_j^i(Y_t)$ for the OBS leverage component, and its contribution to overall systemic risk. The subscript i and j denote {BOR, INT, OBS, FX} and the domestic banks, accordingly. The domestic banks included are seven commercial banks (Kookmin [KB], Shinhan [SH], Woori [WOO], Hana [HA], Standard Chartered [SC], Citibank Korea [CI] and KEB [FO]), and six local banks (Kyongnam Bank [KN], Kwangju Bank [KW], Daegu Bank [DAE], Busan Bank [BU], Chunbuk Bank [JO] and Jeju Bank [JE]). The total number of individual banks is 13, with seven being a group of larger banks and the rest being a group of local banks.

Figure 9: Marginal contributions of individual banks for the FX leverage component



Note. This figure illustrates the time series behavior of individual banks' normalized $u_j^i(Y_t)$ for the FX leverage component, and its contribution to overall systemic risk. The subscript i and j denote {BOR, INT, OBS, FX} and the domestic banks, accordingly. The domestic banks included are seven commercial banks (Kookmin [KB], Shinhan [SH], Woori [WOO], Hana [HA], Standard Chartered [SC], Citibank Korea [CI] and KEB [FO]), and six local banks (Kyongnam Bank [KN], Kwangju Bank [KW], Daegu Bank [DAE], Busan Bank [BU], Chunbuk Bank [JO] and Jeju Bank [JE]). The total number of individual banks is 13, with seven being a group of larger banks and the rest being a group of local banks.