Systematic Cyclicality of Systemic Bubbles:
Evidence from the U.S. Commercial Banking System

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Abstract

This paper investigates the extent of vulnerability in the U.S. commercial banking system through a pro-cyclical interaction between the market-wide risk perception and system-wide asset management behavior. Based on a Markov regime-switching model, the proposed diagnostic framework clearly illustrates its ability to provide an early warning signal of the build-up and unwinding of fragility in the financial system and the real economy for a counter-cyclical structure of regulatory policy. Empirical results demonstrate an asset pricing implication, as the proposed systemic bubble index is a significant factor that affects the investment opportunity set of stock investors for financial firms but not for non-financial firms.

JEL classification: C13, G01, G21, G28

Keywords: Systemic bubble; Financial crisis; Cyclicality; Early warning signal; Markov regime-switching model

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1 Introduction

Since the onset of the 2007-09 global financial crisis, the extant literature has stressed the importance of accurate and timely information on systemic risk for effective financial regulation and macro-prudential monetary policy. At the center of this challenge is the critical task of identifying the real-time dynamics of risk propagation in the financial system as a whole − one that addresses unobservable systemic implications prevailing in the financial system by considering its interaction with the business cycle. Accordingly, it is of paramount importance to develop a novel framework for quantifying the risk of an aggregate disruption in the financial system along with adverse feedback effects to the real economy in a timely manner.[1]

To formulate macro-prudential capital standards in the post-crisis era, the Basel Committee on Banking Supervision (BCBS) has proposed a *counter-cyclical* structure of regulatory policy as a countermeasure for the existing *pro-cyclical* policy of forcing banks to restrict their lending during a downturn.[2] It follows that such a capital-charge cyclicality in the banking system indeed amplifies business cycle fluctuations, and the recurring pro-cyclicality exacerbates a financial crisis; see Adrian & Brunnermeier (2011), Shin (2010), Brunnermeier, Crockett, Goodhart, Persaud & Shin (2009) and others. The objective of the counter-cyclical regulation is to avoid such an amplification mechanism and mitigate pro-cyclicality by encouraging banks to build up capital buffers during periods of excess credit growth.

The rationale behind the counter-cyclical structure of regulatory policy is that the realization of systemic risk tends to appear with a noticeable lag in the accumulation of system-wide bubble. During the early stages of a recession, a negative shock drives down asset prices, then decreases the value of borrowers' collaterals. The ensuing contraction in the capital of the leveraged banking system leads to a reduction in their credit supply, amplifying the economic distress from a system-wide leverage adjustment that fuels cyclical downturns with fire sales of good assets or recovery of good loans. This feature is closely related to the myopic *de facto* risk measurement in the banking sector, which mainly relies on contemporaneous signal from the market or backward-looking information such as past profit flows, sales growth, and credit scores. As such, measurable risk tends to be underestimated when the bubble is being built-up, and overestimated when the problem is realized. It is evident that adding a financial burden on already distressed

[1]Refer to the speech at the Council on Foreign Relations by Bernanke (2009) for more details on a macro-prudential approach to regulate systemic risk.

[2]See Consultative Documents by the BCBS in December 2009 and July 2010 for details.

institutions will accelerate such a self-reinforcing propagation effect through the *leverage cycle* in the transmission of negative shocks to the real economy; see Geanakoplos (2010) for details.

In this regard, a perceptive measure of systemic vulnerability is indispensable for detecting *early-warning signals* towards the counter-cyclical regulatory approaches in a proactive manner. It is not surprising that financial market data has been widely employed as a forward-looking indicator of systemic fragility because of its high-frequency availability and reliability with rapid response to innovations.[3] However, it is worth noting some concerns regarding careless (and possibly reckless) credence in market-based information as a basis for measuring systemic risk, which is conceptually different from systematic (or market) risk. Whereas systematic risk refers to the undiversifiable risk intrinsic to the entire financial market, systemic risk is recognized as a different source of fundamental risk that lies dormant beneath the intertwined financial networks. As pointed out by Benoit, Colletaz, Hurlin & Perignony (2013), however, both systemic and systematic risks may be empirically and almost perfectly correlated if the systemic risk measurement is solely grounded by the financial market data.[4] Consequently, the signals from the market-based indicators inevitably contain false-alarm prone noises orthogonal to the development of systemic risk owing to the psychological aspects related to the risk premium effect.

Another potential pitfall of market-based systemic indicators, usually captured by the dynamics of asset price volatilities, lies in the *volatility paradox*, i.e., the build-up of systemic risk is cultivated in low volatility environments. Brunnermeier & Sannikov (2012) explain this phenomenon as endogenous risk (i.e., risk self-generated within the system) by studying the full equilibrium dynamics of an economy with financial frictions. Brunnermeier & Oehmke (2013) assert that this volatility paradox is associated with excessive leverage and maturity mismatch in the banking system. It certainly triggers the pro-cyclicality between the financial market and the system from levering up on risky securities along with the resulting leverage cycle. It leads us to the fundamental reasoning that it can be dangerous to inconsiderately adopt asset price volatility as an exclusive and exogenous measure of systemic risk. In other words, a blind dependence on market-based

[3]For example, the CoVaR measure introduced by Adrian & Brunnermeier (2011) and marginal expected shortfall (and systemic expected shortfall, which is its extended version) suggested by Acharya, Pedersen, Philippon & Richardson (2010) make use of equity market data. Other examples include the (risk-neutral) probability of default, proposed by Huang, Zhou & Zhu (2012), based on the market credit default swap data.

[4]For instance, Figure 4 in Benoit et al. (2013) illustrates the strong relationship between an equity-based systemic indicator (marginal expected shortfall, MES) and the corresponding beta specific to financial institutions, implying the homogeneous quality of information between two risk measures.

risk measures can be misleading towards overreaction to or understatement of the negative shock, indicating that policy makers need to be cautious before taking macro-prudential policy actions. In this context, Borio (2010) argues for the paradox of financial instability in which *"asset prices are unusually strong, leverage measured at market prices artificially low, and risk premia and volatilities low precisely when risk is highest."* In the same vein, a naive counter-cyclical monetary policy based solely on market data can be myopic and lead to a sub-optimal regulation, causing a substantial abuse of social welfare and capital. Other than market-based measures, however, only a few authors have devised distinctive measures with the consideration of (potentially) lagging systemic indicators. For instance, Giesecke & Kim (2011) developed dynamic systemic risk measures based on a system-wide default prediction by using historical default data (and market variables as covariates), and Shin (2010) proposed non-core liabilities tax as a macro-prudential regulation from the balance sheet information. Shin (2013) supported this argument by comparing three types of early warning indicators of financial instability – those based on financial market prices, those based on normalized measures of total credit and those based on liabilities of financial intermediaries. Gray & Jobs (2010) proposed a systemic risk measure based on the Merton's structural model which can be naturally interpreted as market volatility adjusted pseudo-leverage.

Our analysis mainly focuses on commercial banks because of their central role as a transmission channel in the amplification of the business cycle through pro-cyclical interaction between the financial system and the real economy. Massive securitization of loans and securities of bank's balance sheet has led to *market pro-cyclicality* in the way of connecting commercial banks' balance sheets and asset prices in the market. The core of the market pro-cyclicality problem is associated with the interaction between the mark-to-market asset valuation and the active asset management in the banking system, along with the propagation and amplification channels of market-wide aggregate shocks throughout the entire financial system. Brunnermeier & Sannikov (2012) pointed it out as *"financial frictions lead to the amplification of shocks, directly through leverage and indirectly through prices."* As Adrian & Shin (2010) put it differently, the degree of bank's risk-taking through the *balance-sheet* channel is closely related to the liquidity fluctuations owing to unpredictable common asset-price shocks through the *market* channel. That is, the system-wide balance sheet management in response to the aggregate asset price trend generates a positive or negative feedback loop, followed by a chain of spillover effects, which is crucial in gauging systemic risk; see Tasca & Battison (2012). As a result, the market pro-cyclicality certainly generates a systemic bubble regarding the financial instability. Baron & Xiong (2014) find that bank credit expansion accompanied by a lower equity premium predicts an increased crash risk in the stock market. From an analogous perspective, Hahm, Shin & Shin (2012) argue that systemic vulnerability to a crisis is signaled by a significant amount of non-traditional sources of funding (non-core bank liabilities), namely the components of bank funding other than retail deposits, grounded by their liability-side of balance sheets. Although we can view the system-wide balance sheet in terms of both liabilities and assets, we mainly focus on the asset side in that the dynamics of systemic liquidity depends more upon assets (e.g., bank credit, interbank loans, and cash assets) than liabilities (e.g., deposits, borrowings, and trading liabilities).[5]

There are several prerequisites for early-warning indicators of systemic instability. The most crucial prerequisite for a systemic early warning indicator lies in its appropriate timing. BCBS emphasizes that macro-prudential policies take time to become effective; see Consultative Documents in December 2009 and July 2010. Drehmann & Juselius (2013) stipulated that *"signals should arrive at least one and a half years but no more than five years ahead of a crisis"* for a meaningful systemic risk diagnosis.[6] Another necessary condition is the stability of the signal. Drehmann & Juselius (2013) also claimed that *"policy makers tend to base decisions on trends rather than react to changes in signaling variables immediately."* If the signal becomes stable, persistent, and less uncertain, it will provide regulators with more flexible and decisive policy actions. The last requirement for systemic indicators, as practical toolkits for central banks and regulators, is that the signals should be straightforward and easy to interpret to enhance transparency for financial disclosure. The end result, grounded by a parsimonious modeling approach with readily accessible data set, should serve as a public good.[7]

The proposed macro-measure of systemic bubble fulfills the prerequisites mentioned above and contains comprehensive and timely information on the evolution of systemic bubbles by considering a dynamic propagation mechanism through market and balance-sheet information. We adopt a Markov regime-switching model with multiple latent states to detect a harbinger of switching from a normal to a distressed regime, in order to provide detailed implications on the system-wide resilience as a whole. Specifically, we allow the three latent states to decompose the time-series data into (i) a macro-prudential state ($S_t = 1$), (ii) a bubble build-up state ($S_t = 2$), and (iii) a crisis state ($S_t = 3$). The rationale behind the design of our systemic bubble index is that the overall risk appetite

[5]Drehmann, Borio, Gembacorta, Jimenéz & Trucharte (2010) empirically supported the argument that a credit aggregate is superior to a money aggregate (M1 or M2) in terms of measuring system-wide liquidity.

[6]Caruana (2010) pointed out that it can also be problematic if signals arrive at very early stage as policy measures are costly.

[7]Duan & Van Laere (2012) introduce a new approach that is predicated on the provision of credit ratings as a *public good* as opposed to the currently predominant for-profit business model.

in the commercial banking system affects its system-wide asset management behavior, and an early warning signal of systemic risk can be detected by capturing the dynamics of the system-wide risk-taking appetite regimes by combining both market and balance-sheet information sets.

Our diagnostic framework clearly demonstrates its ability to provide an early warning signal of the build-up and unwinding of fragility in the financial system for a counter-cyclical structure of regulatory policy. Empirical results show that the proposed systemic bubble index has a strong predictive power over 18-, 21-, and 24-month periods. The time-series behavior of the estimated systemic bubble index provides a reasonable explanation of the seemingly counter-intuitive "volatility paradox" phenomenon in the financial market. Moreover, our framework enhances transparency grounded by a non-proprietary public data set that is easily accessible in a timely manner, and a parsimonious modeling structure without substantial model risk so that it can be readily understood and easily communicated by regulators. Finally, our empirical results demonstrate an asset pricing implication as the systemic bubble index turns out to be a significant state variable that affects the investment opportunity set of stock investors in the financial sector. The results also highlight that *systemic* risk has been perceived as an independent factor of *systematic* risk for financial firms but not for non-financial firms.

The remainder of this paper is organized as follows. Section 2 introduces our diagnostic approach, including our model specification and the design of a systemic bubble index based on a Markov regime-switching model. Section 3 introduces the selected variables with data descriptions. Section 4 presents empirical results and their implications, and Section 5 provides the concluding remarks.

2 Diagnostic approach

This section proposes our diagnostic approach at the modeling stage to address the market pro-cyclicality in the commercial banking system. Specifically, we introduce our model set-up for detecting the evolution of systemic vulnerability by specifying the pro-cyclical interaction between the market-wide risk perception and aggregate system-wide asset management behavior.

2.1 Market pro-cyclicality

Our study investigates the extent of vulnerability in the financial system as a whole. Central to this issue is the *market pro-cyclicality* in the banking system, i.e., a pro-cyclical interaction between the market-wide risk perception and system-wide asset management behavior. We focus on commercial banks, considering their central role as a transmission channel between the financial system and the real economy in the amplification of business cycles. Unlike the case of non-financial (real) sectors, the dynamics of the banking-sector leverage is driven by the variation in the size of the aggregate balance sheet, with system-wide equity being fixed. Namely, commercial banks tend to expand their lending when their risk perception is systemically low and the systemic bubble is building up in the business cycle upswing. Subsequently, the asset-side of their balance sheets will be filled with systemically risky assets in excess of the pool of relatively safer assets from a systemic viewpoint. Our objective is to make a sharp distinction between this *systemic bubble build-up* stage from the macro-prudential stage before most of the contemporaneous financial indicators deteriorate in the crisis stage.

2.2 The baseline model

Time is continuous and indexed by t. The uncertainty in the economy is governed by a fixed complete probability space $(\Omega, \mathcal{F}, \mathbb{P})$. In this economy, the *aggregate* commercial banking system is assumed to have two asset classes X and Y, where X_t denotes the time-t value of (systemically) risky assets and Y_t denotes that of safe (or less risky) assets, respectively. Each asset value, denoted by $A \in \{X, Y\}$, is represented as the product of its price per unit (P^A) and quantity held by banks (Q^A), that is, $A_t = P_t^A \cdot Q_t^A$. Subsequently, the evolution of P_t^A and Q_t^A is assumed to follow the geometric Brownian motions given by

$$\frac{dP_t^A}{P_t^A} = \left(r_t + \lambda_t^A\right) dt + \sigma_P^A dW_t^A \tag{1}$$

$$\frac{dQ_t^A}{Q_t^A} = u_t^A dt + \sigma_Q^A dB_t^A, \tag{2}$$

where r_t is the time-t instantaneous risk-free rate, λ_t^A denotes the risk premium, u_t^A is the rate of asset management controlled at time t, and the two standard Brownian motions W_t^A and B_t^A are mutually independent as exogenous aggregate shocks. This setting implies that the expected bilateral impact between P_t^A and Q_t^A comes from the (possibly endogenous) relationship between λ_t^A and u_t^A.

Here, we let ξ_t denote the time-t *market-wide (or systematic) risk* factor, and adopt a single-factor pricing model given by $\lambda_t^A = \beta^A \xi_t$, where the factor loading, β^A, is comparable to the capital asset pricing model (CAPM) beta. Moreover, we specify that $u_t^A = \eta_t^A \xi_t$ in the sense that η_t^A denotes the *aggregate pro-cyclical systemic reaction* of asset management in response to the market-wide risk factor ξ_t. For instance, both u_t^A and η_t^A take significantly negative values in case of the fire-sale of asset A at time t. This top-down modeing approach is consistent with the financial accelerator model (Bernanke, Gertler & Gilchrist (1999)), which proposes that adverse shocks tend to be amplified by worsening financial market as credit expansion is based on the collateralized asset value owing to asymmetric information between lenders and borrowers in the banking system. Hence, a fall in asset prices deteriorates the balance sheets of the banks and the resulting deterioration has a negative impact on their investments and asset allocations.[8]

By Itó's lemma, the aforementioned setting leads to the following stochastic differential equation (SDE) for the asset value dynamics given by

$$\frac{dA_t}{A_t} = \left(r_t + \lambda_t^A + u_t^A\right) dt + \sigma_A dz_t^A \tag{3}$$

where $\sigma_A = \sqrt{\left(\sigma_P^A\right)^2 + \left(\sigma_Q^A\right)^2}$ and z_t^A is another standard Brownian motion. That is, the (expected) instantaneous excess return of A_t is governed by $\left(\lambda_t^A + u_t^A\right) dt = (\beta^A + \eta_t^A)\xi_t dt$. In addition, we suppose that z^X and z^Y are correlated in the sense that $E\left(dz_t^X dz_t^Y\right) = \rho_t dt$ holds.

To represent the system-wide presence of optimism or risk taking in the aggregate asset management, we observe $I_t = X_t/Y_t$ from the aggregate balance-sheet information. Then, Itó's lemma yields the following SDE given by

$$d \log I_t = \alpha dt + \Psi_t \xi_t dt + \Sigma_t d\hat{z}_t, \tag{4}$$

where

$$\alpha = -\frac{1}{2}\left(\sigma_X^2 - \sigma_Y^2\right), \quad \Psi_t = \left(\beta^X - \beta^Y + \eta_t^X - \eta_t^Y\right), \quad \Sigma_t = \sqrt{\sigma_X^2 + \sigma_Y^2 - 2\rho_t \sigma_X \sigma_Y},$$

and $\hat{z}_t$ is another standard Brownian motion which represents an exogenous aggregate

[8] Semmler (2011) rephrased the financial accelerator model, originally proposed by Bernanke et al. (1999), as *"credit expansion is based on the collaterals; as the value of collaterals moves, credit cost moves counter-cyclically and credit volume pro-cyclically, having an amplifying effect on ups and downs in real activities."*

shock in the evolution of I_t. Our main interest is to examine how banks adjust their asset portfolios according to the market-wide risk perception, and how their aggregate portfolio adjustments have an impact on the real economic activity and financial distress. In this context, the degree of system-wide *market pro-cyclicality* is captured by Ψ_t in (4).

2.3 Markov regime-switching model

For the purpose of empirical analysis, we propose a parsimonious Markov regime-switching (MRS) model by discretizing the time axis and assuming that the *market pro-cyclicality coefficient* Ψ_t and the system-wide asset management volatility Σ_t share the same discrete regimes at each t. An MRS model is characterized by a different set of parameters so that each regime has different dynamics and a regime shift can change the dynamics of all the time-varying parameters at the same time.[9] In the Markov setting, the conditional distribution of any states S_{t+1} given the information set $\mathcal{F}_{t-1}$ and S_t is only dependent on the present value S_t. In other words, the state process is independent of the history of the process in the sense that $\mathbb{P}\left(S_{t+1}=j \mid S_t=i, \mathcal{F}_{t-1}\right)=\mathbb{P}\left(S_{t+1}=j \mid S_t=i\right)=p_{ij}$, where p_{ij} is the transition probability that the state at time $t+1$ will be j when the preceding state is i. The probability is non-negative and by construction $\sum_{j=1}^{N} p_{ij}=1$ holds for $i=1,2,\ldots,N$. As a result, parameters of MRS are the outcome of an unobserved discrete state process with unknown transition probabilities. An MRS model is estimated by considering the joint conditional probability density function of a given data set and state process, S_t. A maximum likelihood estimation (MLE) method will produce relevant parameters of each regime along with unobserved probabilities of regime change.[10]

By discretizing the time axis of (4), we suppose that $\Delta \log I_t$ follow the three-state MRS model given by

$$\Delta \log I_t=\alpha+\Psi_{S_t}\xi_t+\Sigma_{S_t}\varepsilon_t, \tag{5}$$

where $S_t \in \{1,2,3\}$ is an unobserved latent variable of multiple discrete regimes and ε_t is a standard Gaussian process.[11] The time-series behavior of $\Delta \log I_t$ is in a stationary log-

[9]MRS models have been recognized as useful tools to capture non-linearity in financial econometrics literature. Following pioneering work by Hamilton (1989), regime-switching models have been applied to analyze different classes of asset movements, changes in government policy, and financial crises empirically. Examples of various applications include changes in the business cycles and monetary policy investigated by Hamilton (1988) and Ang & Bekaert (2002). and recent trials to explain the financial crisis discussed by Borio & Lowe (2002), Hesse & González-Hermosillo (2009) and Billio, Getmansky, Lo & Pelizzon (2012), among others. A regime-switching model of corporate default rates has been developed by Giesecke, Longstaff, Schaefer & Strebulaev (2011) by identifying three distinct regimes.

[10]Details regarding the Markov chain and MRS are provided in Hamilton (1994), Harris (1997), and Kim & Nelson (1999).

[11]If we assume that the volatilities of X_t and Y_t are time-varying, we can simply convert a constant α

difference form. Notice that each regime has different dynamics and is characterized by a different set of parameters, so that a regime shift can change the entire evolution of $\log I_t$ in response to ξ_t thereafter. Specifically, we allow the three latent states to decompose the time-series data into (i) a macro-prudential state ($S_t = 1$), (ii) a bubble build-up state ($S_t = 2$), and (iii) a crisis state ($S_t = 3$).

By estimating the MRS model (5), the probability of the persistence of each state and its expected duration can be obtained in real time. Moreover, the extracted state-dependent probabilities are economically interpretable by associating an endogenous risk propagation mechanism throughout the entire financial system and the economy. This paper proposes (5) as our parsimonious model to avoid over-fitting in non-linear optimization, where each innovation ε_t follows the independent standard Gaussian distribution.[12]

2.4 Design of the systemic bubble index

Motivated by the baseline model and the discretized MRS model (5), we presume that a system-wide risk appetite can be evaluated in terms of how commercial banks' asset management (represented as $\Delta \log I_t$) is loaded on the market-wide risk perception (represented as ξ_t) in a regime-dependent manner. That is, the state-dependent *market pro-cyclicality coefficient* Ψ_{S_t} in (5) indicates how the aggregate commercial banks adjust their asset portfolios in response to the market-wide shocks in each regime. As such, the system-wide asset management behavior plays a key role in understanding the market pro-cyclicality based on the market risk perception.

In addition to a bank's role as a portfolio manager within the financial industry, agency theories provide some formal underpinnings for its role in describing business cycle fluctuations by utilizing the pro-cyclical relationship between the market and the balance-sheet channels. Firms relying on bank credit may be cut off credit temporarily when financial markets are in a bad shape, and this tendency leads to an increase in external finance premiums. As the investment and output growths move together with the expansion of commercial banks' investment related assets, interest rate differentials should also be inversely related to loans and leases and other investment-related assets. In addition, the literature also motivates a financial propagation mechanism by providing a rationale for why the agency costs of external finance may fluctuate counter-cyclically. These counter-cyclical movements in the wedge between external and internal finance, in

into a regime dependent α_{S_t} as well.

[12]For a numerical estimation of (5), we adopted the *MS Regress* package, a MATLAB toolbox implemented by Perlin (2012).

turn, introduce a sort of accelerator effect on investment, ultimately magnifying investment and output fluctuations; see Bernanke et al. (1999) for example.

In the 'bubble build-up' state ($S_t = 2$), commercial banks are willing to face uncertainties for a higher premium by increasing the proportion of their (systemically) risky assets. The banks display excess system-wide risk-taking behavior with the pro-cyclical availability of cheap funding such as deposits, implicitly guaranteed by the Federal Deposit Insurance Corporation (FDIC) and non-core liabilities with relatively low interest rates. It will lead to excessive monetary liquidity and easy credit in the financial system based on substantially low margin standard by the banks, inducing vulnerable asset price inflation owing to leveraged speculation in the financial markets. We refer to this phenomenon as a *systemic bubble* as it is the trigger for the leverage cycle in the transmission of negative shocks described by Geanakoplos (2010). Moreover, externalities in interbank network are also relevant in that banks actively participate in the interbank market to smooth out idiosyncratic liquidity risks, and subsequently, more aggressive banks exert an externality on others by subsidizing liquidity. On recalling that the internal cost is smaller than the cost of obtaining liquidity outside the unsecured market, nobody leaves the interbank market. Liquidity is still traded, but the interest rate rises to reflect the presence of riskier banks. Knowing that it is difficult to default owing to the rampant too-big-to-fail and/or too-interconnected-to-fail illusions, commercial banks can enjoy fairly high interest rates by externalizing the systemic bubble. Banks continue to engage in this risk-taking behavior until it becomes impossible for the entire system to endure the system-wide imbalance any longer. For the reason given above, we expect a significantly positive sign of the market pro-cyclicality coefficient $\Psi_{S_t=2} > 0$, and its absolute value is expected larger than that of the coefficient specific to the 'macro-prudential' state $\Psi_{S_t=1}$.[13]

The systemic bubble bursts in the 'crisis' state ($S_t = 3$), and a plummeting of asset prices brings about the collapse of unsustainable systemic resilience with inevitable deleveraging. Most risk-aversion indices from the market soar during this period, as banks tend to fly to the quality to reserve liquidity by taking short positions on systemically risky assets and long positions on systemically safer assets, showing the negative correlations between risky and safe assets. Banks do roll debts with short-term maturities or (fire) sell longer-term primary securities before maturity and lend loans and leases no further by increasing margins, thus avoiding financial distress by meeting withdrawals of short-term debts. Brunnermeier & Oehmke (2013) stress that a *run-up phase*, in which bubbles and imbalances form, and a *crisis phase*, during which risk that has built up in

[13] Without loss of generality, we can assume that the proxy for the market-wide risk takes on non-negative values in this argument.

the background materializes and the crisis erupts, cannot be seen in isolation. In this regard, the sign of the $\Psi_{S_t=3}$ is expected negative during the crisis.

In this context, the objective is to make a proactive distinction between the systemic bubble build-up state ($S_t = 2$) and the macro-prudential state ($S_t = 1$), prior to the realization of the crisis state ($S_t = 3$). For reasons mentioned above, we propose a systemic bubble index (henceforth, SBI) defined as the weighted average of the state dependent Ψ coefficients given by

$$(\text{SBI})_t = \sum_{i=1}^{3} \Psi_{S_t=i} P_t^{(i)}, \tag{6}$$

where $P_t^{(i)}$ is the estimated time-t (filtered or smoothed) probability specific to each state $i = 1, 2, 3$. Our premise is that the overall risk appetite in the commercial banking system affects its asset management behavior, and an early warning signal of systemic risk can be detected by capturing the dynamics of the system-wide risk-taking regime shifts extracted from a combination of both market and balance sheet information sets. Accordingly, we can interpret $(\text{SBI})_t$ as the time-t expectation of the aggregate commercial banks' risk-taking appetite to indicate how much of the systemic bubble commercial banks have accumulated in the system. This argument will be empirically verified in Section 4.

3 Data and variable description

Our empirical study aims to examine how banks adjust their asset portfolios according to the market-wide risk perception, and the macro impact of such an aggregate portfolio adjustment on the economy and financial system. This section specifies the selection of the relevant balance-sheet variables that are closely related to the asset portfolio management of commercial banks, and several macro-financial variables as proxies of the market-wide risk appetite, the real economic activity, and the degree of financial distress, respectively.

3.1 System-wide asset management

Commercial banks dynamically manage their asset composition according to their risk-taking appetite, and we claim that this system-wide asset management behavior should be related to the cyclicality of systemic bubbles. As most of the banking profits stem from managing their core assets, it is important to analyze the asset management dynamics in the aggregate balance sheet to address the system-wide profit seeking (or risk taking) preference. For example, in the case of a market turbulence where there are aggressive changes in financial asset prices, liquidity dry-ups, and other negative spillover effects, radical changes in the system-wide asset composition induce some crucial information about banks' systemic risk perception. In this regard, we focus on examining the role of traditional commercial banks because of their central role as a transmission channel in the amplification of the business cycle through pro-cyclical interaction between the financial system and the real economy. It is noteworthy that the persistency and magnitude of the financial crisis has a strong correlation with fluctuations in the balance sheets of traditional commercial banks rather than those of investment banks.[14]

The asset side of a commercial bank's balance sheet typically consists of bank credit (securities and loans/leases), interbank loans, cash assets, and other assets. Specifically, we claim that loans and leases (with relatively longer duration and lower credit quality) are systemically riskier than securities (most of which are liabilities of the U.S. government, U.S. government agencies, and U.S. government-sponsored enterprizes) in bank credit. In the meanwhile, we view that cash assets are systemically safer than interbank loans in the sense that a high degree of interconnectedness systemically increases the exposure to imperfectly observed common risk factors and potential contagion effect (or adverse feedback loop) in the banking system. Figure 1 verifies the above-mentioned arguments by showing the cyclical time-series behavior of the system-wide asset management with the aggregate asset components of the U.S. commercial banking system. During the recent financial crisis, the commercial banking system certainly decreased their proportion of systemically risky assets (loans and leases in bank credit and interbank loans), and shifted their asset portfolio towards systemically safer assets (securities in bank credit and cash assets) in a cyclical manner.

Accordingly, we define I_t in (5) as a ratio of a sum of loans and leases and interbank loans (i.e., systemically risky assets) over a sum of securities and cash (i.e., systemically less risky assets) given by

$$I_t = \frac{X_t}{Y_t} = \frac{(\text{Loans and Leases})_t + (\text{Interbank Loans})_t}{(\text{Securities})_t + (\text{Cash})_t}. \tag{7}$$

Notice that I_t, as a proxy for the system-wide asset management tendency, can be interpreted as the aggregate commercial banks' behavior of managing asset portfolios to

[14]Prior studies regarding financial instability have placed much emphasis on the role of market-based financial intermediaries such as the Wall Street investment banks; see Adrian & Shin (2010) and Hahm et al. (2012), among others. Notice that the role of market-based financial intermediaries as marginal traders leads to their amplifying impact on market fluctuations with the development of state-of-the-art securitization techniques.

Assets	Liabilities
Bank credit	Deposits
Securities in bank credit	Borrowings
Loans and leases in bank credit	Trading liabilities
Interbank loans	Other liabilities
Cash assets	Equity
Trading and other assets	

Table 1: Selected Assets and Liabilities of Commercial Banks in the United States. This table shows the basic balance sheet structure of the commercial banking system from the H.8 Assets and Liabilities of Commercial Banks in the United States (seasonally adjusted) released by the Board of Governors of the Federal Reserve System.

optimize their expected profit (and risk) profiles, which can be decomposed into a premium (risky) component from the changes of loans and leases and interbank loans value, and a cost (safe) component from the opportunity cost of securities and cash. Their dynamic asset portfolio management is motivated by their risk-taking appetite towards risk premia specific to the banking system.

With regard to data, we used H.8 Assets and Liabilities of Commercial Banks in the United States (seasonally adjusted) released by the Board of Governors of the Federal Reserve System. We obtained an estimated monthly aggregate balance sheet information of all U.S. commercial banks from the H.8 release, which is primarily based on monthly reported data from a sample of approximately 875 domestically chartered banks and foreign-related institutions.[15] Table 1 shows the basic balance sheet structure of the commercial banking system from the H.8 Assets and Liabilities of Commercial Banks in the United States, and Figure 2 shows the time-series behavior of X_t, Y_t (left axis) and I_t (right axis) from January 1986 to December 2012 on a monthly basis.

3.2 Market-wide risk perception

On recalling that bank credit is composed of securities and loans/leases, it is natural to focus on interest rate spreads to reflect the dynamics of the time-value and the risk-premium effects. The commercial banking system is indeed exposed to interest rate risks as they borrow short-term and lend long-term through their core leverage management. For example, an increase in the short-term interest rate leads to a lower net interest margin (NIM), thereby causing potential maturity mismatch problems. In this regard,

[15] As of December 2009, U.S. branches and agencies of foreign banks accounted for approximately 60 of the weekly reporters and domestically chartered banks made up the rest of the sample.

market-based interest rate differentials usually provide a natural interpretation of the incentive of banking asset portfolio management of buying one unit of a risky asset (X_t) and selling one unit of a less risky asset (Y_t).

Given that we focus on investigating how commercial banks adjust their proportions of balance sheet components corresponding to the various risks, specially stemming from financial sector distress, we take the Treasury - Eurodollar (TED) spread, defined as the difference between the three-month London Interbank Offered Rate (LIBOR) and three-month Treasury Bill (TB) interest rates, as our representative indicator for measuring commercial banking sector distress in the interbank lending market. Among several market-wide risk perception proxies, TED is of special interest specific to the banking system from an economic perspective.[16] In times of uncertainty, banks charge higher interest for unsecured loans, which increases the LIBOR rate. Further, banks want to get first-rate collateral, which makes holding Treasury bonds more attractive and pushes down the Treasury bond rate. Therefore, the TED spread widens along with lack of trust in the banking system. In addition, the TED spread effectively captures the liquidity risk from the funding side in the financial sector and describes the flight-to-liquidity concept. Being compatible with the time-series evidence, monetary economic theories also provide some formal underpinnings for earlier work on financial crisis, which emphasized sharp increases in the spread as the precursor to financially induced disruptions in real activity. When the banking industry is in distress as uncertainty rises, banks tend to charge more for unsecured loans and fly to quality. In a distress situation, this collective movement makes Treasury Bills more attractive, which leads to an increase of the TED spread; see Brunnermeier (2009) for this argument. We obtained three-month LIBOR rates from Bloomberg.

[16] There are several spread-based measures as well. The term spread, defined as the difference between the yields on long-term and short-term Treasury securities, has been found useful for predicting macroeconomic variables such as output growth, inflation, industrial production, consumption, and recessions. Numerous studies find that the term spread predicts output growth and recessions for up to one year in advance. However, a handful of studies also find that its usefulness varies across countries and over time, and the ability of the term spread to forecast output growth has diminished in recent years. The credit spread is motivated primarily by theories such as the balance sheet channel that emphasizes linkages between the quality of borrowers' balance sheets and their access to external finance. Fluctuations in credit spreads reflect shifts in the effective supply of funds offered by financial intermediaries in the presence of financial market frictions, which may have crucial implications for the usefulness of credit spreads as predictors of economic activity. In the latter case, a deterioration in the capital position of financial intermediaries leads to a reduction in the supply of credit, causing an increase in the cost of debt finance (the widening of credit spreads) and a subsequent reduction in consumer spending and industrial production.

3.3 Proxies for business cycle and financial condition

Several macro-economic variables are employed in our subsequent analysis to verify the predictive power of our proposed measure for future macro-economic and financial cycles. Presumably, the gross domestic product (GDP) growth rate may be the most relevant macro-economic variable as a proxy for the real economic activity. Considering its data frequency limitation, however, we adopt the Chicago Fed National Activity Index (CFNAI) studied by Allen, Bali & Tang (2012), among others.[17] As a monthly index of the U.S. aggregate economic activity, the CFNAI is designed to assess overall economic activity and related inflationary pressure by capturing the dynamics of the overall economic activity. It is defined as a weighted average of 85 existing monthly indicators of national economic activity with an average value of zero and a standard deviation of one. Since economic activity tends to have a trend growth rate over time, a positive index reading corresponds to growth above trend and a negative index reading corresponds to growth below trend.

In addition to the CFNAI, we also consider the Adjusted National Financial Conditions Index (ANFCI) data set to focus on the time-series variation of activities specific to the financial sector. The ANFCI provides information on comprehensive U.S. financial conditions in money markets, debt and equity markets, and traditional and shadow banking systems. As U.S. economic and financial conditions tend to be highly correlated in a pro-cyclical manner, Chicago Fed presents the ANFCI, which isolates a component of financial conditions uncorrelated with economic conditions to provide an update on financial conditions relative to current economic conditions. Similar to the CFNAI, the ANFCI is a weighted average of a large number of variables (105 measures of financial activity), each expressed relative to their sample averages and scaled by their sample standard deviations.[18] We obtained both CFNAI and ANFCI time-series data from the official website of the Federal Reserve Bank of Chicago. Figure 3 shows the time-series behavior of the CFNAI and the ANFCI during 1986-2012 at monthly frequencies.

To provide some perspective on the predictive performance of our SBI measure on

[17] For example, industrial production and unemployment were studied by Kollmann & Zeugner (2012). The industrial production index is an economic indicator that measures real output for all facilities located in the United States manufacturing, mining, and electric, and gas utilities excluding those in U.S. territories. The unemployment rate represents the number of unemployed as a percentage of the labor force.

[18] The ANFCI removes the variation in the individual indicators attributable to economic activity and inflation, as measured by the three-month moving average of the Chicago Fed's NAI and three-month percent change in the Personal Consumption Expenditures (PCE) price index, prior to computing the index.

the aggregate credit vulnerability, we also employ the corporate vulnerability index (CVI) provided by the Risk Management Institute (RMI).[19] The CVIs are a set of indicators that gauge economic environments in a new dimension as a new suite of indices produced by RMI's credit research initiative. RMI probabilities of default (RMI PDs) of individual firms are used in the CVI to produce bottom-up measures of credit risk in economies, regions, and portfolios of special interest. We obtained the data from the RMI's official webpage on the value-weighted CVI of the U.S. economy, for which the RMI PDs are aggregated with each firm and weighted by its market-capitalization so that the size of each firm is taken into account.

4 Empirical results

This section includes our empirical results. Our study period extends from January 1986 to December 2012.[20] Table 2 reports the descriptive statistics of our full data set. We first propose a new systemic index that measures how much the systemic bubble has swollen in the commercial banking system from the fitted model. The systemic bubble index differs from other systemic risk measures in that the information from the market and the system-wide balance sheet is combined to generate a comprehensive early warning signal for systemic risks. Accordingly, we extract a dynamic trajectory of the systemic bubble index through which we provide evidence of commercial banks' pro-cyclical asset management behavior in response to the changes in the market-wide risk perception.

We then show that the time-series behavior of aggregate commercial banks' risk appetite is counter-cyclical. In other words, we verify that the proposed systemic bubble index has a strong predictive power for future macro-economic and financial cycles of over 18 to 24 months into the future. Finally, we investigate the implication of the proposed systemic bubble index from the asset pricing perspective by examining whether the estimated systemic bubble index is a significant state variable that affects the investment opportunity set of investors.

[19] In July 2012, the RMI launched the CVI, which is predicated on the provision of (both aggregate and individual) credit ratings as a public good; see Duan & Van Laere (2012) for a reference. All CVI series are available only since the first trading day of 1996.

[20] This period was determined by the availability of the LIBOR rates to construct TED spreads in our data set for estimating the systemic bubble index.

4.1 The estimated systemic bubble index

We allow three latent regimes, as illustrated in Section 2.3, to decompose the state of the banking system into (i) macro-prudential ($S_t = 1$), (ii) systemic bubble build-up ($S_t = 2$), and (iii) crisis ($S_t = 3$) regimes with respect to the resiliency of the system. As a proxy for measuring the market-wide perception of financially induced disruptions, the TED spread provides a useful basis for gauging the severity of the prevailing credit and liquidity risk premium in the banking system. As the TED spreads take on positive values ($\xi_t > 0$), the MRS model (5) implies that a strong system-wide risk taking on their asset management emerges when commercial banks' risk preference hovers over the bubble build-up state with a positive market pro-cyclicality factor loading $\Psi_{S_t} > 0$. However, the systemic risk aversion with a counter-cyclical $\Psi_{S_t} < 0$ would surface as the bubble of widespread financial imbalances unwind abruptly, when the crisis indicated by the overall macro-economic index is realized. The regime shift can take place as even minor (but systemically non-negligible) events may lead to a re-pricing of risk and an endogenous unraveling of the systemic bubble, which adversely affects most parts of the system and the financial markets in a pro-cyclical manner.

Table 3 reports the results of maximum likelihood estimation of the model (5) from January 1986 to December 2012. All the estimated parameters are statistically significant at 1% confidence level. Note that the signs of $\Psi_{S_t=1}$ and $\Psi_{S_t=2}$ are significantly positive and the estimated $\Psi_{S_t=3}$ coefficient is negative as expected. This observation clearly demonstrates the systemic pro-cyclical risk-taking preference with respect to the changes in the market circumstances. In particular, the estimated coefficient for the 'bubble build-up' regime ($\Psi_{S_t=2}$) is significantly larger than the one for the 'macro-prudential' regime ($\Psi_{S_t=1}$) along with substantially greater state-dependent volatility, i.e., $\Sigma_{S_t=2} > \Sigma_{S_t=1}$. The observed aggressive systemic risk-taking preference in the 'bubble build-up' state is consistent with the stylized facts of a 'run-up' phase, as described in Brunnermeier & Oehmke (2013). The positive coefficient of the 'bubble build-up' state (with its large absolute value) indicates that commercial banks do not unwind their portfolio position to prepare for the possible liquidity shock, but keep increasing $I_t = X_t/Y_t$. In other words, if the commercial banking system is in the 'bubble build-up' state with a reasonable level of market risk perception, the banking system tends to increase the overall systemic leverage to maximize their profits. As a result, a preference of risky assets over safe assets becomes relatively stronger. Simply put, the the externalities produced by such liquidity pooling via the interbank market results in the predatory portfolio behavior over the common liquidity pool, which in turn results in the significantly positive market pro-cyclicality coefficient $\Psi_{St=2}$ along with excessive risk-taking behavior in the system. In the meanwhile, the 'macro-prudential' state ($S_t = 1$) is indicated by the estimated value of $\Psi_{S_t=1}$ that is less than one-third the magnitude of the estimated $\Psi_{S_t=2}$. In this prudent regime, commercial bank's risk preference is systemically tolerable while encouraging their premium taking from asset portfolio management in a sustainable manner.

As expected, the significantly negative $\Psi_{S_t=3}$ coefficient in the crisis regime can be interpreted as the flight-to-quality or liquidity-hoarding tendency in the system. When the level of financial distress reaches an unbearable threshold, most market participants inevitably head toward liquidity. Notice that the absolute difference between the magnitudes of $\Psi_{S_t=2}$ and $\Psi_{S_t=3}$ is around 4.38. This absolute difference clearly illustrates a radical speed of portfolio unwinding, not to mention the largest value of the estimated volatility $\Sigma_{S_t=3}$. One distinctive feature is that the magnitude difference of the volatilities between the 'macro-prudential' state ($S_t = 1$) and the 'bubble build-up' state ($S_t = 2$) is mediocre, while the magnitude difference of the Ψ coefficients is relatively substantial. The estimated Σ_{S_t} in (5) increases as the correlation takes on increasingly negative values, and the extreme negative values of the correlation can be interpreted as the flight-to-quality phenomenon.

Figure 4 and Figure 5 depict the time-series behaviors of the filtered and smoothed probabilities of each state implied by the fitted model (5), respectively. The capability of the fitted MRS model in capturing the boom and burst dynamics of systemic bubbles is clearly indicated. Figure 6 shows the dynamics of the estimated systemic bubble index (SBI) given by (6) based on the fitted model (5). There are several intriguing features in the time-series behavior of the fitted SBI. First of all, the SBI captures two 'systemic bubble build-up' periods in the mid-1990s and 2000s effectively, and the index weighted by the state probabilities (both filtered and smoothed) shows two early warning signals before the bubble collapses, one before the near-collapse of Long-Term Capital Management in 1998 and another before the 2008 financial crisis. Next, the technology bubble burst in the stock market around early 2000s has seemingly worked contrariwise in commercial banks' balance-sheet adjustment perspectives. Finally, the extent of the 2008 global financial crisis of was unprecedented and its duration lasted for longer than two years. The difference between the recent global financial crisis and other recessions resides in the change of balance-sheet asset composition in the system. Commercial banks abruptly started to participate in the fire-sale and liquidation of their assets, which caused prices to plummet in most classes of assets, which is related to the fat-tailed and clustered volatility in terms of financial statistics. Overall, the change in balance sheets may have had an aggravating influence on the economy pro-cyclically.

Figure 6 also clearly demonstrates that the equity market volatility tends to drop when the systemic bubble is building up and systemic leverage is rising. The pairwise correlations of the SBI with the S&P500 volatility are -0.5874 (filtered) and -0.6003 (smoothed), respectively. Such a counter-intuitive phenomenon has been coined as the *volatility paradox*, and the endogenous relationship between high systemic bubble levels and unusually low volatility levels is counter-cyclical.[21] Our results address that the volatility paradox arises endogenously as claimed by Brunnermeier & Sannikov (2012). Accordingly, policymakers should treat contemporaneous market-based risk measures (such as equity volatilities) with care, as they are prone to underestimate the fragility of the system when their levels are substantially low. From the stability perspective, the SBI weighted by the smoothed state probability is proposed as a policy-oriented early warning indicator.

4.2 Forecast evaluation

We examine whether a systemic bubble pro-cyclically impacts the entire economy and financial system with a time lag.[22] We specify a predictive regression model to investigate the predictive power of the proposed SBI indicator given by

$$Y_{t+h} - Y_t = \beta_0 + \beta_1(\text{AR})_t + \beta_2(\text{SBI})_t + \sum_{n\geq 1} \beta_{n+2}(\text{Controls})_t^n + \varepsilon_t, \tag{8}$$

where Y_{t+h} is a macro-measure of the overall economic or financial conditions in period h (18, 21 and 24 months) ahead. This setting is motivated by Drehmann & Juselius (2013) in that *"signals should arrive at least one and a half years (but no more than five years) ahead of a crisis"* for a meaningful systemic risk diagnosis. In (8), $(\text{AR})_t$ is the first difference of the dependent variable ($Y_t - Y_{t-1}$) over the last month to control for the autocorrelation, $(\text{Controls})_t^n$ denotes a group of control variables at time t, and ε_t represents the corresponding prediction noise. The specification of our predictive regression model is motivated by Stock & Watson (2002).

We select two market-based control variables: the term spread and the liquidity

[21] Crockett (2000) stated that *"the received wisdom is that risk increases in recessions and falls in booms. In contrast, it may be more helpful to think of risk as increasing during upswings, as financial imbalances build up, and materializing in recessions."* Borio & Drehmann (2009) argue that *"the system looks strongest precisely when it is most vulnerable, so this is one reason why (macro) stress tests, given the current state of technology, can so easily lull policymakers into a false sense of security, as they did before the current crisis."*

[22] Allen et al. (2012) reported that the levels of systemic risk in the banking sector pro-cyclically impacts the entire economy through its aggregate lending activity.

spread. The term spread (TS), defined as the difference between the yields on long-term (ten years) and short-term (three months) Treasury fixed-income securities, is known as a significant predictor of future recessions; see Estrella & Hardouvelis (1991) and Estrella & Trubin (2006). We also incorporate the liquidity spread (LS), defined as the difference between the three-month repo rate and the three-month TB interest rate, to highlight the informational difference between the risk perception in the short-term lending market and the fitted systemic bubble index.[23] Note that we additionally penalize our systemic bubble index by adding $I_t = X_t/Y_t$ as one of the regressors into the predictive regression. With regard to the dependent variables, we focus on the CFNAI, the ANFCI and the value-weighted CVI as measures of aggregate economic activity, financial distress and aggregate credit risk, respectively; see Section 3.3 for details.

Table 4 summarizes the estimation results of the model (9) with our full data set. We employ CFNAI, ANFCI and the value-weighted CVI as regressands to test the pro-cyclical impacts of the SBI on the business cycles, financial conditions and aggregate credit risk prevailing in the economy, respectively. The t-statistics in parentheses are adjusted by Newey & West (1987) standard errors for heteroscedasticity and autocorrelation for each series.[24] In general, the selected explanatory variables explain a significant portion of the dynamics of the dependent variables, as the adjusted R^2 ranges from 19.5% to 45.0%, and generally increases as the forecasting horizon becomes longer.

Our main finding is that the fitted SBI exhibits a significant predictive power over all forecasting horizons and the estimated coefficients are of the expected sign with univariate reasoning. The coefficient linking the fitted SBI to the CFNAI is significantly negative for all prediction horizons, whereas the systemic bubble, measured by the SBI, is estimated to significantly increase the financial distress (ANFCI) in the future. This observation confirms that the proposed SBI is a relevant factor to forecast upcoming economic recessions, future turbulences in the financial system even after controlling for other variables. However, the forecasting power for the overall real economic activity indicated by CFNAI is not as significant as that of the financial conditions proxied by ANFCI. The coefficients of the SBI over CFNAI for the 18-, 21- and 24-month horizons are statistically significant at the 10%, 10% and 5% levels, respectively. Note that not every economic recession originates from the commercial banking system, such as the 'Internet Bubble' recession

[23]The three-month repo rate is available on Bloomberg since January 1990. We extended the data span by running a regression of the repo rate on the LIBOR rate for the 1990-2012 period and using the predicted value from that regression for the 1986-89 period; see footnote 10 in Adrian & Brunnermeier (2011).

[24]Following Newey & West (1994), we set the number of lags using the formula: $L = \text{floor}\left(4 \times \frac{T}{100}\right)^{2/9}$, where *floor* denotes the floor function and T equals the number of observations.

during the early 2000s. On the other hand, the coefficients on the TS lose their statistical significance, when the SBI competes with them over ANFCI. That is, in the presence of the SBI, the predictive power of the market-based term spread is limited to the real economic activity. In contrast, the signals from the SBI can tell whether the economic recession indeed comes from the systemic imbalance in the financial system. As a complementary predictor to other market-based variables, we should not overlook that the proposed SBI has a meaningful forecasting power for both the macro-economic activity and financial distress by its comprehensive nature related to market pro-cyclicality. In the meanwhile, it is noteworthy that I_t does not have any meaningful forecasting power in the presence of other variables.

Next, we turn to a more in-depth exploration of the relationship between the proposed SBI and the economy-wide vulnerability indicated by the value-weighted CVI. Controlling for other variables, the estimated SBI indeed predicts the aggregate credit risk, proxied by the value-weighted CVI prior to 18, 21 and 24 months, respectively. The estimated coefficients of the SBI are significantly positive on the value-weighted CVI at the traditional confidence levels, and of expected positive sign by univariate reasoning. It is noteworthy that the estimated coefficients of I_t lose their significance over all horizons in the presence of other variables. As shown, the proposed SBI is more relevant to the prediction of the macro-level credit vulnerability downturns (e.g., potential default clustering in the system) rather than ordinary business fluctuations.

As a robustness analysis, we additionally examine whether the previous empirical results are contaminated by a post-crisis bias. Bussiére & Fratzscher (2006) pointed out that the post-crisis period should be excluded from the forecast evaluation, because macro variables typically go through an adjustment process in recovery periods. To address this issue, we re-estimated the SBI with a sub-sample after dropping the recovery period from January 2009, and then perform the predictive regression analysis accordingly. As shown in Table 5, the predictive power of the SBI is generally consistent on each dependent variable across different forecasting horizons, and only marginal difference in the performance of the model is shown when dropping the recovery period from the sample. This result confirms the robustness of the SBI's prediction power when the post-crisis bias is addressed.

Overall, both market-based signal and system-wide balance sheet information, if properly extracted and combined, are indeed helpful to predict the cycles of the economy, the financial system and the prevailing credit risk in a complementary manner. As every crisis has its own traits, risk measures based solely on market data, which may fail to notice the different dimensions of each crisis, are myopic measures that can promote inflexible policy actions. We empirically verify that the combination of systemic variables related to market pro-cyclicality is better suited to analyze the mechanism of aggregate cycles over time.

4.3 Asset pricing implications

We have verified that it is systemically informative to diagnose the asset management behavior of commercial banks in response to the market-wide risk perception. Naturally, their regime-dependent risk-taking behavior imposes intriguing implications on the asset pricing aspect as well. Based on the modified inter-temporal capital asset pricing model (ICAPM) specification, the asset pricing test shows that the portfolios of financial firms indeed price the SBI risk factor, but not the portfolios of non-financial firms.

The original ICAPM of Merton (1973) proposes the equilibrium risk-return relationship for any risky asset i given by

$$\mu_i = \Lambda\sigma_{im} + \Pi\sigma_{ix}, \tag{9}$$

where μ_i denotes the unconditional expected excess return on risky asset i, σ_{im} denotes the unconditional covariance between the excess returns on the risky asset i and the market portfolio m, and σ_{ix} denotes the unconditional covariance between the excess returns on the risky asset i and the state variables x governing the investment opportunity set. Here, the coefficient Λ measures the relative aggregate systematic (or market) risk aversion, and Π represents the market-wide compensation for bearing risks related to shifts in the state variables x. The ICAPM predicts that when the investment opportunity is stochastic, investors adjust their investment to hedge against unfavorable shifts in the investment opportunity set and achieve inter-temporal consumption smoothing. Hence, covariances with state of the investment opportunities induce additional risk premiums on an asset. Specifically, equation (9) states that in equilibrium, investors are compensated in terms of expected returns for bearing market risks and the risk of unfavorable shifts in the investment opportunity set. Many studies test the significance of an inter-temporal relation between expected returns and risks in the aggregate stock market. However, even the existence of a positive risk-return tradeoff for market indices has not been universally proved in previous studies. Bali & Engle (2010) ascribed the reason to the non-observable properties of the two conditional moments, the conditional mean and volatility of stock market returns, and they proposed the dynamic conditional correlation (DCC) model as an extended version of ICAPM. Since economy-wide levels of uncertainty are related to aggregate risk-taking willingness in the financial sector, we use this DCC incorporated version of ICAPM to test a conditional asset pricing model with the market and systemic bubble index.

We subsequently test whether the conditional time-varying exposures of financial firms to *systematic* and *systemic* risk factors predict their future returns. Following Allen et al. (2012), we form 10 value-weighted size portfolios of financial and non-financial firms, respectively. Next, we estimate the time-varying conditional covariances between monthly excess returns on each portfolio using the modified DCC model of Bali & Engle (2010).[25] Specifically, in the setting of (9), we presume that the estimated systemic bubble index is the sole state variable x. Then, we generate the market portfolio and time-varying conditional covariances between monthly excess returns and the systemic bubble index. If the proposed SBI factor is priced in the conditional ICAPM framework, it can be viewed as a factor that is correlated with innovations in investment opportunities, similar to Merton (1973)'s characterization of business cycle fluctuations. We also perform an extended analysis with the inclusion of Fama-French three factors.[26] The sample ranges from January 1986 to December 2012 to match our data span. In general, we set the final estimation equation by adding portfolio specific alphas and residuals, resulting in the following panel regression given by

$$R_{i,t} = \alpha_i + \Lambda\sigma_{im,t} + \Pi\sigma_{ix,t} + \sum_{n\geq 1} \Gamma_n \sigma_{iy,t}^{(n)} + \varepsilon_{i,t}, \tag{10}$$

where $R_{i,t}$ is the excess return on portfolio i and $\sigma_{iy,t}^{(n)}$ is the covariance between the excess return on the risky asset i and the n-th control factor y_n.

Table 6 reports the positive risk-return relationship as predicted by the ICAPM theory. After controlling for a firm's fixed effects, the market risk-return coefficient Λ of market portfolio is positive and highly significant, implying a strongly positive link between expected returns and market risk, both for the value-weighted portfolios of financial firms and non-financial firms. The results reported in Table 6 also indicate a significantly positive market price of the systemic bubble for financial firms, but not for non-financial firms. In other words, equity portfolios of financial firms that are highly cor-

[25] See section 4.4 of Allen et al. (2012) for reference.

[26] The average return on the 'Small minus Big' size factor, SMB, and the average return on the 'High minus Low' book-to-market factor, HML, are calculated as the method in the Fama & French (1993). Specifically, (HML) = 1/2 (Small Value + Big Value) - 1/2 (Small Growth + Big Growth), and (SMB) = 1/3 (Small Value + Small Neutral + Small Growth) - 1/3 (Big Value + Big Neutral + Big Growth). We have obtained the historical data of both SMB and HML from Kenneth French's website.

related with the systemic bubble carry a significant premium relative to equity portfolios of non-financial firms. Interestingly enough, the estimated Π turns out to be statistically insignificant in cases of all firms and non-financial firms, leading to question whether the cause of insignificance stems from the 2008 financial crisis. These results indicate that equity portfolios of financial firms with higher sensitivity to increases in the systemic bubble are expected to generate higher returns next period, while equity portfolios of non-financial firms will not play a role in the portfolio pricing. The significantly positive slope coefficients on $\sigma_{ix,t}$ in the conditional ICAPM framework indicate that the systemic bubble plays a significant role for market participants and proxies for innovations in the investment opportunity set of the financial sectors. This observation is consistent even after the size and growth factors are controlled by including the SMB and HML factors in the regression specification.

In summary, our proposed systemic bubble index is a relevant state variable that affects the investment opportunity set of financial sector investors. In other words, when investing in financial firms, investors care about the potential financial distress, so the stocks' covariation with the aggregate systemic bubble certainly affects investment and consumption opportunities.

5 Conclusion

This paper investigates the effect of market pro-cyclicality in the financial system by using a Markov regime-switching model to accurately measure and detect a systemic bubble in a timely manner. Our proposed analytical framework displays illustrative phases of prior major events based on their own characteristics and corresponding propagation channels. Consequently, we develop a comprehensive methodology to measure cross border systemic financial risks by capturing the pro-cyclical interaction between the market-wide risk perception and system-wide asset management behavior through the market and balance-sheet channels. Based on a Markov regime-switching model, the proposed diagnostic framework clearly demonstrates its ability to provide an early warning signal of the build-up and unwinding of fragility in the financial system for a counter-cyclical structure of regulatory policy. Empirical results demonstrate an asset pricing implication of the proposed systemic indicator in that the *systemic* risk is priced as an independent factor of the *systematic* risk for financial firms but not for non-financial firms.

Much of the systemic risk literature has focused on the role of market-based indicators in order to provide an early warning signal of financial instability. However, our empirical results confirm that not only market-based leading variables but also (potentially) lagging systemic variables, such as balance sheet information, can aid in measuring systemic vulnerability more precisely and appropriately. Our proposed systemic bubble index successfully fulfills the policy requirements for early warning indicators: the appropriate timing, stability, and transparency of the signal based on the easy accessible data set. As a complementary tool to other systemic risk measures, our proposed methodology can provide a comprehensive systemic risk diagnosis for a better understanding of the interconnectedness of financial institutions and financial markets to monitor the resiliency of the financial system for the macro-prudential supervision of financial stability.

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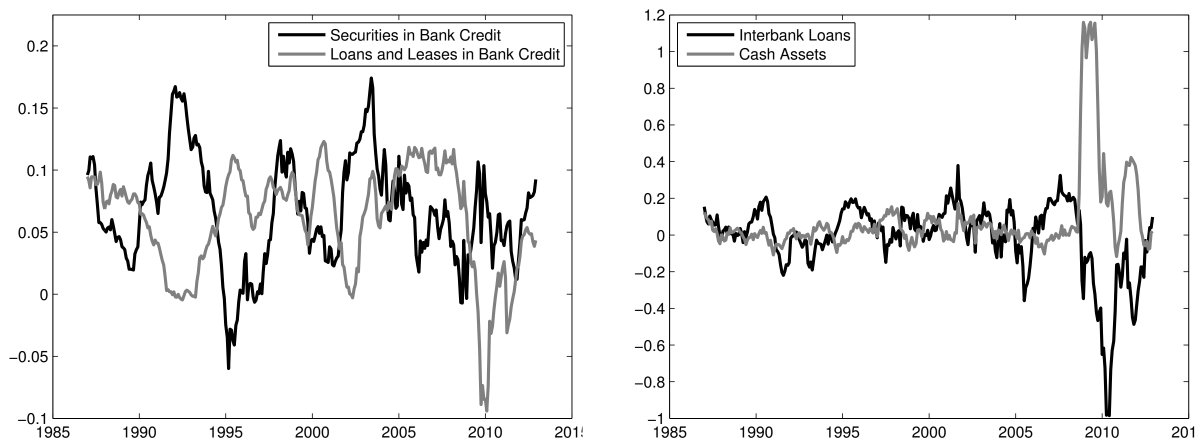

Figure 1: Annual growth rates of the aggregate asset components of the U.S. commercial banking system. This figure shows the trailing 1-year returns of the securities and loan and leases in bank credit (left panel) and the interbank loans and cash assets (right panel) of commercial banks in the United States from January 1987 to December 2012 on a monthly basis.

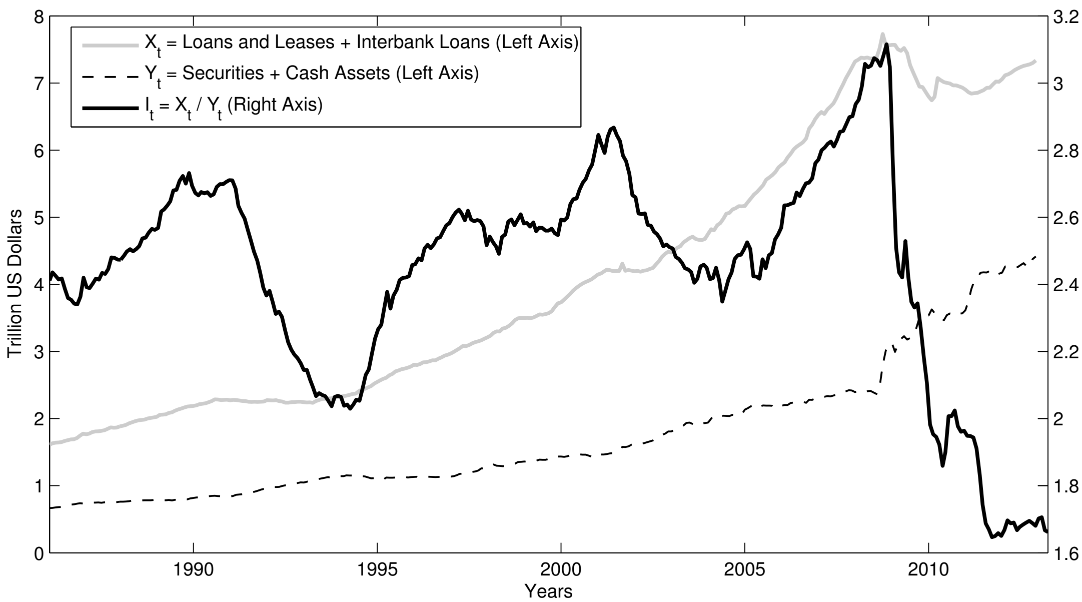

Figure 2: Dynamics of the asset management behavior in the U.S. commercial banking system. This figure shows the time-series behavior of X_t, Y_t (left axis) and I_t (right axis) from January 1986 to December 2012 on a monthly basis, where $X_t =$ (Loans and Leases + Interbank Loans), $Y_t =$ (Securities + Cash Assets) and $I_t = X_t/Y_t$ as described in (7).

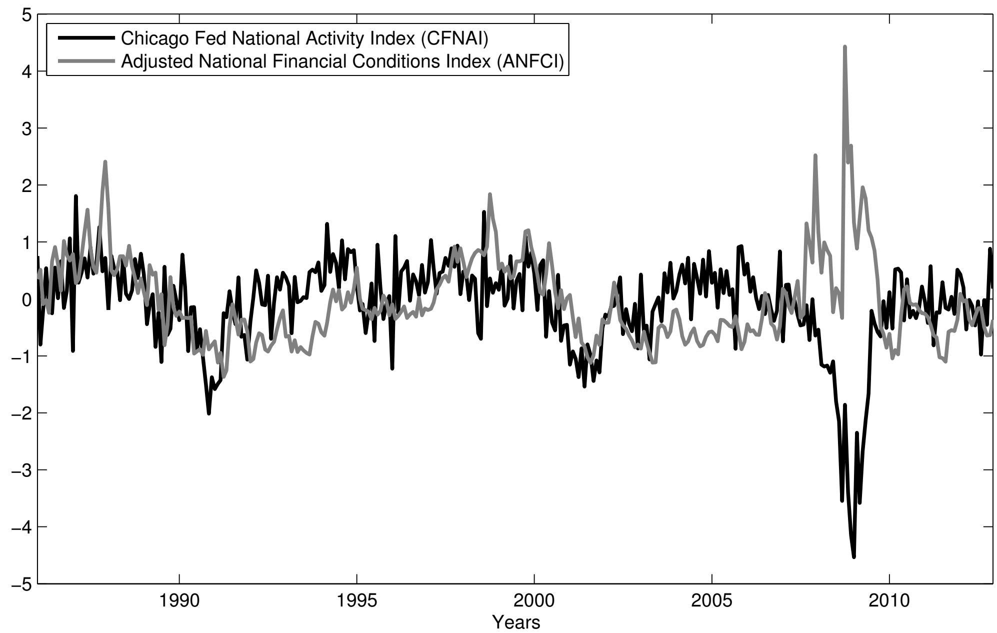

Figure 3: Time-series behavior of CFNAI and ANFCI. This figure shows the time-series behavior of the Chicago Fed National Activity Index (CFNAI) and the Adjusted National Financial Conditions Index (ANFCI) during 1986-2012 at monthly frequencies. A monthly index of the U.S. aggregate economic activity, the CFNAI is defined as a weighted average of 85 existing monthly indicators of national economic activity with an average value of zero and a standard deviation of one. The ANFCI isolates a component of financial conditions uncorrelated with economic conditions to provide an update on financial conditions relative to current economic conditions. The ANFCI is a weighted average of a large number of variables (105 measures of financial activity) each expressed relative to their sample averages and scaled by their sample standard deviations. The pairwise correlation is -0.1353.

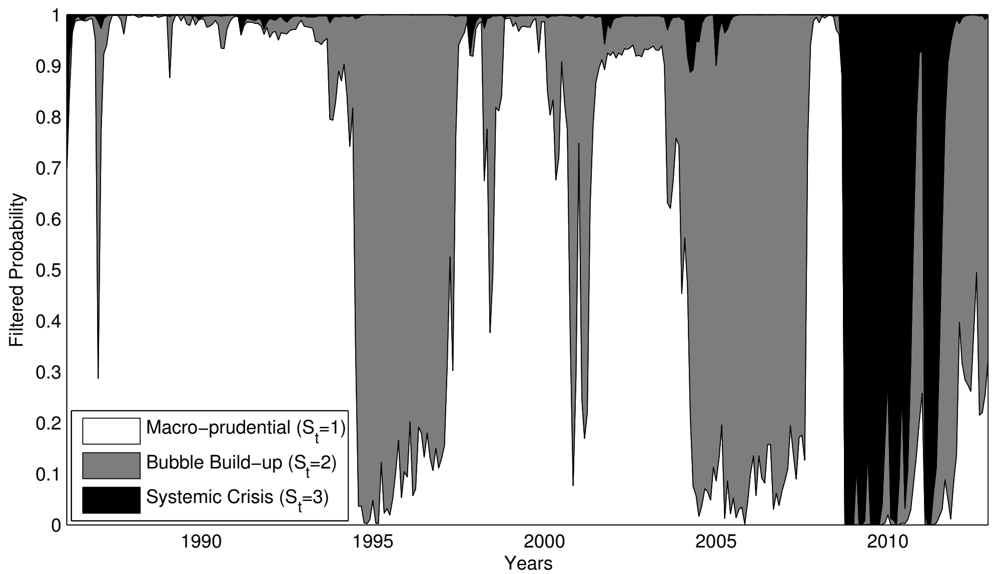

Figure 4: Filtered probability of each state implied by the fitted model (5). This figure shows the time-series behavior of the smoothed probability of being in each state during 1986-2012 at monthly frequencies. States 1, 2, and 3 consist of the periods in which the estimated parameters of the fitted model (5) take on values when the independent variable is the monthly TED spread as a proxy of the market-wide risk factor (ξ_t), and the dependent variable is the monthly log-difference of the ratio of a sum of loans and leases and interbank loans over a sum of securities and cash.

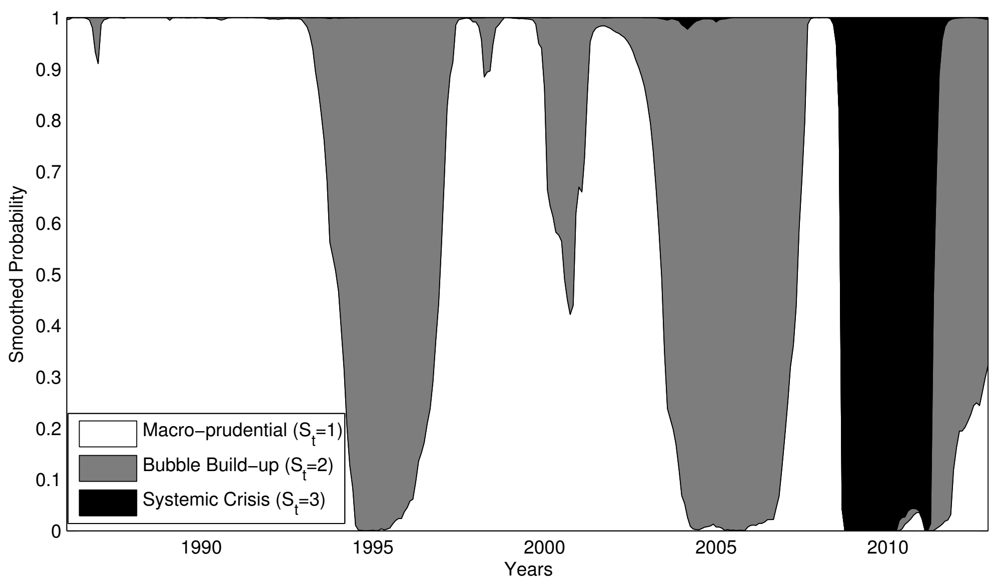

Figure 5: Smoothed probability of each state implied by the fitted model (5). This figure shows the time-series behavior of the smoothed probability of being in each state during 1986-2012 at monthly frequencies. States 1, 2, and 3 consist of the periods in which the estimated parameters of the fitted model (5) take on values when the independent variable is the monthly TED spread as a proxy of the market-wide risk factor (ξ_t), and the dependent variable is the monthly log-difference of the ratio of a sum of loans and leases and interbank loans over a sum of securities and cash.

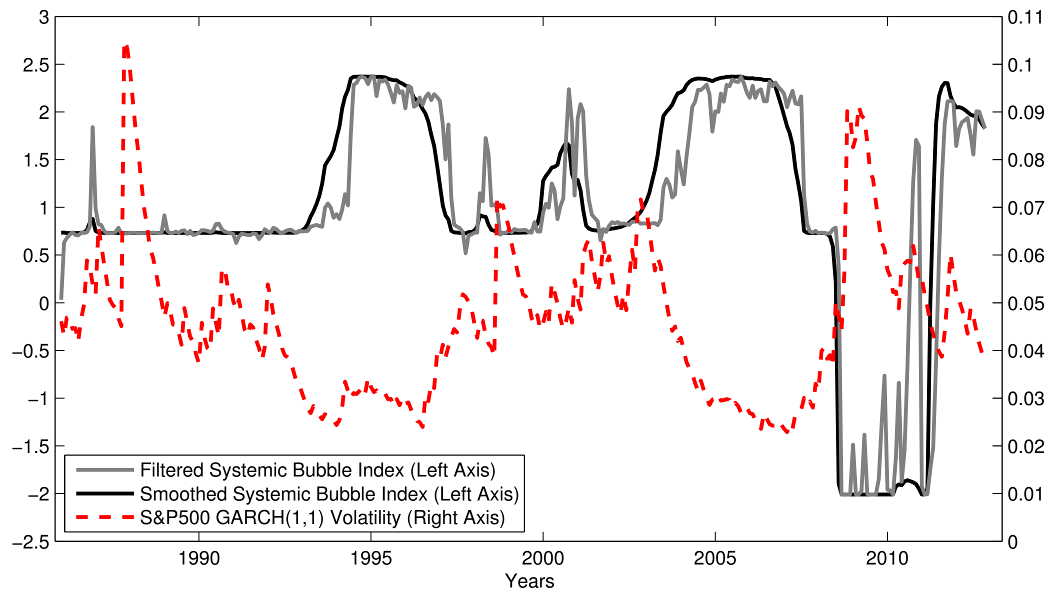

Figure 6: The estimated SBI and the S&P500 index volatility. This figure shows the time-series behavior of the filtered and smoothed SBI implied by the fitted model (5) along with the S&P500 index volatility based on the GARCH(1,1) model from 1986 to 2012. The pairwise correlations of the SBI with the S&P500 volatility are -0.5874 (filtered) and -0.6003 (smoothed), respectively.

Panel A: Summary statistics of the SBI components						
	Securities	Loan & Lease	Interbank	Cash	I_t	TED(%)
Obs.	324	324	324	324	324	324
Mean	1312036	3864391	235708	435574	2.4393	0.6344
Median	1116033	3315223	209315	273558	2.5044	0.5318
Max	2736598	7287203	466335	1745746	3.1153	3.3886
Min	450272	1455465	112717	206025	1.6468	0.1184
Std	660706	1914136	84647	412044	0.3188	0.4388

Panel B: Summary statistics of macro-economic and financial variables						
	CFNAI	ANFCI	CVI	SBI	TS(%)	LS(%)
Obs.	324	324	204	323	324	324
Mean	-0.1084	-0.0488	24.1349	0.9871	1.8357	0.4385
Median	0.0060	-0.2192	19.7100	0.7803	1.8250	0.2300
Max	1.8055	4.4307	85.4400	2.3707	3.9400	2.5193
Min	-4.5349	-1.3685	6.4500	-2.0102	-0.6900	-0.2600
Std	0.8230	0.7553	15.1192	1.1753	1.1462	0.5198
Skewness	-1.7772	1.4319	1.4937	-1.2333	-0.1433	1.3551
Kurtosis	8.8493	7.0671	5.3108	4.4172	1.9233	4.2315

Panel C: Pair-wise correlation matrix						
	CFNAI	ANFCI	SBI	TS	LS	CVI
CFNAI	1.0000	-0.1353	0.3977	-0.0334	0.0202	-0.6055
ANFCI		1.0000	-0.3000	-0.1465	0.4087	0.4207
SBI			1.0000	-0.3543	-0.0864	-0.5374
TS				1.0000	-0.2457	0.0882
LS					1.0000	0.1673

Table 2: Descriptive statistics. This table reports the indicated summary statistics of the selected variables at monthly frequencies from January 1986 to December 2012. Panel A reports summary statistics of four individual balance sheet components comprising I_t in millions of dollars along with the Treasury-Eurodollar (TED) spread. I_t is defined as a ratio of a sum of loans and leases and interbank loans (i.e., systemically risky assets) over a sum of securities and cash (i.e., systemically safe assets) resulting in I_t =(loans and leases + interbank loans)/(securities and cash). All commercial banking balance sheet information is obtained from the Federal Reserve Statistical Release H.8, Assets and Liabilities of Commercial Banks in the United States. TED is defined as the difference between the three-month LIBOR interest rate and the three-month TB yield. Panel B reports the summary statistics of macro-economic and financial variables. A monthly index of the U.S. aggregate economic activity, CFNAI, is defined as a weighted average of 85 existing monthly indicators of national economic activity with an average value of zero and a standard deviation of one. ANFCI is a weighted average of a large number of variables (105 measures of financial activity), each expressed relative to their sample averages and scaled by their sample standard deviations by isolating a component of financial conditions uncorrelated with economic conditions to provide an update on financial conditions relative to current economic conditions. CVI is the value-weighted corporate vulnerability index of the U.S. economy, for which the RMI PDs are aggregated with each firm and weighted by its market-capitalization so that the size of each firm is taken into account. SBI is the fitted systemic bubble index defined in (6). Term spread (TS) is defined as the difference between the yields on long-term and short-term Treasury securities. We employ a 10-year treasury constant maturity rate proxy for long-term security, and a three-month TB from secondary market rate proxy for short-term security. Liquidity spread (LS), defined as the difference between the three-month repo rate available from Blommberg and the three-month TB interest rate. Due to the limitation of data span of the repo rates, we followed the methodology introduced by Adrian & Brunnermeier (2011) in footnote 10. TED, TS and LS are reported in percent. Panel C reports the pair-wise correlation matrix for the full sample, where the pair-wise correlation with CVI is reported for the balanced sub-sample from January 1996.

Panel A: Maximum likelihood estimates (t-statistics)			
	Ψ_{S_t}	Σ_{S_t}	Expected Duration
Macro-prudential State	0.7302***	0.0081***	43.58 months
($S_t = 1$)	(5.5880)	(9.4117)	
Bubble Build-up State	2.3710***	0.0100***	29.58 months
($S_t = 2$)	(6.8656)	(6.1647)	
Systemic Crisis State	-2.0102***	0.0278***	29.75 months
($S_t = 3$)	(-3.0718)	(3.6629)	

Panel B: Markov transition probability matrix (standard errors)			
	$S_t = 1$	$S_t = 2$	$S_t = 3$
$S_t = 1$	0.9771	0.0338	0.0000
	(0.0721)	(0.0368)	(0.0278)
$S_t = 2$	0.0169	0.9662	0.0336
	(0.0144)	(0.0902)	(0.0602)
$S_t = 3$	0.0060	0.0000	0.9664
	(0.0091)	(0.0080)	(0.1581)

Table 3: Results from the maximum likelihood estimation of the MRS model (5). This table reports the parameter estimates from the maximum likelihood estimation of the regime-switching model (5) along with the estimated Markov transition probability matrix from January 1986 to December 2012. The dependent variable is the monthly log-difference of the ratio of a sum of loans and leases and interbank loans over a sum of securities and cash. The independent variable is the monthly TED spread, defined as the difference between the three-month LIBOR interest rate and the three-month TB yield (in decimal), as a proxy of the market-wide risk factor (ξ_t). The t-statistics are shown in parentheses. The estimated α of the model is -0.0064 with t-statistics of -5.6772. (*** significant at 1% level, ** significant at 5% level, * significant at 10% level)

	Economic Activity (CFNAI)			Financial Distress (ANFCI)			Aggregate Credit Risk (CVI)		
	h=18	h=21	h=24	h=18	h=21	h=24	h=18	h=21	h=24
AR	-0.4608***	-0.5083***	-0.5608***	-0.4633***	-0.3536***	-0.4412***	-0.7362*	-0.8873**	-1.0966**
	(-8.6585)	(-9.2109)	(-10.7916)	(-3.9909)	(-3.4796)	(-5.4706)	(-1.3394)	(-1.7171)	(-1.1266)
SBI	-0.1802*	-0.2106*	-0.2379**	0.2842***	0.3119***	0.3536***	5.0229**	5.7714***	6.8833***
	(-1.3170)	(-1.6481)	(-1.9878)	(3.2776)	(3.5308)	(3.4804)	(2.1982)	(2.4336)	(3.0042)
I_t	-0.3308	-0.0003	0.5714	-0.1096	-0.4175	-0.7409*	2.9369	-4.7253	-9.1707
	(-0.5175)	(-0.0006)	(1.1829)	(-0.3116)	(-0.9412)	(-1.4065)	(0.2093)	(-0.3389)	(-0.7110)
TS	0.2679***	0.3322***	0.4575***	-0.0224	-0.0945	-0.1361*	-2.2150	-4.8933**	-7.4231***
	(3.0452)	(3.9864)	(4.7394)	(-0.2669)	(-1.0460)	(-1.3345)	(-1.1724)	(-2.1838)	(-7.0579)
LS	-0.3146**	-0.4157***	-0.4123**	-0.2308*	-0.3084**	-0.4165***	27.0467**	25.4359**	20.3174**
	(-1.9345)	(-2.6143)	(-2.2659)	(-1.3831)	(-1.8537)	(-2.3442)	(2.246)	(2.3265)	(1.9707)
Adj.R^2	0.3007	0.3334	0.3944	0.1947	0.2047	0.2470	0.3287	0.3752	0.4501

Table 4: Estimation results of the predictive power of the systemic bubble index with the full sample. This table summarizes the estimation results of (8) for macro-economic activity, financial distress and aggregate credit risk with for the full sample period from January 1986 to December 2012. The dependent variables in the regression model (8) are CFNAI, ANFCI and the value-weighted CVI, respectively. AR is the first difference of the dependent variable $(Y_t - Y_{t-1})$ over the last month. SBI is the fitted systemic bubble index proposed by (6). I_t is the ratio of a sum of loans and leases and interbank loans (i.e., systemically risky assets) over a sum of securities and cash (i.e., systemically safe assets) resulting in I_t =(loans and leases + interbank loans)/(securities and cash). TS is the yield differential between the ten-year Treasury bond and the three-month Treasury bill. LS is the difference between the three-month repo rate available from Blommberg and the three-month TB interest rate. Due to the limitation of data span of the repo rates, we followed the methodology introduced by Adrian & Brunnermeier (2011) in footnote 10. The t-statistics in parentheses are adjusted by the Newey-West procedure for heteroscedasticity and autocorrelation with lag = 5 (CFNAI and ANFCI) and lag = 4 (CVI), respectively. A constant is included in each specification, but is not reported in the table. (*** significant at 1% level, ** significant at 5% level, * significant at 10% level)

	Economic Activity (CFNAI)			Financial Distress (ANFCI)			Aggregate Credit Risk (CVI)		
	h=18	h=21	h=24	h=18	h=21	h=24	h=18	h=21	h=24
AR	-0.4759***	-0.4598***	-0.5672***	-0.3801***	-0.4590***	-0.3481***	-0.9091**	-1.0006***	-1.1254**
	(-8.3857)	(-8.3115)	(-10.6611)	(-3.2658)	(-3.4715)	(-4.6324)	(-1.9406)	(-2.4076)	(-2.5795)
SBI	-0.2553*	-0.3796***	-0.3516**	0.3099**	0.2998***	0.4267***	2.1031	3.4899**	5.0043***
	(-1.4744)	(-2.4286)	(-2.2217)	(2.3319)	(3.26)	(3.2485)	(1.1926)	(1.8645)	(2.4706)
I_t	0.3862	1.2076**	0.9807**	-0.3315	-0.8770*	-0.422	28.6749*	13.0896	0.7829
	(0.6322)	(1.7025)	(1.9486)	(-0.6923)	(-1.5033)	(-0.7227)	(1.4929)	(0.7818)	(0.052)
TS	0.2936***	0.3176***	0.3518***	-0.1045*	-0.1847**	-0.0973	-1.6607	-4.2156**	-6.6750***
	(2.8872)	(2.6002)	(3.2248)	(-1.3315)	(-2.0273)	(-1.0092)	(-0.7478)	(-1.7061)	(-2.5628)
LS	-0.1703	-0.2991*	-0.2207	-0.4133***	-0.4131***	-0.5878***	15.6554**	15.9339**	12.1698*
	(-0.7623)	(-1.4853)	(-0.8628)	(-2.8024)	(-3.1045)	(-4.0349)	(1.6713)	(1.8032)	(1.4869)
Adj.R^2	0.2291	0.2782	0.3052	0.2604	0.302	0.3471	0.2209	0.2436	0.3185

Table 5: Estimation results of the predictive power of the systemic bubble index with the sub-sample by excluding the recovery period. This table summarizes the estimation results of (8) for macro-economic activity, financial distress and aggregate credit risk for the sub-sample period by excluding the recovery period from January 2009 in the estimation of the systemic bubble index. The dependent variables in the regression model (8) are CFNAI, ANFCI and the value-weighted CVI, respectively. AR is the first difference of the dependent variable ($Y_t - Y_{t-1}$) over the last month. SBI is the fitted systemic bubble index proposed by (6). I_t is the ratio of a sum of loans and leases and interbank loans (i.e., systemically risky assets) over a sum of securities and cash (i.e., systemically safe assets) resulting in I_t =(loans and leases + interbank loans)/(securities and cash). TS is the yield differential between the ten-year Treasury bond and the three-month Treasury bill. LS is the difference between the three-month repo rate available from Blommberg and the three-month TB interest rate. Due to the limitation of data span of the repo rates, we followed the methodology introduced by Adrian & Brunnermeier (2011) in footnote 10. The t-statistics in parentheses are adjusted by the Newey-West procedure for heteroscedasticity and autocorrelation with lag = 5 (CFNAI and ANFCI) and lag = 4 (CVI), respectively. A constant is included in each specification, but is not reported in the table. (*** significant at 1% level, ** significant at 5% level, * significant at 10% level)

		Intercept	SBI	Market	SMB	HML
All Firms	(1)	-0.0062***	0.0538	4.4049***		
		(-2.8947)	(1.1494)	(5.6803)		
	(2)	-0.0051**		5.2935***	-0.0100	0.0384**
		(-2.2269)		(6.0114)	(-0.4444)	(2.0818)
	(3)	-0.0053**	0.0648	5.3482***	-0.0114	0.0391**
		(-2.3099)	(1.3809)	(6.0682)	(-0.5063)	(2.1161)
Financial Firms	(1)	-0.0014	0.1224***	2.4631***		
		(-0.9579)	(2.6245)	(3.5859)		
	(2)	-0.0015		1.0076	0.0636**	0.0255
		(-1.0394)		(1.1378)	(2.5073)	(1.2053)
	(3)	-0.0021	0.1204**	1.0188	0.0646**	0.0217
		(-1.4555)	(2.5765)	(1.1515)	(2.5493)	(1.0242)
Non-financial Firms	(1)	-0.0078***	0.0456	4.7840***		
		(-3.1771)	(0.9828)	(6.0125)		
	(2)	-0.0060**		6.0612***	-0.0213	0.0371**
		(-2.2954)		(6.8224)	(-0.9982)	(2.0392)
	(3)	-0.0062**	0.0610	6.1169***	-0.0223	0.0379**
		(-2.3725)	(1.3118)	(6.8780)	(-1.0434)	(2.0811)

Table 6: Conditional ICAPM with the market and systemic bubble index. This table reports the results of the common slope estimates Λ, Π and Γ_n from the panel regression model (10). The parameters are estimated by controlling for a firm's fixed effects, the monthly excess returns on the market portfolio, and the 10 value-weighted size portfolios of financial and non-financial firms for the sample period from January 1986 to December 2012. SBI is the fitted systemic bubble index proposed by (6). Market is the excess market return, calculated as the value-weighted return of all CRSP firms incorporated in the United States and listed on the NYSE, AMEX, or NASDAQ over the risk free rate. The average return on the 'Small minus Big' size factor, SMB, and the average return on the 'High minus Low' book-to-market factor, HML, are calculated as the method in Fama & French (1993). We have obtained the historical data of both SMB and HML from Kenneth French's website. The sample ranges from January 1986 to December 2012. The t-statistics in parentheses are adjusted for heteroscedasticity and autocorrelation for each series and contemporaneous cross-correlations among the portfolios. (*** significant at 1% level, ** significant at 5% level, * significant at 10% level)