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Financial Imbalances, Systemic Stress, and Macroprudential Implications

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ABSTRACT: The effectiveness of macroprudential policy framework depends to a large extent on how the process of monitoring and assessing systemic risks and the calibration of macroprudential policy tools are operationalized in practice. This paper has two main contributions. First we propose an enhanced composite indicator, the Systemic Vulnerabilities Index (SVI), which captures the buildup of systemic vulnerabilities. The index is built on an innovative approach that uses optimal aggregation of subindices, and without imposing exogenous constraints. Specifically, making use of the Principal Component Analysis (PCA) for a broad set of relevant input variables, we determine their relative importance in contributing to the buildup of systemic vulnerabilities. Subsequent use of Monte Carlo simulation techniques allows us to select the optimal SVI that best predicts future credit losses. The proposed SVI captures both time and sectoral dimensions of the buildup of risks. We provide evidence showing a superior performance of the SVI, compared to the traditional credit-to-GDP gap in documenting risk accumulation. We investigate the relationship between our SVI and financial condition index and provide evidence of a negative correlation between the two, whereby a loosening of financial conditions is associated with more accumulation of imbalances. Second, we provide a framework that guides on how the SVI can be used for increasing Countercyclical Capital Buffer (CCyB) beyond its neutral level. Specifically, we propose a mapping that shows how the SVI can help determine the timing of setting a CCyB beyond the neutral rate as well as its magnitude.

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WORKING PAPERS

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Glossary

BCBS	Basel Committee for Banking Supervision
BMA	Bayesian Model Averaging
CCyB	Countercyclical Capital Buffer
CISS	Composite Indicator of Systemic Stress
CRE	Commercial Real Estate
DSTI	Debt-Service-to-Income
ECB	European Central Bank
ESRB	European Systemic Risk Board
EWMA	Exponentially Weighted Moving Average
GFC	Global Financial Crisis
HP	Hodrick-Prescott
LTV	Loan-to-Value
NPL	Non-performing Loan
PCA	Principal Component Analysis
RMSE	Root Mean Square Error
SRI	Systemic Risk Indicator
SVI	Systemic Vulnerabilities Index

I. Introduction

In 2010, following the 2007–09 Global Financial Crisis (GFC), the Basel Committee for Banking Supervision (BCBS) introduced the countercyclical capital buffer (CCyB) as part of Basel III reforms to ensure a more resilient banking system. The Basel standard prescribes several elements of the CCyB, but others are left to national discretion.[1] Making use of this discretion, and in order to increase the resilience of the banking sector and maintain the flow of credit to the real economy in periods of stress, several jurisdictions have chosen to adopt positive neutral CCyB. With this, the CCyB is set at a rate above zero even when risks are judged to be neither subdued nor elevated (BCBS, 2022). While the main motivations for introducing a positive neutral CCyB are broadly similar across jurisdictions—including: increasing the share of buffers that can be released in case of crisis; enhancing the flexibility in using the CCyB; and accounting for uncertainty in the identification of systemic risks—different approaches have been used in setting CCyB beyond its neutral level (BCBS, 2024).

The aim of this paper is to offer a systematic approach to setting CCyB beyond its neutral level. To this end, we first propose an enhanced composite indicator—the Systemic Vulnerabilities Index—that facilitates a comprehensive monitoring of systemic vulnerabilities in the financial sector. Indeed, the effectiveness of the macroprudential policy framework depends to a large extent on how the process of monitoring and assessing systemic risks, as well as the calibration of macroprudential policy tools, are operationalized in practice. Identifying a measure that properly captures the financial imbalances is therefore of the first order. Our enhanced composite indicator is later used to offer a mapping into CCyB and ultimately helps determine the timing of increasing CCyB beyond its neutral rate as well as the magnitude of such increases.

A number of studies consider excessive credit growth, or the credit-to-GDP gap,[2] to identify the buildup of economic vulnerabilities, since these studies found this measure to be the best "single" variable for predicting a financial crisis two to three years ahead (e.g. BCBS, 2010). However, the literature also highlights a number of challenges. They include: (i) a limited time span of the available variables and potential structural breaks (BIS Quarterly Review, March 2014); (ii) a "starting point problem" where initial values strongly influence the outcome of statistical filters (Drehmann et al., 2014; European Central Bank, 2017); (iii) unreliability in real-time, as estimates are often revised significantly with new data (Orphanides and van Norden, 2002; Edge and Meisenzahl, 2011); (iv) parameter dependence, where results are sensitive to the choice of smoothing parameters (Ravn and Uhlig, 2002); and (v) delayed signaling, as credit is more persistent than GDP, potentially widening the credit-to-GDP gap during an economic downturn (Giese et al., 2014). Beyond that, Frait and Komárková (2012) argue that the credit-to-GDP ratio is only a rough measure of leverage in the economy on the basis of which it is hard to identify turning points between phases of the financial cycle in a timely manner. Although Basel Committee guidance (BCBS, 2010) refers to activating and increasing the buffer in response to "excessive credit growth", as measured by the credit-to-GDP gap, this gap can stay negative for an extended period of time, leading to a lack of buffer as highlighted in section IV (below).

Several studies have pointed instead to the use of a composite indicator based on a set of variables (sub-indicators) measuring swings in risk. For example, Holló et al. (2012) first proposed in the macroprudential context a methodology of aggregating sub-indicators into a single indicator using standard portfolio theory and called it a Composite Indicator of Systemic Stress (CISS). This indicator has since been adopted by the

[1] See for example Basel framework, Risk-Based Capital Requirements (RBC 30).

[2] Credit-to-GDP gap is computed as the difference between the credit-to-GDP ratio and its Hodrick-Prescott (HP)-filtered value.

European Central Bank (ECB) for regular monitoring of systemic stress in euro area financial markets (ECB, 2012). Building on that methodology, Plašil et al. (2015) construct a composite indicator using variables representing risk perceptions in the financial sector and calibrate this indicator to capture the credit losses experienced by the Czech banking sector during the Global Financial Crisis (GFC). This indicator is used operationally by the Czech National Bank (CNB) as part of its macroprudential policy toolkit for assessing cyclical risks and guiding countercyclical capital buffer decisions (CNB, 2018).

Our composite indicator—the Systemic Vulnerabilities Index (SVI)—is constructed by drawing on best practices from the literature on financial stress and early-warning indicators. The paper contributes to the emerging literature on systemic vulnerabilities by first enriching the methodology developed by Holló et al. (2012) and Plašil et al. (2015) based on standard portfolio theory. Our approach innovates by calibrating the weights of subcomponents in a data-driven, predictive manner. The added innovations or refinements are achieved by replacing expert judgment with a data-driven approach using Principal Component Analysis (PCA) to determine which underlying risk indicators (credit growth, asset price inflation, leverage measures, etc.) account for the largest share of common variance in the data, thus diagnostically ranking their importance in vulnerability accumulation. We then employ Monte Carlo simulation techniques to determine the weight combination that optimizes the SVI's forecasting performance for future non-performing loans (NPLs).

In essence, the PCA ensures that we capture the key latent drivers of systemic risk accumulation, while the Monte Carlo optimization ensures the final index is empirically tuned to predict credit losses or NPLs. Specifically, after determining the ranking or relative importance of the subindices using the PCA, the optimal set of weights—selected from approximately 100,000 simulated combinations—is the one that minimizes the error term between actual NPLs and those predicted by the composite indicator. The Monte Carlo simulation is repeated until the optimal weights stabilize and marginal changes diminish. The resulting SVI captures the time dimension and the sectoral contributions to systemic risk accumulation. Based on country-specific historical episodes the SVI is shown to be superior to the credit-to-GDP gap in documenting risk accumulations.

Specifically, we deploy a comprehensive toolkit, Bayesian Model Averaging (BMA), to account for model uncertainty and identify robust predictors, time-varying parameter regressions (Kalman filter based) to capture any structural changes in predictor effectiveness and rolling out-of-sample forecasts to simulate real-time prediction performance. Our analysis covers both a broad out-of-sample period and a focused back-test of the pre-GFC period to gauge its early warning capabilities. The results show that SVI-based forecasting models significantly outperform those based on the credit-to-GDP gap in predicting NPL dynamics. The SVI not only yields lower out-of-sample forecast errors, but also provides early and more pronounced warnings of impending NPL deteriorations, particularly evident in the run-up to the GFC.

Our methodology yields an estimated SVI that is different from the index in Plašil et al. (2015), owing to the added innovations. For example, the choice of our variables is country-dependent rather than relying solely on standard broad-based variables. Our simulations do not have fixed limits—which make the simulation results sensitive to stopping points—but rather the number of simulations for each country is determined based on the stabilization of the optimal weights, particularly by increasing the simulation number at each iteration by ten thousand until marginal changes in weights diminish. PCA technique, rather than judgment, also enhances the aggregation process through the determination of the relative importance of the variables. Our carefully constructed composite vulnerability index enhances financial sector monitoring and offers a more comprehensive tool beyond the traditional credit gap for macroprudential policy decision making.

We also provide evidence of a negative correlation between financial conditions and the estimated SVI, whereby a loosening of financial conditions is associated with higher accumulation of imbalances. Finally, the SVI sheds light on the sectoral contributions to systemic risk accumulation. These findings have important policy implications. An improved early warning indicator can inform CCyB decisions by signaling the need for proactive capital buildups when systemic risks are growing. The framework offers useful insight on the timing of setting CCyB beyond the neutral rate as well as its magnitude.

The rest of the paper is organized as follows. Section II reviews the existing literature. Section III offers a deep dive into the methodology. Section IV estimates the SVI for the United States and Iceland and presents a comparative analysis of the SVI performance versus other indicators. Section V analyzes the correlation between SVI and financial conditions. Section VI discusses policy implications and section VII concludes.

II. Literature Review

While the literature on the evolution of financial markets is extensive, our understanding of financial imbalances remains limited. This is because much of the literature typically addresses specific components of financial imbalances. For instance, some studies concentrate only on the consequences of asset price and credit booms, rather than considering a comprehensive list of indicators of broad-based vulnerabilities (for example, Bernanke, Gertler, and Gilchrist, 1996; Gilchrist and Zakrajsek, 2008; Ivashina and Scharfstein, 2010 and Mian and Sufi, 2010). Others focus on financial crises, which represent extreme downturn phases of cycles in extracting financial cycle information (for example, Kaminsky et al., 1998; Reinhart and Rogoff, 2011; Shin, 2013, and Giordani et al., 2017).

As in many fields of economics, there is no widely accepted method for gauging financial imbalances. Indicators are often extracted using turning point analysis, statistical filters, or unobserved components models focusing mainly on individual variables (for example, Claessens et al., 2011, 2012; Aikman et al., 2015; Borio et al., 2012; Durbin and Koopman, 2012; Koopman and Lucas, 2005 and Galati et al., 2016). While a "single variable" like the credit-to-GDP gap is attractive to policymakers as one of the best single indicators of broad-based imbalances, due to its simplicity and ease of communication, it is important to note that focusing in isolation on individual variables whether it is a credit-to-GDP gap or property prices to capture financial imbalances is inherently incomplete. Early work by Borio and Lowe (2002) shows that combining credit and asset prices provides better early warning signals of financial distress.

A few studies went beyond individual variables and constructed systemic risk indicators using a composite indicator (for example, Holló et al., 2012; Lang et al., 2019 and Plašil et al., 2015). Specifically, Holló et al. (2012) introduce a financial stress index, the Composite Indicator of Systemic Stress (CISS), to measure the current state of instability in the financial system for the euro area. Its specific statistical design is shaped according to standard definitions of systemic risk. The aggregation scheme featuring systemic risk is based on five market-specific segments—the banking sector, the non-bank financial intermediaries, money markets, securities (equities and bonds) markets, and the foreign exchange markets. For each of these five segments, the level of stress is measured on the basis of three raw stress indicators capturing certain symptoms of financial stress. The resulting 15 individual financial stress measures are aggregated based on basic portfolio theory. The aggregation accordingly takes into account the time-varying cross-correlations between the subindices. As a result, the CISS puts relatively more weight on situations in which stress prevails in several market segments at the same time. As such it captures the idea that financial stress is more systemic and thus more dangerous for the economy as a whole if financial instability spreads more widely across the whole financial system. The second element of the aggregation scheme featuring systemic risk is the fact that the “portfolio weights” attached to each of the five subindices are determined on the basis of their relative importance for real economic activity, specifically, their average relative impact on industrial production growth.

Lang et al. (2019) evaluated the performance of a broad set of early warning indicators and developed a domestic systemic risk indicator (d-SRI) to characterize cyclical systemic risks in the Euro area countries. The d-SRI is constructed as a weighted average of six early warning indicators, after they are normalized to the same scale. The strategy for selecting the d-SRI sub-indicators strikes a balance between institutional requirements[3] for monitoring systemic risk and the signaling performance of the indicators. They include bank credit-to-GDP change, the current account balance, the residential real estate price-to-income ratio change, real equity price growth, the debt service ratio change, and real total credit growth. Indicator weights are chosen to maximize the early warning properties of the composite d-SRI for systemic financial crises that are at least partly due to domestic vulnerabilities.

Plašil et al. (2015) developed a financial cycle indicator using data from the Czech economy. The method they employ involves taking a set of variables measuring swings in risk and aggregating them into a single indicator using standard portfolio theory. The indicators are calibrated in such a way as to capture the credit losses that the Czech banking sector experienced during the recent crisis.

None of these studies properly and endogenously determines the optimal weights—yielding the best SVI that optimally predicts future losses in their aggregation method. Their aggregation approach puts some weight on judgment, which could be problematic. For example, Plašil et al (2015) use judgment in ranking the weights on the subindices or input variables, and this influences the ultimate weights selection through optimization technique. In contrast, our approach replaces expert judgment with a fully data-driven process, using PCA to rank variables before applying Monte Carlo simulations to select the optimal weight combination in predicting NPLs. This makes the methodology particularly suitable for calibrating the CCyB beyond the neutral rate.

Schuler, Hiebert, and Peltonen (2017) exploit the co-movement between credit, housing, equity, and bond prices and using a spectral approach offer: (i) a comparative analysis between financial cycles and business cycles and (ii) a first attempt at studying the synchronization of financial cycles across G7 countries. They do not study systemic vulnerabilities per se nor their implications for macroprudential policy.

Drawing from the early research of Holló et al. (2012) and Plašil et al. (2015), this paper first tries to fill the gap in the literature by proposing a more robust approach to estimating broad-based measures of financial vulnerabilities index. Second, it makes use of this index to guide the setting of further increases in CCyB beyond neutral rates along with their magnitudes. The framework is particularly useful for informing decisions on increasing the CCyB beyond its neutral rate, even for countries with limited historical data. We are not aware of any paper that offers a mapping on how a composite indicator can be used in helping determine the timing of increasing CCyB beyond neutral buffer rates along with the magnitudes of such increases.

Our approach uses a broad set of relevant variables. In addition, the weights are calibrated based on the econometrically and economically significant contributions of the input variables to the SVI but also their predictive performance regarding future credit losses. Specifically, we make use of the PCA in determining the

[3] See ESRB recommendation ESRB/2014/1 on guidance for setting countercyclical buffer rates.

relative importance of each input variable and the Monte Carlo simulation techniques in selecting the optimal SVI that best predicts future losses with the number of simulations endogenously determined based on weight stabilization. This holistic approach is applied in constructing the SVIs for Iceland and the US where subindices capture changes in perceptions of financial risk across various segments of the economies. The approach offers an aggregation based on portfolio-theoretic principles, while taking into account the expansions and contractions common to the subindices through their cross-correlations. This approach can aid the timely identification of the build-up phase of systemic risk that can lead to elevated credit losses in the future.

III. Methodology for Constructing the SVI

The SVI is constructed based on a set of variables (subindices) measuring swings in risk, which we aggregate into a single indicator using standard portfolio theory, broadly in the same spirit as Holló et al. (2012), but added enhancements as mentioned above. This construction requires the following steps: (i) the choice of variables that capture the buildup rather than the materialization of risks; (ii) the normalization of the variables to the range (0,1) by using a Gaussian kernel estimate of the cumulative distribution function; (iii) the estimation a time-varying variance-covariance matrix based on the exponentially weighted moving average method (EWMA); (iv) the determination of the ranking of variables in terms of their contributions to risk accumulation using the PCA, which helps guide and structure the subsequent simulation step by prioritizing variables with greater explanatory power for systemic risk; (v) the selection of the set of optimal weights through a Monte Carlo simulation analysis, which produces a SVI that best describes the macrofinancial developments and accumulation of systemic risks; and (vi) the aggregation into a single index using standard portfolio theory.

A. Factors Composing the Systemic Vulnerability Index

Variables that characterize the financial imbalances serve as forward-looking indices of potential issues for financial stability. They are selected on the basis of results of empirical studies (Leaven and Valencia, 2010, 2020; Reinhart and Rogoff, 2011; Luis Brandão-Marques et al., 2019 and Babecký et al., 2013), as well as the IMF (2014), BCBS (2014, and the European Systemic Risk Board (ESRB) recommendations[4],[5]. They include:

Credit to Households and Non-financial Corporations. Many studies consider excessive credit growth essential in the boom-bust cycle. Schularick and Taylor (2012), Dell Ariccia et al. (2012), Drehmann et al. (2011), Drehmann et al. (2014), Borio (2014) and Jordà et al. (2013 and 2015) in their studies of financial crises find that credit booms are leading predictors of the probability and severity of the crisis.

Property Prices. Increased investors' willingness to take on risk often leads to residential and commercial real estate (CRE) prices staying high relative to fundamentals or historical norms (Allen and Rogoff, 2011; Borio et al., 2012; Giese et al., 2014; Borio, 2014 and Adrian et al., 2014). Consequently, elevated valuation pressures

[4] The ESRB outlines six categories of indicators deemed valuable during the buffer-setting phase—overvaluation of property prices, credit developments, external imbalances, strength of bank balance sheets, private sector debt burden, mispricing of risk—and models that combine the credit-to-GDP gap and a selection of the above measures. In terms of releasing the buffer, they advise financial market stress indicators (e.g., spreads between money market interest rates or banks' CDS premiums) and general systemic stress measures (e.g., composite stress indicators). The BCBS recommends utilizing similar types of indicators.

[5] Other country-specific variables relevant to defining cyclical risks in the country could also be considered. For instance, in the case of emerging economies, indicators such as the amount of foreign exchange reserves and the equilibrium real exchange rate could be usefully considered.

may increase the possibility of significant drops in asset prices, which could negatively impact banks' balance sheets and foster investment pessimism.

Debt Burden. Excessive borrowing by businesses and households exposes the borrowers to distress if their incomes decline or the assets they own fall in value. In these cases, businesses and households with high debt burdens may need to cut back spending, affecting economic activity and causing losses for investors (Giese et al., 2014; Juselius and Drehmann, 2015).

Lending Conditions. Lending conditions serve as indicators of financial risk perceptions on the credit supply side and are critical for predicting future crises (Giese et al., 2014). Loose lending conditions could increase future financial vulnerabilities (Adrian et al., 2016; Barajas et al., 2021). During economic upswings, banks may offer lower interest rates to attract less creditworthy yet riskier borrowers, often underestimating the inherent risks. Conversely, when risks materialize, banks tend to overly tighten lending conditions, resulting in financing constraints for the sound part of the real economy, a phenomenon known as a credit crunch.

Equity Prices. They can offer a comprehensive perspective on market participants' expectations, highlighting any potential over-optimism related to future asset prices (Giese et al., 2014; Adrian et al., 2014). Moreover, the occurrence of an equity price bubble appears to exacerbate subsequent economic downturns, if it is accompanied by a real estate bubble and high credit growth (Jorda et al, 2015).

Current Account Deficit. This may indicate the formation of external imbalances, economic overheating, and challenges in servicing debt obligations in the future. Giese et al. (2014) and Plašil et al. (2015) highlight that substantial and persistent current account deficits could indicate growing vulnerabilities, particularly in smaller open economies. Borio (2014) asserts that credit and asset price booms often coincide with a deterioration in the current account.

B. Gaussian Kernel Transformation of the Input Variables

Variables are standardized to the unit interval [0, 1] using kernel estimates of the cumulative distribution function, where the minimum value of the transformed variable corresponds to the lowest point of the cycle, while the maximum value indicates the peak. This transformation is derived from the historical distribution of the variable, making it easy to interpret each observation's relative position within the distribution. Additionally, it provides mutually comparable values of underlying variables. At the same time, it is sample dependent, and estimates might change as new data arrives. However, this is not critical, since we are interested in identifying the position of the economy in the financial cycle.

C. Estimation of Time-varying Variance Covariance Matrix by EWMA

The dynamic relationship between variables entering the SVI methodology is formally captured by time-varying correlations. The time-varying correlation coefficients were estimated recursively using the exponentially weighted moving average (EWMA) method with a smoothing factor[6] of $\lambda = 0{,}93$ (RiskMetrics, 1996). If the covariance σ_{ij}, and variance σ_i^2 (or σ_j^2), at time $t-1$ are known, the correlation coefficient $\rho_{t,ij}$, can be approximated using the following formulas:

[6] The higher the smoothing factor the more stable and smoother the estimated correlation coefficient. Holló et al. (2012) set the value at 0.93, for Euro area data, Plašil et al. (2015) used 0.94 for Czech data.

$$\sigma_{t,ij} = \lambda\sigma_{t-1,ij} + (1-\lambda)\widetilde{s_{t,i}}\,\widetilde{s_{t,j}}$$

$$\sigma_{t,i}^2 = \lambda\sigma_{t-1,i}^2 + (1-\lambda)\widetilde{s_{t,i}}\,\widetilde{s_{t,i}}$$

$$\rho_{t,ij} = \sigma_{t,ij}/(\sigma_{t,i}\sigma_{t,j})$$

As per Holló et al. (2012), $\widetilde{s_{t,i}} = (s_{t,i} - 0.5)$ denote the values of the individual subindices after subtracting their theoretical median. The initial correlation coefficients at time t = 1 are also estimated using the EWMA method applied to the time series in reverse order from the most recent observation to the oldest.

D. Ranking of the Weights Using Principal Component Analysis (PCA)

Before simulating the weights of the input variables, it is useful to ascertain the relative importance of each input variable. In this regard, the PCA is applied. By breaking down the input variables into a subset of linearly independent principal components, PCA helps identify the most informative sources of variation. We use the first Principal Component, which explains most of the variation of the initial set, and subsequently regress it against the standardized input variables to identify the extent to which each of them contributes to the principal component. This allows us to distinguish the relative importance of the input variables. While PCA does not determine the final weights, it helps guide and structure the Monte Carlo simulation by reducing reliance on arbitrary judgment and narrowing the space for optimization. This approach helps to discipline the simulation process.

E. Estimation of the Shares for Each Subindex Using Monte Carlo Simulations

We first generate a large number of random weight vectors for the candidate indicators (constraining weights to be positive and to sum to 1). For each weight vector, we construct an SVI as a weighted combination of the transformed indicators. The weights are calibrated based on their predictive performance regarding future credit losses (NPLs). The final calibration of the weight vector was determined using Monte Carlo simulation techniques. Different weight distributions were simulated, and the vector that yielded the best predictions of non-performing loans (NPLs) six quarters ahead (measured by RMSE) was selected. Across possible risk materialization measures, NPL was chosen, because stress tests (including second round effects analysis), aiming to determine the potential need for capital injection and also for CCyB, generally assess the losses generated by the materialization of risks. The number of simulations is determined based on the stabilization of the optimal weights, particularly by increasing the simulation number by ten thousand until marginal changes in weights diminish. The choice of six quarters aligns with the operational timeline required for banks to implement a non-zero countercyclical capital buffer. This period includes the data publication lag, and the time needed for decision-making regarding the capital buffer setting.

F. Systemic Vulnerabilities Composite Index (SVI) Aggregation

The aggregation is based on the portfolio theory, going back to Markowitz (1952). Following Holló et al., (2012) and Plašil et al., 2015), the aggregation method can be formulated as follows:

$$SVI_t = (w^o s_t)' C_t (w^o s_t) \tag{1}$$

Where SVI_t represents the systemic vulnerabilities index and defined on the interval from 0 (indicating low risk) to 1 (indicating high risk), w^o is a vector of optimal weights, s_t is a matrix of transformed variables, and C_t is a time-varying variance-covariance matrix with the off-diagonal elements $c_{t,ij}$ restricted by (2):

$$c_{t,ij} = \begin{cases} \rho_{t,ij} & if \ \sigma_{t,ij} \geq 0 \\ 0 & if \ \sigma_{t,ij} < 0 \end{cases} \tag{2}$$

In line with our goal to capture the buildup of imbalances across different variables, we restricted the correlations to emphasize co-movements among positively related variables. This is in contrast with unrestricted correlations, where negative and positive correlations would cancel each other out, resulting in an aggregation similar to a simple average. Having restrictions on correlations allows us to detect early imbalances leading to the buildup of systemic risks.

As the aggregation method considers the time-varying cross-correlation structure of the variables, the SVI takes higher values when variables are increasing across all monitored segments. The stronger the correlations between the transformed variables (subindices), the stronger the signal sent out by the SVI about overall changes in risk over the cycle. This feature is particularly relevant from a macroprudential standpoint, especially in determining the CCyB.

The higher the index, the higher the financial risk generally observed in the economy, regardless of whether this reflects a willingness by market participants to take on more risk or a limited ability to manage rising risks. The properties of the aggregation method can be easily understood with a simplified example involving just three subindices:

$$\begin{aligned} SVI_t = & \left(w_1 s_{t,1} + w_2 \rho_{t,12} s_{t,2} + w_3 \rho_{t,13} s_{t,3}\right) w_1 s_{t,1} + \\ & +\left(w_1 \rho_{t,12} s_{t,1} + w_2 s_{t,2} + w_3 \rho_{t,23} s_{t,3}\right) w_2 s_{t,2} + \\ & +\left(w_1 \rho_{t,13} s_{t,1} + w_2 \rho_{t,23} s_{t,2} + w_3 s_{t,3}\right) w_3 s_{t,3} \end{aligned} \tag{3}$$

From equation (3), we can see that the total weight of a subindex in the SVI is influenced not only by the weights w but also by the value of each of the expressions within the parentheses. This value, in turn, depends on the correlations between the given subindex and other variables. For instance, if subindex s_1 is not correlated with s_2 and s_3, its contribution to the the SVI will be lower. Conversely, variables that are strongly positively correlated with each other will have a larger positive effect on the final value of the SVI. In other words, variables that exhibit strong co-movement will, all else being equal, contribute the most to the value of the SVI.

IV. Estimation of the SVI for the United States and Iceland

For the estimation, the paper focuses on a major economy, the United States (US) and a relatively smaller economy, Iceland. The US offers an interesting case study to assess the ability of the composite index to properly capture risk accumulation, given the pre-GFC buildup of risks particularly in the real estate sector through subprime mortgages. Iceland's financial crisis experience also makes it a good test case for using the SVI in tracking the buildup of vulnerabilities.

A. Data

The US and Iceland SVIs were constructed to measure the accumulation of risks in the US and Iceland, respectively. For each country, SVI includes indicators/variables covering a range of demand and supply factors that characterize cyclical swings in financial risk in line with the description in section III-. The variables are ranked by prioritizing those with the strongest explanatory power based on the PCA. Monte Carlo simulations are then used to help select the optimal SVI. The specific details regarding the variables and their ranks, and transformations for each country are provided in Annex 1.

Important drivers of the estimated indicator of systemic vulnerabilities for the US are household and corporate debts, property and equity valuations, credit spreads, and the current account balance for the period from 2001Q1 to 2023Q1. The transformed variables are depicted in Figure 1 within the interval of 0 to 1, where 1 represents the historical maximum and 0 represents the minimum of each variable.

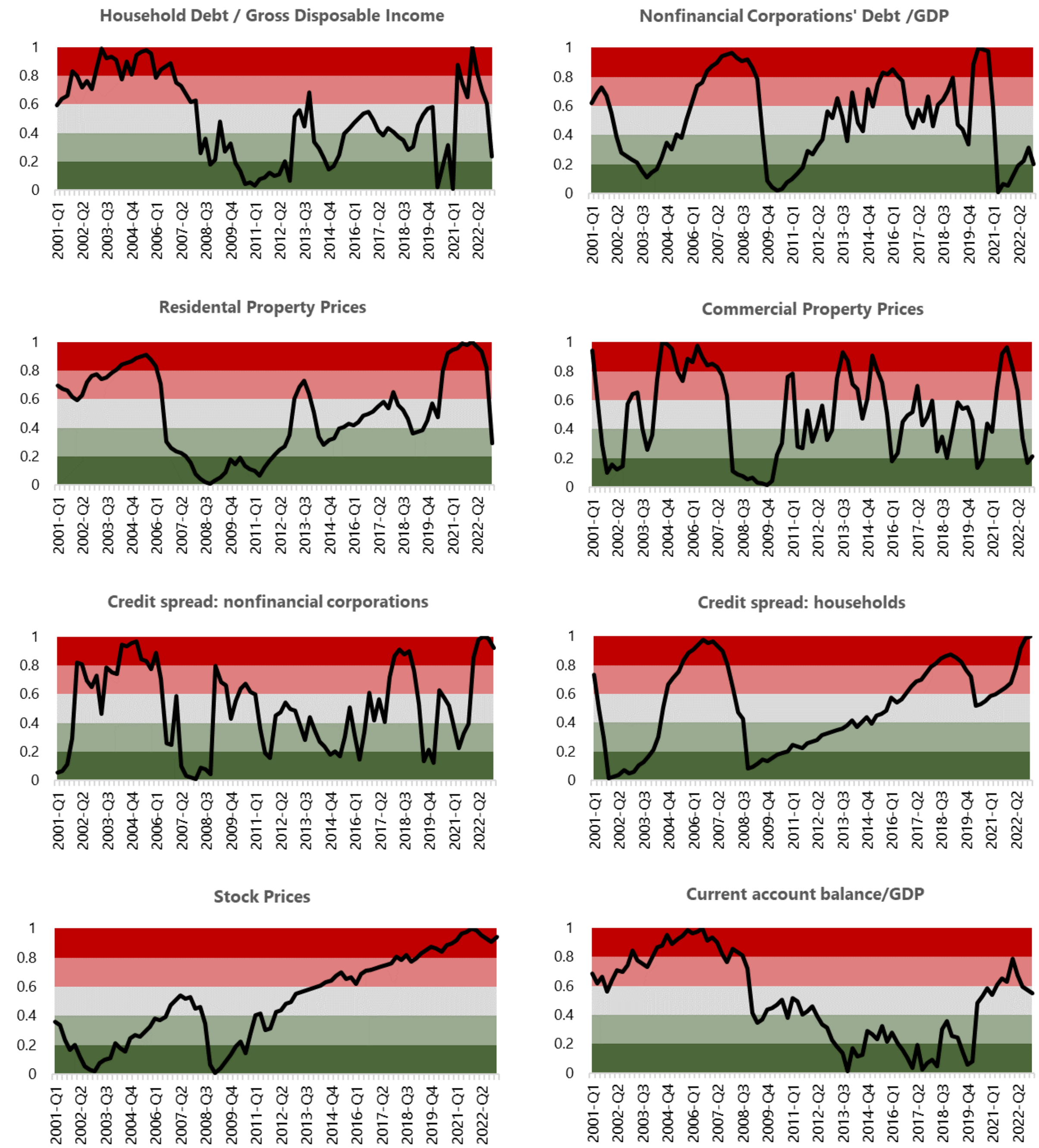
For Iceland, we consider up to nine variables in the construction of the SVI. They include variables related to new loans to households and non-financial corporations[7], property prices, credit spreads, and the current account balance for the period from 2013Q4 to 2022Q2. The transformed variables are shown in Figure 2.

The synchronization of variables throughout the cycle can be illustrated using historical quantiles. The left panel of Figure 3 and Figure 4 respectively displays the count of US and Iceland variables surpassing the 80th quantile during the specified period, while the right panel shows those falling below the 20th quantile, correspondingly. These quantities can serve as straightforward indicators of co-movement in both expansionary and contractionary phases of the cycle. The proposed methodology to estimate the SVI formally captures this phenomenon through time-varying correlations.

Figure 3 depicts that more than sixty percent of the variables reached their historical peak between 2005-2006, and half of the variables did so in 2022 in the case of US. In the case of Iceland, as Figure 4 shows, more than fifty percent of the variables reached their historical peaks in 2020Q4 and 2021Q4.

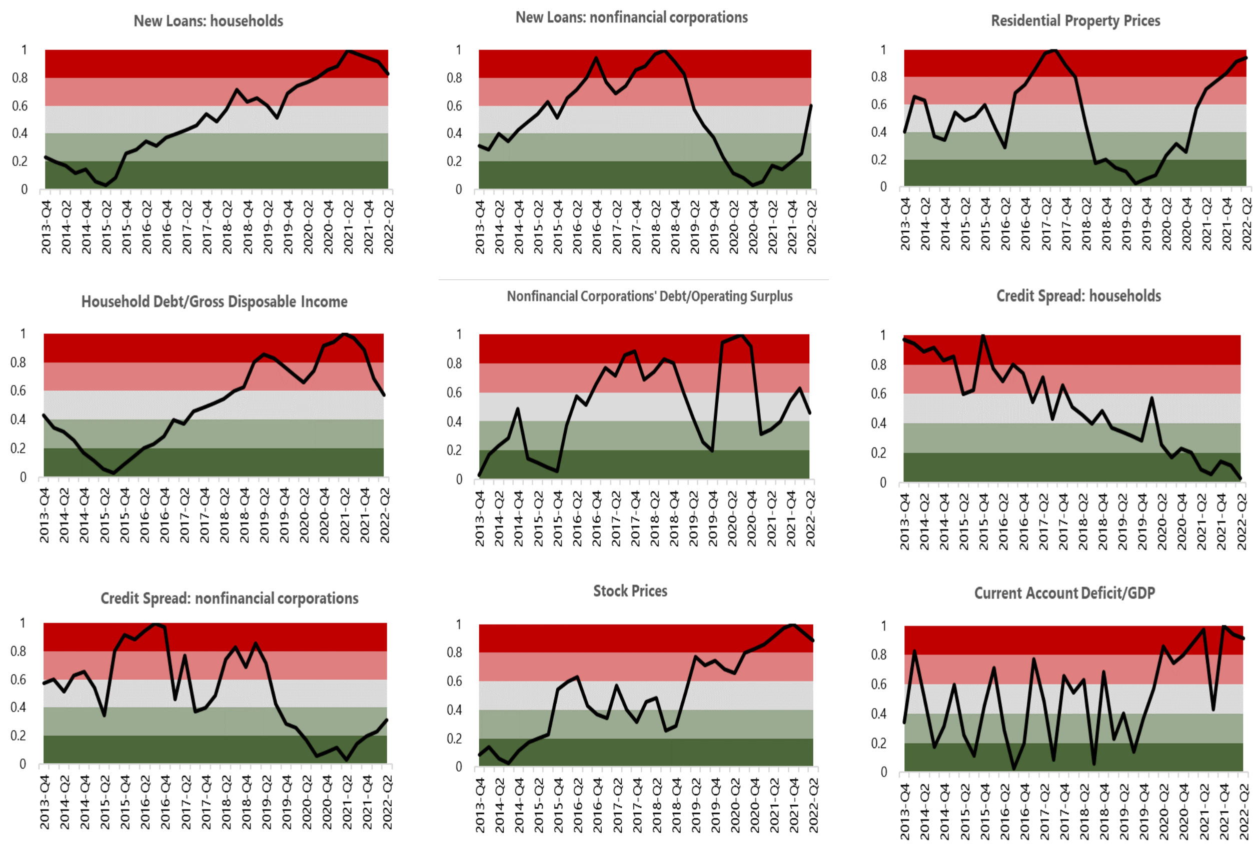
[7] New loans to households and non-financial corporations were included for Iceland, and for the US where data were available. Unlike credit stock measures, loan flow data more accurately reflect current lending activity and better capture ongoing risk accumulation in the financial system.

Figure 1. USA: Gaussian Kernel Transformation of the Input Variables (from 0 (trough) to 1 (peak))



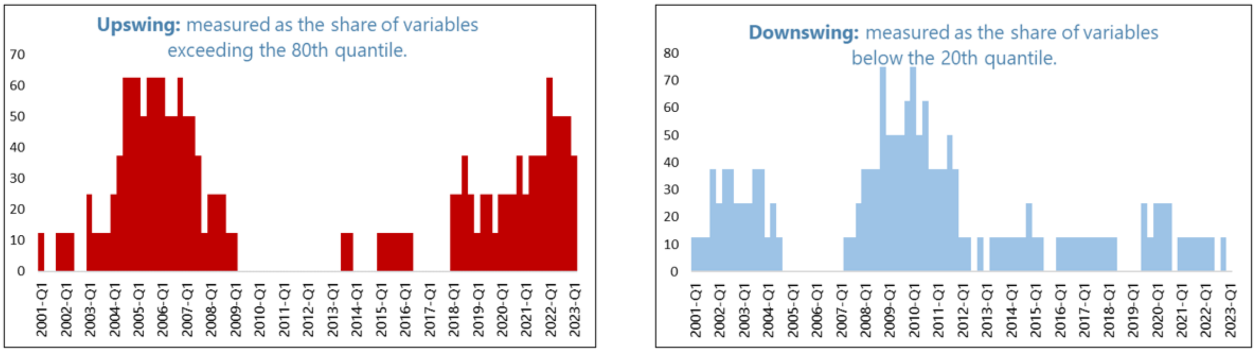
Sources: DNB, Haver Analytics, S&P, and Authors' calculations.

Figure 2. Iceland: Gaussian Kernel Transformation of the Input Variables (from 0 (trough) to 1 (peak))



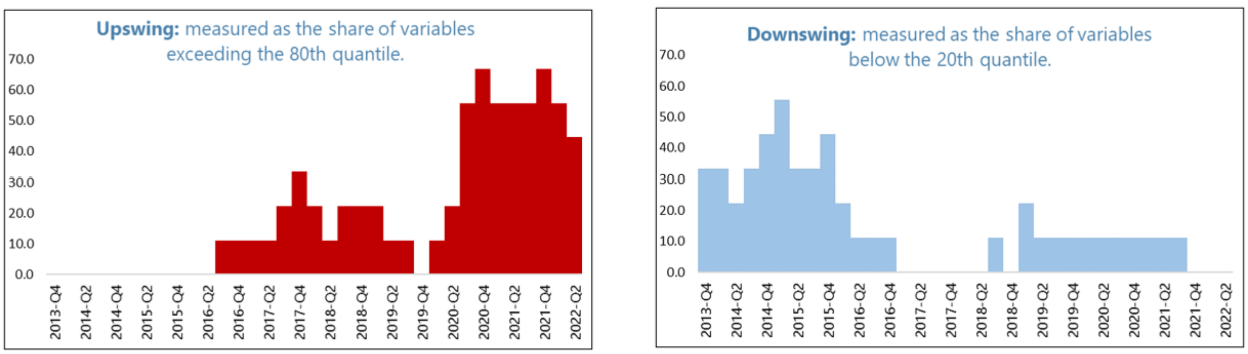
Sources: Central Bank of Iceland, Haver Analytics, and Authors' calculations.

Figure 3. USA: Share of Variables Indicating Co-movements



Source: Authors' calculations.

Figure 4. Iceland: Share of Variables Indicating Co-movements



Source: Authors' calculations.

B. Estimations

After obtaining all transformed variables, we aggregate them into one index using Monte Carlo simulation techniques. We simulate different weight distributions to find the optimal weights (w^o) for variables that best predict loan losses in the six quarters ahead. The number of simulations increases by ten thousand until marginal changes in weights diminish and optimal weights stabilize. The distribution of different weights and the time-varying correlation C_t allow us to construct a pool of 110,000 SVIs for the USA (Figure 5) and 130,000 SVIs for Iceland (Figure 7). We then select the best SVI based on its predictive power for non-performing loans for the USA and Iceland. The predictive power of SVI on future credit losses allows the use of the SVI in setting the countercyclical capital buffer.

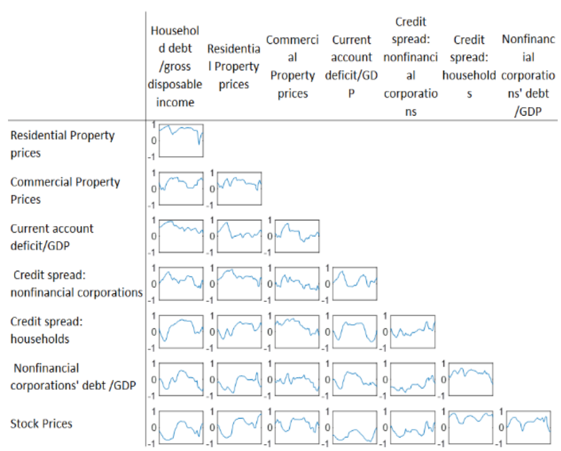
Estimation for the United States

The estimated weights suggest that household debt, property prices (both residential and commercial), the current account deficit, and lending conditions captured by credit spreads provide the main signals for forecasting the materialization of financial risks. These subcomponents collectively account for more than 76 percent of the weights in the composite SVI constructed for the US. Figure 6 shows the evolution of the US SVI along with its decomposition by eight subindexes.

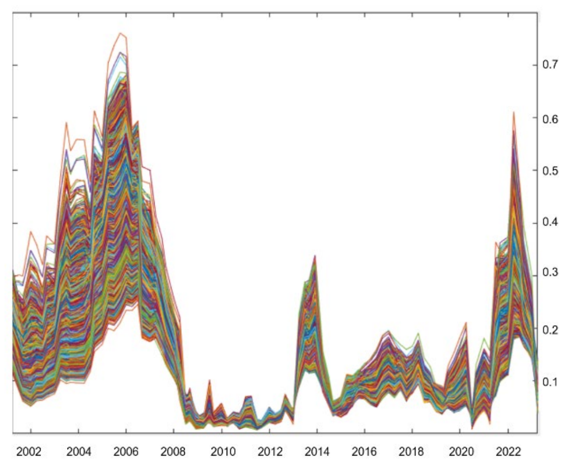
The estimated SVI for the US reflects well the historical dynamics of booms and busts in the US (Figure 6). Following an extended period of cheap credits in the 2000s, with both long-term mortgage rates and the federal funds rate declining to historically low levels by mid-2003, some vulnerabilities started building up in the US economy. These include (i) an acceleration of home price appreciation to double-digit rates; (ii) a dramatic weakening of credit standards in mortgage lending; (iii) an excess of savings held by global institutional investors seeking high-quality and high-yield assets; (iv) loose underwriting standards; (v) a complex and opaque securitization process; and (vi) a speculation based on the presumption that housing prices would continue to increase (Claessens, Kose, and Terrones, 2011).

Figure 5. Estimation of the SVI for the United States

Time Varying Correlation Between Variables

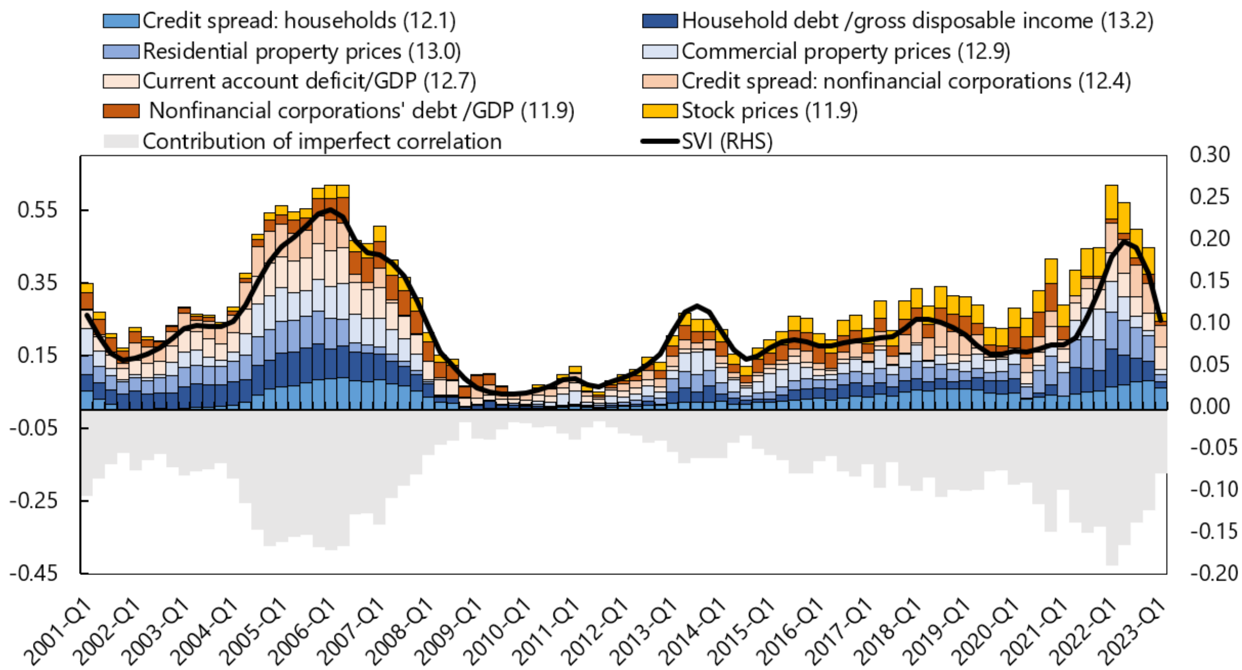


Finding the Best SVI Using Monte Carlo 110,000 Simulation Draws /1



Note: /1 SVI takes values from the interval [0, 1].
Source: Authors' calculations.

Figure 6. USA: Systemic Vulnerabilities Index (SVI) and Decomposition by Eight Subindexes



Note: SVI takes values from the interval [0, 1]. A low value of the SVI indicates the trough of the financial imbalances, while high values indicate the peak of the financial imbalances. Negative contributions indicate an imperfect correlation between variables, whereas near-zero contributions suggest growing correlation in specific areas of financial risk. The numbers in parentheses show the calibrated weight of each variable.
Sources: DNB, Haver Analytics, S&P, and Authors' calculations.

These vulnerabilities or imbalances reached their peak in 2006, as the boom in US housing prices abruptly reversed course. Housing price declines accelerated in 2007, leading to the largest single-year drop in US home sales in more than two decades. The downturn prompts a collapse of the US subprime mortgage industry. The mortgage problems propagated globally as hedge funds and banks around the globe reveal substantial holdings of mortgage-backed securities. These developments led to some key events, including (i) the fire sale of Bear Stearns in March 2008; (ii) the US government seizing control of federal mortgage insurers Fannie Mae and Freddie Mac on September 7, 2008; and later (iii) the collapse of Lehman Brothers on September 15, 2008. They culminated in the 2007–09 GFC.

It is interesting to note that the full swing of the GFC materializes about 6 quarters after the peak of the imbalances predicted by our SVI estimate, in line with the 6-quarter lag in our estimate. The spread from the subprime industry to other sectors could be explained by some feedback effects between house price and credit cycles as disruptions in one market exacerbate weaknesses in the other, owing to collateral constraints and complementarities between credit and housing finance. These feedback effects often exhibit full materialization with some time lag. Overall, during the GFC, residential and commercial property prices, current account deficits, household debt, and lending conditions captured by credit spreads were the main contributors to the estimated SVI and systemic risks (see Figure 6).

The GFC was followed by significant deleveraging as well as stringent regulation and as a result the vulnerabilities highlighted above receded afterward as evidenced by the downward trend of the SVI post-GFC. That period of calm was followed by Brexit and the Chinese selloff that sent stocks tumbling globally (perhaps owing to increased globalization), contributing to a slight increase in the SVI in 2016. However, the impact of these two events was subdued, reflecting the resilience of the US financial sector. Risk accumulation has since been somewhat mild until 2020 when the COVID-19 pandemic hit, leading to supply chain and production disruption and acceleration of vulnerabilities, captured by an upward trend of the SVI over 2021-2022. Household debt, residential property prices, corporate sector lending conditions, and stock prices were the main contributors to the increases in the estimated SVI and systemic risks during the pandemic (Figure 6). The subsequent policy measures have eased the financial and economic risks as evidenced by the downward trend of the SVI over end-2022-2023. Overall, the SVI, as an early indicator of systemic vulnerabilities, performs well and captures all episodes of systemic stress (see Annexes II and III).

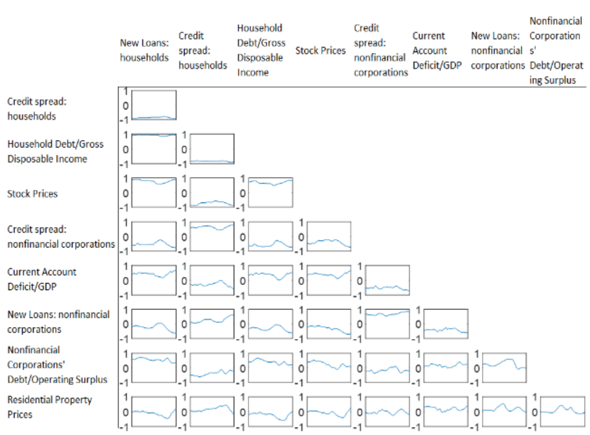
Estimation for Iceland

In the case of Iceland, new loans to households and non-financial corporates, residential property prices, and household debt, are the main drivers for forecasting the materialization of financial risks and account for around 79 percent of the weights in the composition of Iceland's SVI. The estimated SVI for Iceland, along with its contributors, is shown in Figure 8.

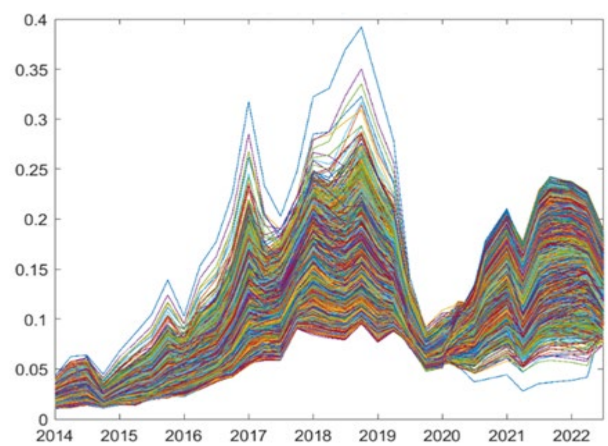
The estimated SVI for Iceland accurately reflects the historical dynamics of macrofinancial developments in the country. The out-of-sample performance further supports the index’s robustness and relevance as a tool for monitoring systemic risk as the dynamics of the index are not sample sensitive, suggesting its fit as new data become available and its predictive power (Annex IV). The index is also closely linked with future risk materialization. For example, as illustrated in Annex IV, the materialization of risk captured by the peak in NPLs in the second quarter of 2020 occurred 6-7 quarters after the peak in SVI in the third quarter of 2018, confirming the SVI predicting power of risk materialization six quarters ahead.

Figure 7. Estimation of the SVI for Iceland

Time Varying Correlation Between Variables

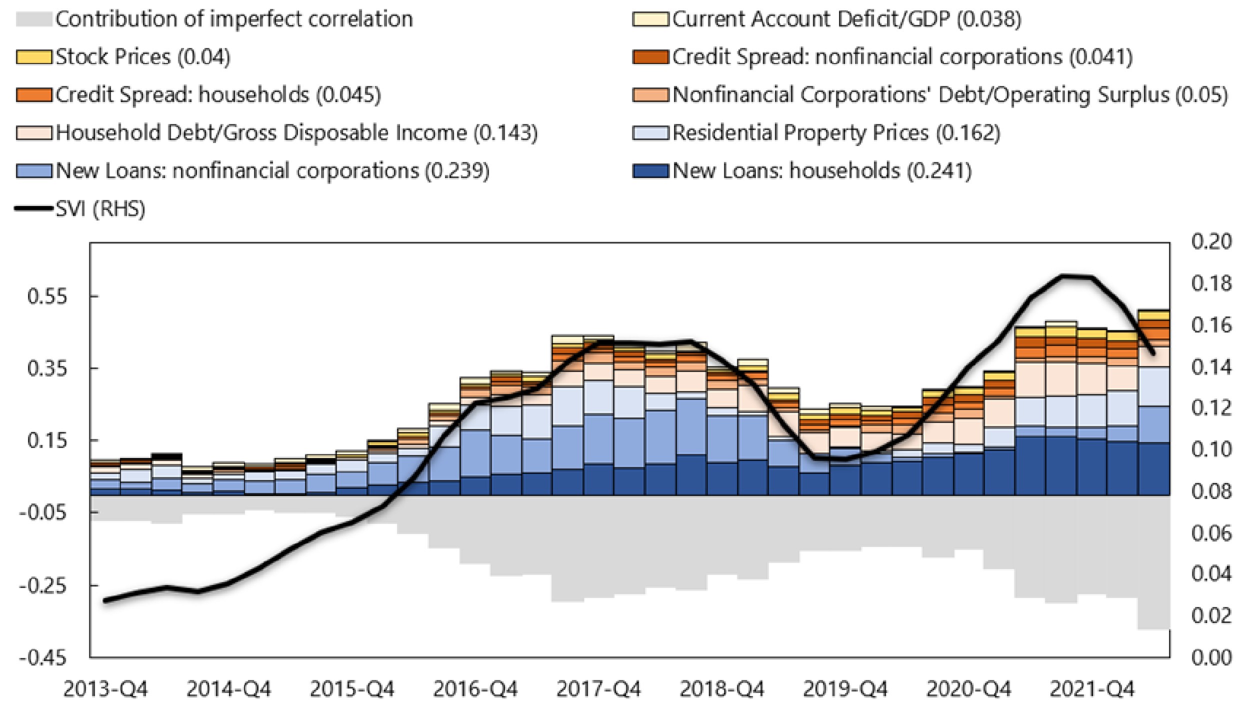


Finding the Best SVI Using Monte Carlo 130,000 Simulation Draws/1



Note: 1/ SVI takes values from the interval [0, 1].
Sources: Authors’ calculations.

Figure 8. Iceland: Systemic vulnerabilities Index (SVI) and Decomposition by Nine Subindexes



The numbers in parentheses show the calibrated weight of each variable.

Note: SVI takes values from the interval [0, 1]. A low value of the SVI indicates the trough of the financial cycle, while high values indicate the peak of the financial cycle. Negative contributions indicate an imperfect correlation between variables, whereas near-zero contributions suggest growing interconnectedness in specific areas of financial risk.

Sources: Central Bank of Iceland, Haver Analytics, and Authors' calculations.

Nevertheless, while the SVI can forecast future changes in NPLs with reasonable accuracy, its predictive properties should be interpreted with caution, as they may change over time. As illustrated in Figure 8, the period from 2017 to 2018 represents an initial expansionary phase of the financial cycle, characterized by sustained economic growth accompanied by increasing optimism and risk tolerance. This expansion was driven by rising demand for mortgage loans, fueled by historically low mortgage rates and increasing property prices. During this period, high real house prices were accompanied by growing private sector debt, particularly corporate debt. The resulting systemic vulnerability peak (late 2017 and early 2018) was followed by a gradual transition to a downward phase, driven by the Central Bank of Iceland's tight macroprudential policies aimed at addressing risks (Figure 13).

Recent data suggest that the financial cycle exhibited signs of accumulating cyclical risks during the COVID-19 crisis. However, systemic risks begun to decline from the local peak reached at the end of 2021 but remained above their historical median level. The recent decrease in the SVI was due mainly to developments in loans to households and a sizeable drop in the correlation between the individual SVI subindices. Net new household loans slowed down significantly, accompanied by declining year-on-year changes in household debt to gross disposable income. In short, Iceland's SVI effectively explains macrofinancial developments in the country.[8]

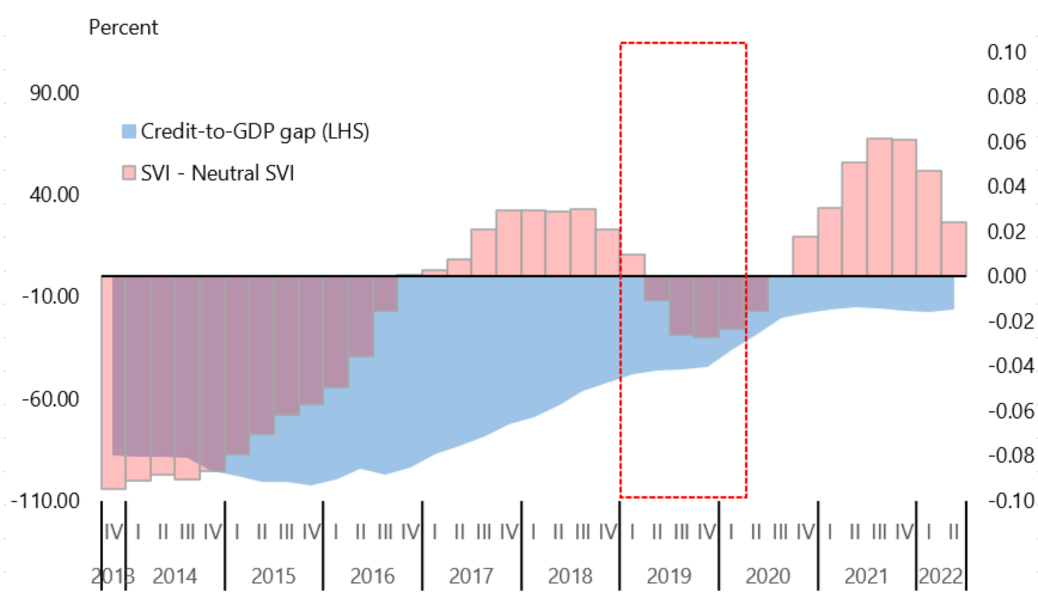
[8] The methodology developed here was applied to Iceland in the context of the country's 2023 Financial Sector Assessment Program and was well received by the authorities. The same also applies to Netherlands.

C. Systemic Vulnerabilities Index Performance Versus Other Indicators

We highlighted above in line with the literature the shortcomings of the existing indicators tracing the relationship between economic activities and financial fluctuations. Here, we focus on the credit-to-GDP gap based on the HP filter given its use by the BCBS in guiding the setting up of CCyB to showcase the superior performance of our SVI indicator. For Iceland, as displayed in Figure 9, the credit-to-GDP gap is by-and-large off in predicting risk accumulation in the Icelandic economy, particularly during the COVID-19 pandemic. It is largely negative over an expanded period of time. For the US, while the credit-to-GDP gap shows some evidence of excess credit in the leading up to the GFC, it could not account for the severity of risk accumulation compared to the SVI and the same pattern holds for the pandemic period (Figure 10). In addition, the gap stays negative for an extended period of time, which is misleading for taking action on a releasable capital buffer (see section IV).

Moreover, we make use of comprehensive econometric techniques to further provide empirical evidence supporting SVI as a superior early warning indicator of NPLs compared to the credit-to-GDP gap (Annex III). Specifically, using the Bayesian Model Averaging (BMA), we evaluate multiple SVI-based model specifications incorporating different autoregressive lag structures and compare them with models based on the credit-to-GDP gap. NPL forecasts with SVI-based models consistently deliver lower RMSEs compared to the credit gap-based model. The best-performing SVI model also achieves significantly better results in time-varying parameter models estimated via the Kalman filter, confirming robustness to evolving macro-financial dynamics. Diebold-Mariano tests validate the statistical significance of these differences in forecast performance. Across all specifications, samples, and evaluation techniques, the SVI demonstrates superior predictive power without signs of overfitting, establishing it as a reliable and forward-looking indicator of systemic risk (Annex III).

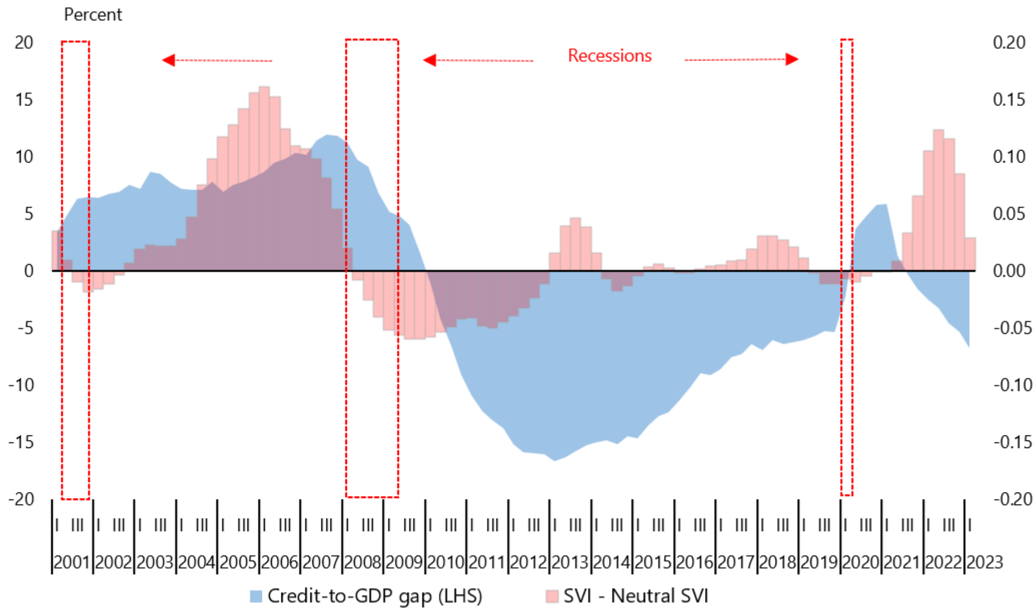
Figure 9. Iceland: Systemic Vulnerabilities Index and Credit-to-GDP Gap



Note: The blue shaded region represents the credit-to-GDP gap using a Hodrick-Prescott one-sided filter with λ=400,000. SVI-Median (SVI) represents the difference between the systemic vulnerabilities index and its risk-neutral level. The dashed red bars denote periods of economic contraction.

Sources: Central Bank of Iceland, and Authors' calculations.

Figure 10. US: Systemic Vulnerabilities Index and Credit-to-GDP Gap



Note: The blue shaded region represents the credit-to-GDP gap using a Hodrick-Prescott one-sided filter with λ=400,000. The dashed red bars denote periods of recession as dated by the National Bureau of Economic Research: March 2001-November 2001, December 2007-June 2009, and February 2020-April 2020. SVI-Median (SVI) represents the difference between the systemic vulnerabilities index and its risk-neutral level.

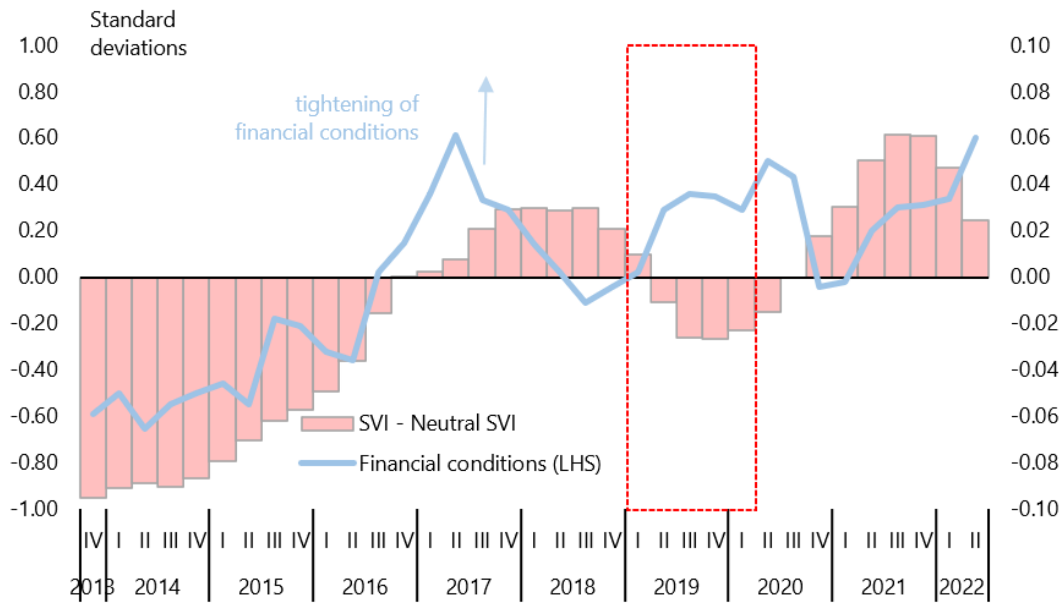
Sources: BIS data portal, Federal Reserve Board, and Authors' calculations.

V. SVI and Financial Conditions

We also investigate the relationship between financial conditions–defined as how easily money and credit flow through the economy via financial markets and the SVI. As can be seen in both the Iceland and the US cases (Figures 11 and 12), a tightening of the financial conditions is associated with less accumulation of vulnerabilities or risks in the economy.

The correlation between Iceland SVI and the Financial Conditions Index is negative and statistically significant, with a Pearson correlation coefficient of - 0.75 based on 35 observations. A standard t-test rejects the null hypothesis of no correlation at conventional significance levels. The relationship strengthens further when the SVI is lagged, with the correlation reaching - 0.79 at a four-quarter lag, suggesting that loosening financial conditions tends to precede increases in systemic vulnerabilities.

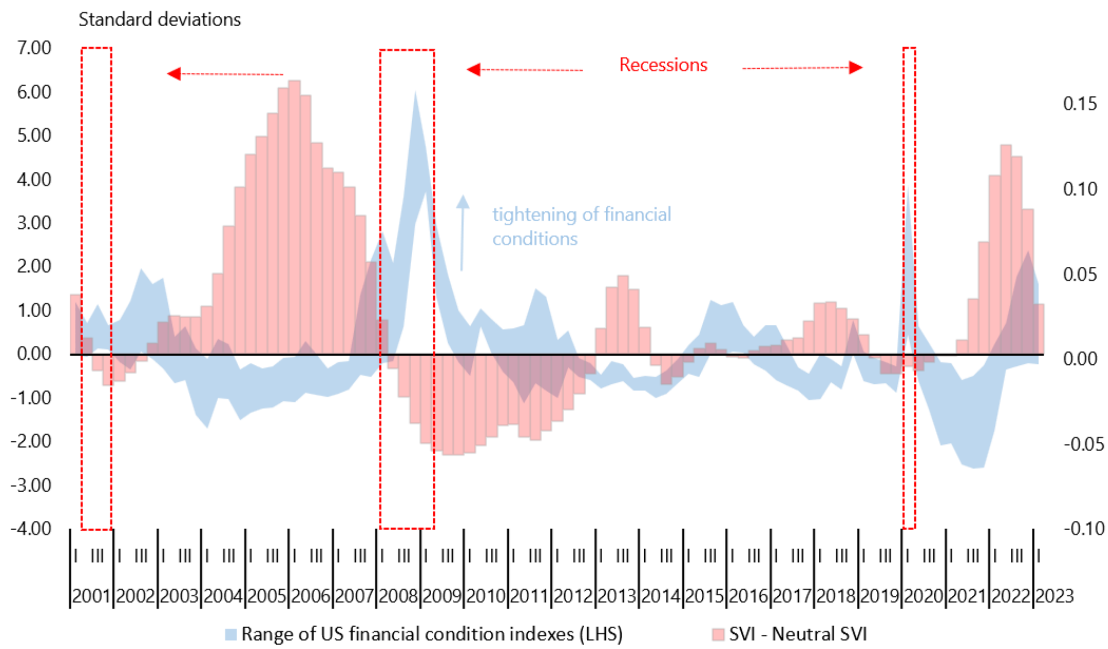
Figure 11. Iceland: Systemic Vulnerabilities Index and Financial Conditions



Note: SVI-Median (SVI) represents the difference between the systemic vulnerabilities index and its risk-neutral level. The dashed red bars denote periods of economic contraction.
Sources: Central Bank of Iceland, and Authors' calculations.

A similar pattern is observed for the US where the correlation between the SVI and the Financial Conditions Index (FCI) is negative and statistically significant, with a Pearson correlation coefficient of - 0.50 based on 89 observations. The relationship becomes stronger when using changes in FCI and lagging the SVI, with the correlation increasing steadily as the lag increases and reaching a maximum of - 0.66 at a four-quarter lag. This pattern also suggests that, loosening financial conditions tends to lead to rising systemic vulnerabilities, corresponding to a gradual increase in SVI.

Figure 12. US: Systemic Vulnerabilities Index and Financial Conditions



Note: The blue shaded region represents the range of 7 standardized financial conditions indexes developed by Bloomberg, Goldman Sachs, and the Federal Reserve Banks of Chicago, St. Louis, Kansas City, the Federal Reserve Board, and the IMF. The upward arrow indicates the direction of the tightening of financial conditions. The dashed red bars denote periods of recession as dated by the National Bureau of Economic Research: March 2001-November 2001, December 2007-June 2009, and February 2020-April 2020. SVI-Median (SVI) represents the difference between the systemic vulnerabilities index and its risk-neutral level.
Sources: Ajello at. el. (2023), IMF GFSR April 2017, and Authors' calculations.

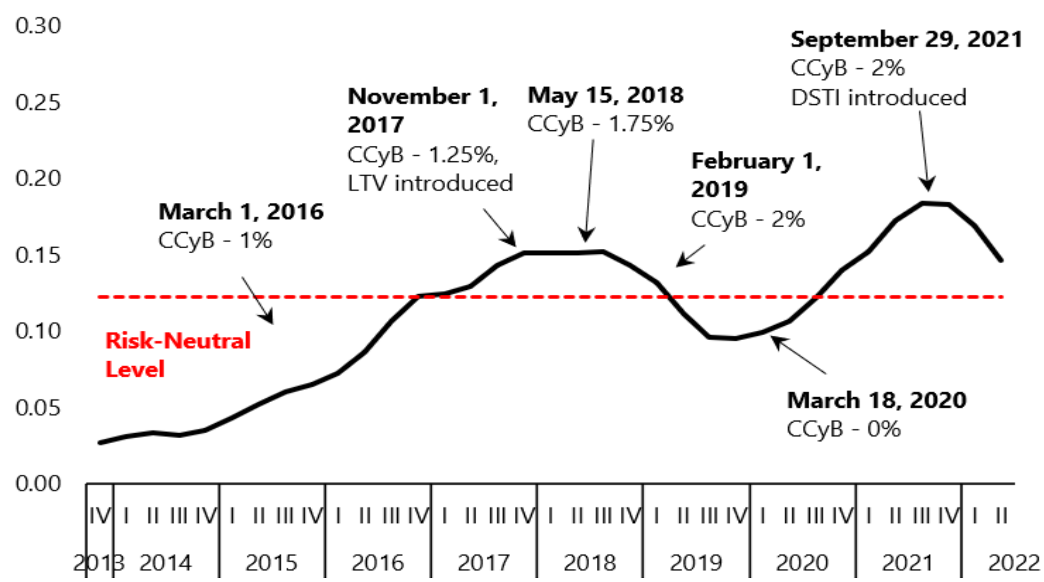
VI. Macroprudential Policy Implications

A. SVI and Macroprudential Policy: An Overview

The concept and estimation of the SVI sheds light on both the build-up and reduction phases of financial imbalances and help identify emerging risks. The process of monitoring and assessing the buildup of systemic risk offers the opportunity to proactively deploy macroprudential policy to rein in emerging vulnerabilities or to take measures to protect against risks crystallizing. Depending on the extent of risk build up, well calibrated macroprudential policy tools could be operationalized in practice. The SVI can help understand sector-specific risks by specifically quantifying sectoral contributions to systemic risks and vulnerabilities such as those arising from households, corporates, and commercial and residential real estate. While policymakers typically rely on dedicated indicators as described in IMF (2014) to inform the calibration of sectoral tools, the SVI provides a valuable complement by capturing how selected sector-specific risks contribute to broader systemic vulnerabilities. The SVI could be useful in signaling the required actions to contain sector-specific risks by indicating the need for a change in the direction of sector-specific macroprudential tools, especially when risks from specific sectors are continuously amplifying and also providing valuable information for establishing an appropriate CCyB rate beyond the neutral rate.

For example, in the case of Iceland, borrower-based measures such as LTV and DSTI were introduced in November 2017 and September 2021 as vulnerabilities were building up via rapid growth in lending, household debt, and residential housing prices (Figure 8). Similarly, the dynamic of raising and lowering bank-based measures such as the CCyB mimics respectively the risk buildup and risk deceleration phases as captured by the estimated SVI and illustrated in Figure 13. More specifically, the Central Bank of Iceland's macroprudential policy, which relies on a comprehensive assessment of vulnerabilities, is consistent with risk accumulation or reduction as observed in the SVI (Figure 13) and underscores the SVI's capability to assess the economy's position within the financial cycle. In this context, the SVI may serve macroprudential purposes more effectively, providing policymakers with a valuable framework for assessing financial imbalances and designing macroprudential policy effectively.

Figure 13. Iceland: Systemic Vulnerabilities Index and CCyB Calibrated Rates



Sources: Central Bank of Iceland, and Authors' calculations.

Below, we explain how the SVI could guide policymakers in deciding when to initiate changes to the CCyB and by how much.

B. CCyB Setting Using SVI

According to the Basel III framework (BCBS, 2010), banks must meet the CCyB with common equity tier 1 capital. While the activation and level of the CCyB are a national discretion, the framework includes mandatory international reciprocity up to levels of 2.5 percent of risk-weighted assets to enhance the effectiveness of the CCyB and ensure a level playing field, where the CCyB applies to both domestic and foreign banks within a jurisdiction. However, jurisdictions can impose a CCyB higher than 2.5 percent.

The rationale behind determining the CCyB rate is to align the size of the buffer with the potential losses the entire banking sector might encounter during future financial stress. In order to offer guidance for setting CCyB using SVI we follow an approach similar to the BCBS (2010) guidance based on the credit-to-GDP gap. For example, according to the BCBS, when the credit-to-GDP ratio is 2 percentage points or less above its long-term trend, the buffer add-on is set at zero percent of risk-weighted assets (RWA). When the credit-to-GDP ratio exceeds its long-term trend by 10 percentage points or more, the buffer add-on is set at 2.5 percent. When the credit-to-GDP ratio is between 2 and 10 percentage points of its trend, the buffer add-on will vary linearly between 0 and 2.5 percent. This implies for example a buffer of 1.25 percent when the credit-to-GDP gap is 6 percentage points or halfway between 2 and 10 percentage points. The threshold estimates based on historical banking crises find that these lower and upper thresholds do not vary significantly across jurisdictions (BCBS, 2010; Drehmann and Tsatsaronis, 2014; ESRB, 2014).

Table 1. Jurisdictions with Early Adopters of a Positive Neutral Rate for the CCyB

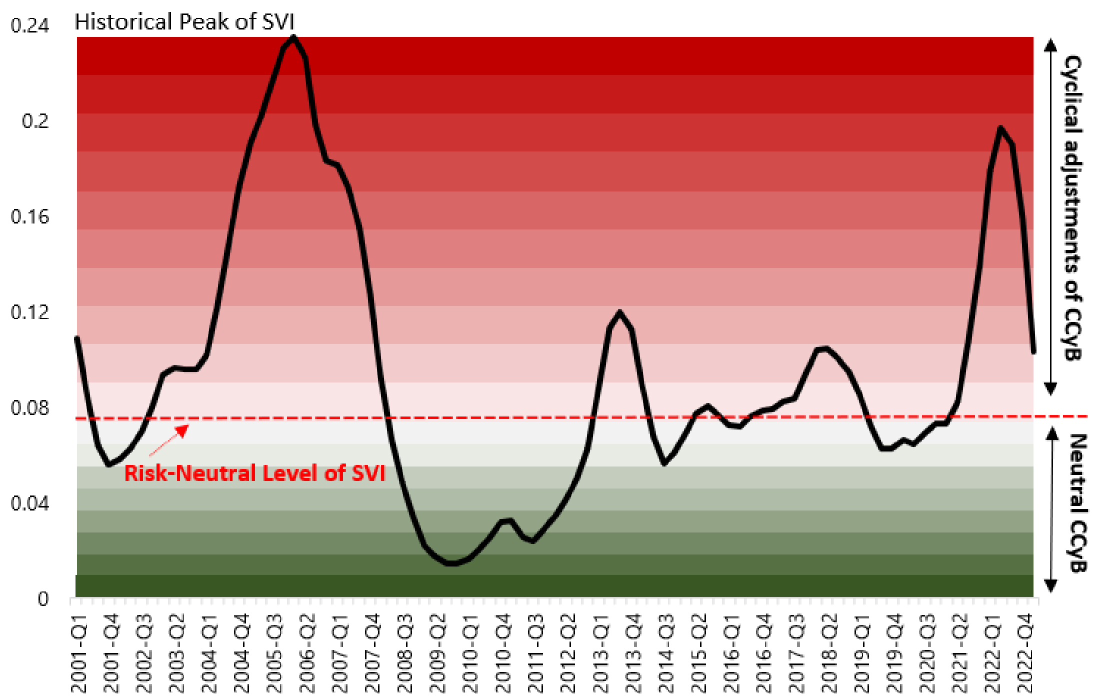
Jurisdictions	Target positive neutral rate	Effective date for target positive neutral rate
Australia	1.00%	1-Jan-23
Hong Kong SAR	1.00%	1-Apr-24
Netherlands	2.00%	31-May-24
South Africa	1.00%	1 January 2026
Spain	1.00%	1-Oct-26
Sweden	2.00%	22-Jun-23
United Kingdom	2.00%	5-Jul-23
Cyprus	1.00%	2-Jun-24
Czech Republic	1.00%	23-May-19
Greece	0.50%	1 October 2026 (0.25% effective from 1 October 2025)
Hungary	1.00%	1-Jul-25
Ireland	1.50%	7-Jun-24
Estonia	1.00%	7-Dec-22
Latvia	1.00%	18-Jun-25
Lithuania	1.00%	1-Oct-23
Poland	2.00%	24 September 2026 (1.0% effective from 24 September 2025)
Slovenia	1.00%	1-Jan-25

Note: In cases where the positive neutral rate was set more than once, the effective date for the target positive neutral rate refers to the most recent date when the positive neutral rate is to be met.
Source: Basel Committee on Banking Supervision (2024).

As the COVID-19 experience highlighted the benefits of releasable capital buffers, there is an international momentum toward increasing the CCyB. In October 2022, the Basel Committee announced that it sees benefits in countries adopting a positive cycle-neutral CCyB. Similarly, the revised Basel Core Principles (Principle 16), published in April 2024, calls for supervisors to be able to require banks to maintain releasable capital buffers. Accordingly, as reported by the Basel Committee (Table 1), several countries have adopted a positive cycle-neutral CCyB (BCBS, 2024). Based on these developments, we set the CCyB buffer add-on to λ percent of RWA (the neutral level, which could be positive) when the credit-to-GDP ratio is 2 percentage points or less above its long-term trend.

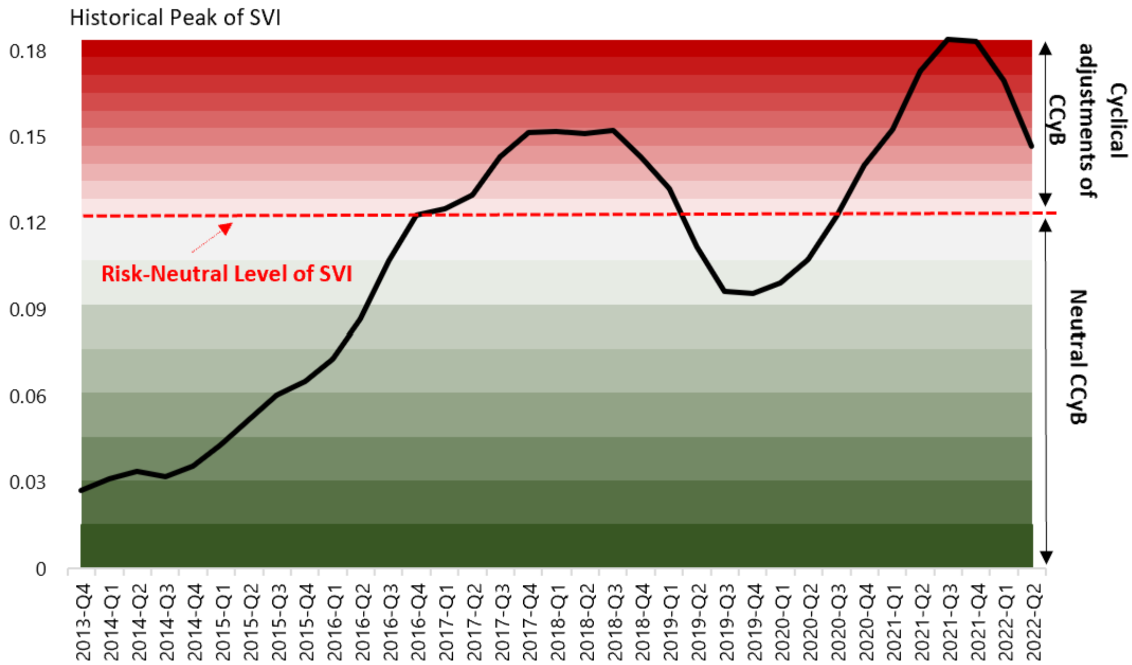
Our approach assumes that the neutral level of cyclical risks an institution is willing to tolerate without the need to take any mitigating actions corresponds to the mode of the Kernel Density Estimate (KDE) applied to the SVI (Annex V). This represents an "equilibrium" situation where the financial cycle is neither significantly subdued nor displaying any significant cyclical risks. Similar to the BCBS approach, when the SVI is less or equal to the mode of the KDE applied to the SVI or neutral level, the buffer add-on will be set at zero. The maximum observed SVI value from its historical peaks could correspond to the maximum CCyB target rate (Figure 14 and 15).

Figure 14. Graphical Illustration of Cyclical Adjustment of CCyB Based on US SVI



Source: Authors' calculations.

Figure 15. Graphical Illustration of Cyclical Adjustment of CCyB Based on Iceland SVI



Source: Authors' calculations.

For SVI values between its neutral level defined by its KDE's mode and its historical maximum value, the mapping between SVI values and CCyB rates could be linearly defined by the line passing through the two points: (A($SVI_{neutral}$, λ), B($Max(SVI_{Peaks})$, λ+2.5)). To sum up, the relationship between SVI and CCyB values will be defined by a mapping function m[9] such that:

$$m(SVI_t) = \begin{cases} \lambda, & if\ SVI_t < SVI_{neutral} \\ \dfrac{2.5(SVI_t - SVI_{neutral})}{Max(SVI_{Peaks}) - SVI_{neutral}} + \lambda, & if\ SVI_{neutral} \leq SVI_t < Max(SVI_{Peaks}) \\ \lambda + 2.5, & if\ SVI_t = Max(SVI_{Peaks}) \end{cases} \quad (4)$$

Thus, the CCyB buffer add-on rate will be λ percent for SVIs below the neutral level, and a linearly increasing rate ranging from λ percent to λ+2.5 percent of risk-weighted assets for SVIs between the neutral and maximum levels.

For instance, the SVI for Iceland in Q2 2022 is 0.15, the historical maximum of the SVI is 0.18, and the neutral is 0.12 (Figure 15). Assuming the neutral rate to be zero and applying the rule for the releasable capital buffer in Iceland's case for Q2 2022 would result in a buffer rate of around 1.25 percent $(i.e. \frac{2.5}{0.18-0.12}(0.15 - 0.12)$.

This approach allows the CCyB rate to be set in a manner that covers potential unexpected credit losses related to cyclical risks, which may materialize in the event of a future shock.

[9] Given two points on the line, (x_1, y_1) and (x_2, y_2), we can determine the equation of the line in the form $y = ax + b$. To find this equation, we first calculate the slope (a) $a = \frac{y_2 - y_1}{x_2 - x_1}$. Next, we find the y-intercept b in determined using the coordinates of one of the points, say (x_1, y_1) : $b = y_1 - ax_1$. With the slope and y-intercept calculated, we can express the equation of the line as: $y = ax + b$.

Despite this suggested approach, it goes without saying that policymakers should exercise judgment, taking into account country specific circumstances. In practice, decisions on buffer calibration typically draw on a range of analytical tools and indicators to ensure a well-rounded assessment of systemic risk. Ultimately, the calibration of the CCyB would depend, among other factors, on policymakers' risk aversion, each country's risks and vulnerabilities, and the banking system's overall capital strength.

CCyB activated at a level beyond the neutral level in the build-up phase should be released during the financial stress phase (IMF, 2014 and BCBS, 2010). In a scenario where an increase in systemic risk is followed by incipient financial stress, the CCyB should be released promptly so that banks can absorb losses while reducing the risk of a credit crunch.

VII. Concluding Remarks

The ultimate objective of macroprudential policy is to preserve financial stability, by limiting the build-up of vulnerabilities, and by increasing resilience to shocks (IMF, 2013). The reinforcement of macroprudential tools through the introduction by the BCBS in 2010 of the CCyB as part of Basel III reforms, drawing on the lessons from the GFC, helped ensure a more resilient banking system. Some elements of the CCyB remain at the discretion of national jurisdictions, and several jurisdictions are making use of this discretion by adopting positive neutral CCyB. However available toolkits to monitor and analyze systemic risk have gaps, underpinning the need for appropriate measurement of systemic vulnerabilities. Moreover, the approaches used by jurisdictions in setting their CCyB beyond the neutral buffer rates vary and are not systematic. This paper contributes to this debate by making two main contributions.

First, we propose an enhanced composite indicator, the Systemic Vulnerabilities Index (SVI), which captures the buildup of vulnerabilities. Our index is built on an innovative approach that uses optimal aggregation of the subindices, and without imposing exogenous constraints. Specifically, making use of the Principal Component Analysis (PCA) for a broad set of relevant input variables, we determine their relative importance in contributing to the SVI. Subsequent use of Monte Carlo simulation techniques allows us to select the optimal SVI that best predicts future losses. The proposed SVI captures both the time and sectoral dimensions of risks and sheds light on the position of the economy in the financial cycle. We provide evidence showing a superior performance of the SVI, compared to the credit-to-GDP gap, in documenting risk accumulation. We investigate the relationship between our composite and financial conditions and provide evidence of a negative correlation between the two, whereby a loosening of financial conditions is associated with more accumulation of imbalances. Our analysis helps identify quantitatively sectoral contributions to systemic risks and vulnerabilities—specifically, how selected sector-specific risks contribute to broader systemic vulnerabilities.

Second, we provide a framework that uses the SVI to set the CCyB beyond its neutral level. Specifically, similar to the Basel buffer guide (BCBS, 2010) that identifies the credit-to-GDP gap as a key indicator for tightening/loosening of the CCyB, we propose a mapping of how the SVI can be used to help determine the timing of increasing CCyB beyond neutral buffer rates as well as on the magnitude of such increases.

Annex I. Input Variables

Priority Order (Highest to Lowest)	Table A1: Iceland SVI Input Variables	Transformation
1	New bank loans to households	an annual moving sum of new loans, bn Krona
2	New bank loans to non-financial corporations	an annual moving sum of new loans, bn Krona
3	Residential Property prices	y-o-y change in house price index, %
4	Household debt/gross disposable income	y-o-y difference, p.p.
5	Non-financial corporations' debt/gross operating surplus	y-o-y difference, p.p.
6	Credit spread: households	(-1) * Spread between the rate on new loans to households and 3M interbank rates
7	Credit spread: nonfinancial corporations	(-1) * Spread between the rate on new loans to NFCs and 3M interbank rates
8	Stock prices	Stock price index
9	Current account deficit/GDP	*(-1), %

Sources: Central Bank of Iceland and Haver Analytics.
Note: All variables were found to be stationary based on the Augmented Dickey-Fuller (ADF) test after transformation and Gaussian Kernel normalization.

Priority Order (Highest to Lowest)	Table A2: US SVI Input Variables	Transformation
1	Household debt/gross disposable income	y-o-y difference, p.p.
2	Residential property prices	y-o-y change in FHFA house price index, %
3	Commercial property prices	y-o-y change in commercial real estate price index, %
4	Current account deficit/GDP	*(-1), %
5	Credit spread: nonfinancial corporations	(-1) * Spread between the rate on new commercial and industry loans and 3M T-bill yields, %
6	Credit spread: households	(-1) * Spread between the rate on new mortgage loans and 3M T-bill yields, %
7	Non-financial corporations' debt/GDP	y-o-y difference, p.p.
8	Stock prices	Standard & Poor's 500 Stock Price Index, three- month average

Sources: DNB, S&P, FRED and Haver Analytics.
Note: All variables were found to be stationary based on the Augmented Dickey-Fuller (ADF) test after transformation and Gaussian Kernel normalization.

Table A3. US: Regression Results for The First Principal Component, (standard deviations from the mean)

Intercept	-3.8***
	(0.01)
Household debt /gross disposable income	1.8***
	(0.01)
Residential Property prices	1.8***
	(0.01)
Credit spread: households	0.9***
	(0.01)
Credit spread: nonfinancial corporations	1.1***
	(0.01)
Nonfinancial corporations' debt /GDP	-0.6***
	(0.00)
Commercial Property Prices	1.3***
	(0.00)
Current account deficit/GDP	1.2***
	(0.01)
Stock Prices	0.1***
	(0.01)
R-Squared	0.9
No. observations	89

Standard errors are reported in parentheses. *, **, *** indicates significance at the 90%, 95%, and 99% level, respectively.

Annex II. List of Possible US Financial Stress Events since 2001

Date	Financial Stress Event	Description
July 30, 2002	Sarbanes–Oxley Act	Regulatory civil and federal accounting law passed in response to Enron and WorldCom accounting scandals.
June 20, 2007	Bear-Stearns 1	Two Bear-Stearns mortgage-focused hedge funds collapse
March 14, 2008	Bear-Stearns 2	The Federal Reserve Bank of New York makes a $25 billion loan to facilitate the JP Morgan purchase of Bear-Stearns
September 12, 2008	Lehman Brothers 1	Friday before Lehman Brothers fails.
September 15, 2008	Lehman Brothers 2	Lehman Brothers declares bankruptcy.
September 16, 2008	Lehman Brothers 3	Reserve Primary Fund (a money market fund) "breaks the buck," and the US government lends AIG $85 billion.
April 18, 2011	US downgrade and euro debt 1	S&P warns that US debt might be downgraded if the debt ceiling is reached, and long-term fiscal plans are not made.
August 5, 2011	US downgrade and euro debt 2	S&P downgrades US debt from AAA to AA+.
August 24, 2015	Chinese sell-off 1	Shanghai Composite index falls 8.48 percent.
January 4, 2016	Chinese sell-off 2	Shanghai Composite Index falls 6.9 percent.
January 7, 2016	Chinese sell-off 3	Shanghai Composite index falls 7 percent within 30 minutes of opening.
June 24, 2016	Brexit	Day after the British voted to exit the European Union.
September 16, 2020	Repo disruption	The repo market experiences a shortage of liquidity, causing rates in US short-term funding markets to spike as high as 5 percent.
February 25, 2020	COVID-19	The S&P 500 falls 3.03 percent in response to the COVID-19 news along with a large oil price shock, starting a long period of high volatility in the market along with a general decline in the indices.
Source: Craig, Ben R. 2020.		

Annex III. SVI Performance Versus Credit-to-GDP Gap

To compare the predictive performance of the proposed SVI against the credit-to-GDP gap in forecasting NPLs (Nonperforming loans to total gross loans), we employ a comprehensive, multi-method evaluation framework using US data.[10] Specifically, we consider multiple models and we make use of Bayesian Model Averaging (BMA) to account for model uncertainty, Kalman filtering to capture time-varying relationships between the explanatory variables (SVI, credit-to-GDP gap) and the dependent variable NPLs. Based on out-of-sample estimations, the SVI consistently outperforms the credit-to-GDP gap forecast accuracy, as measured by root mean squared error —RMSE. The outperformance is statistically validated using Diebold-Mariano tests. In addition, a focused evaluation of the five years (2006-2010) surrounding the Global Financial Crisis (GFC) shows that the SVI displays significantly more accurate and timely forecasts than the credit-to-GDP gap in anticipating the onset of the 2007-2009 systemic stress as explained below.

Bayesian Model Averaging (BMA)

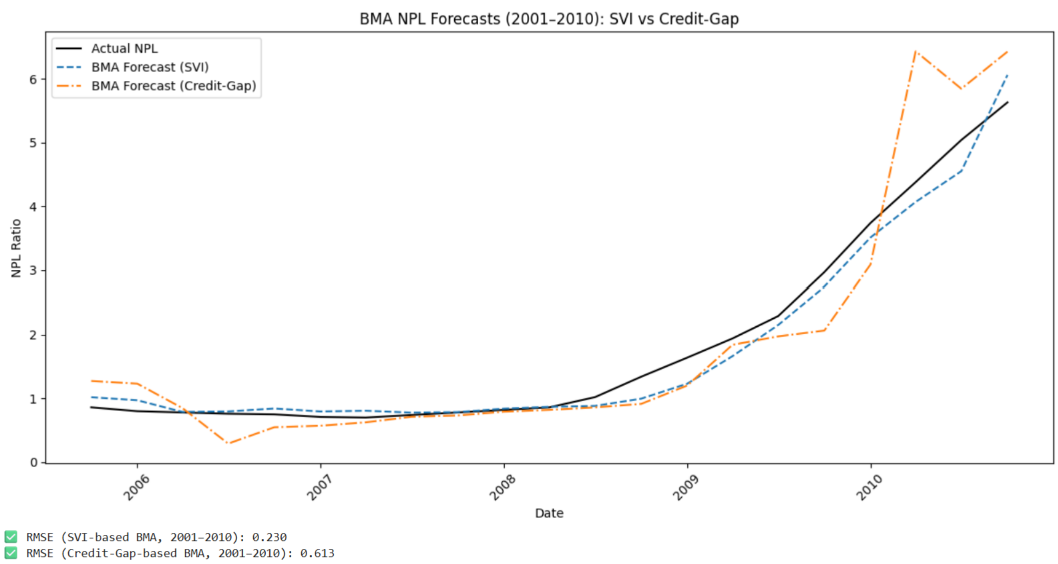
This approach accounts for model uncertainty by averaging over many plausible regression specifications and estimating posterior inclusion probabilities (PIPs) which indicate the probability that each explanatory variable helps explain variations in NPLs. The BMA allows us to rank competing models by their predictive relevance and to quantify the individual contributions of the SVI and the credit-to-GDP gap as explanatory variables of NPLs. We tested a range of forecasting specifications using both the SVI and the credit-to-GDP gap to predict the NPL ratio six quarters ahead, incorporating different autoregressive lags of NPLs (lags -6, -7, -8, and -9), as well as various combinations of these lags. To ensure robustness, we evaluated all the corresponding 14 alternative model specifications (7 with SVI and 7 with credit-to-GDP gap) combining different lag structures with either the SVI or the credit-to-GDP gap. Posterior model weights, derived from inverse forecast RMSEs, allow us to probabilistically rank the SVI-based models and the credit-to-GDP gap models based on their predictive accuracy. This evaluation demonstrates that SVI-based models not only achieve the lowest average forecast errors but also consistently receive the highest posterior inclusion probabilities. For instance, the average forecasted RMSE for the 7 SVI-based models is approximately 0.8, compared to 1.4 for the 7 credit-to-GDP gap models. These RMSEs are based on a fixed 20-quarter training rolling window forecast performance in an iterative process where each model is re-estimated using a fixed-size window of historical data and the estimated model is subsequently used to generate one-step-ahead forecasts. This rolling forecast approach offers a realistic evaluation of the model's predictive performance in a real-time setting.

Overall, out of the 14 models considered, the best-performing model (based on both forecast RMSE and PIP) for the SVI-based specification, achieves an RMSE of 0.7 and a PIP of 64 percent. In contrast, the best Credit-gap-based model has a higher RMSE of 1.2 and a lower PIP of approximately 36 percent. To formally assess whether the difference in forecast accuracy is statistically significant, we conducted a Diebold-Mariano (DM) test comparing the two models (the best SVI-based BMA model, and the best Credit-gap-based BMA model). The results confirm the superiority of the SVI-based BMA model, with a statistically significant difference in forecast accuracy ($t = -2.4$, $p = 0.02$), indicating that it provides more accurate and reliable forecasts than the Credit-gap-based alternative.

[10] Iceland's time series is somewhat too short for a robust empirical analysis.

A focused sub-period analysis of the five years (2006-2010) surrounding the GFC allows us to assess forecast performance under conditions of systemic stress. Specifically, we consider the estimated model over the period 2001–2005 leading up to the crisis and use it to forecast NPLs over 2006-2010. This exercise serves as a natural test for model robustness. As shown below (Annex III Figure 1), the BMA model incorporating the SVI significantly outperforms the Credit-gap-based model. The SVI-based BMA model not only generates more accurate forecasts (RMSE = 0.2 for SVI vs. 0.6 for Credit gap), but it also better captures the timing and severity of the spike in NPLs during 2008–2010. This further reinforces the case for using SVI-based models as early warning tools in macroprudential surveillance.

Annex III Figure 1. NPL Forecasts Based Alternatively on SVI and Credit-to-GDP Gap



Sources: IMF Financial Soundness Indicators and authors' calculations.

Rolling Forecast Evaluation

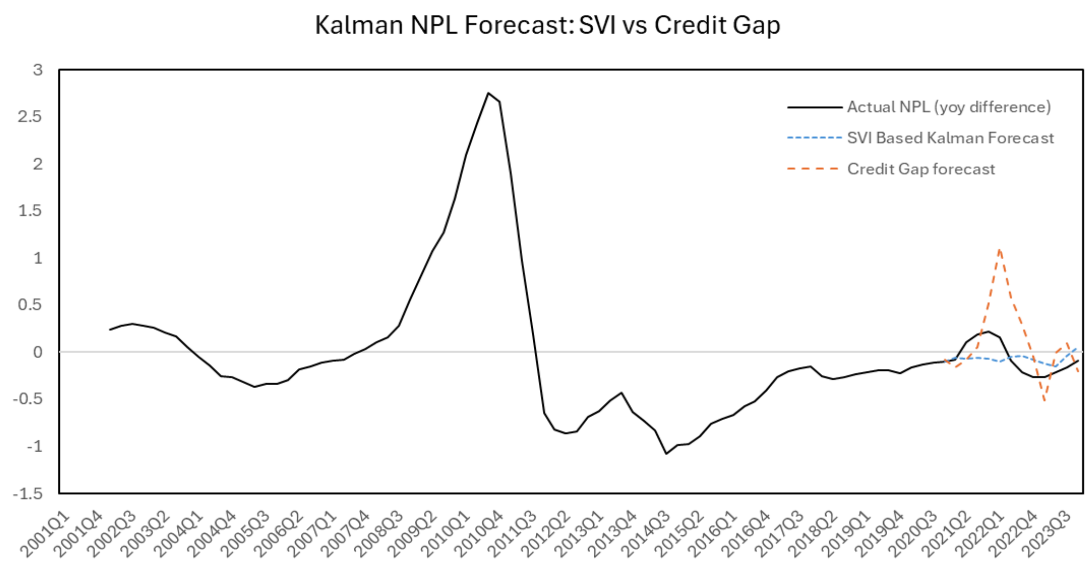
Notice that over the study period (2001-2023), NPLs reached its peak in 2010. Considering the best performing model for each predictor (SVI vs Credit-to-GDP gap), we also simulate real-time forecasting conditions using rolling 20-quarter windows respectively over the period 2001-2010 leading up to the peak in NPLs and over the period 2011-2023 post the 2010 peak in NPLs. At each step, models are re-estimated using only past data, and out-of-sample forecasts are used to generate future NPLs. The SVI-based BMA model achieved an average RMSE of 0.8 during the period 2001–2010 leading up to the peak in NPLs in 2010. For the post NPLs' peak period it stands at 0.5. In comparison, the credit-gap-based BMA model underperforms across all periods, with RMSEs of 1.2 over 2001–2010, and 0.6 over 2011–2023. The SVI consistently outperforms the credit-to-GDP gap in every sub-period, with the performance gap particularly large during the period leading up to the peak in NPLs, highlighting the SVI's early-warning capabilities. These stable and lower RMSEs regardless of the study period further confirm that the SVI is not overfitting.

Kalman Filtering (Time-Varying Parameter Models)

Kalman filtering is used to estimate time-varying coefficients on the predictors in the NPL forecast equations. We apply this approach to the best-performing SVI and Credit-gap-based BMA model specifications. Forecast performance is evaluated using one-step-ahead predictions, with the last 20 percent of observations reserved for out-of-sample validation. Specifically, the final 20 percent of the dataset is set aside for out-of-sample validation and not used in model estimations. One-step-ahead forecasts are generated recursively, with each prediction based solely on information available up to the preceding period, thereby replicating a real-time forecasting environment.

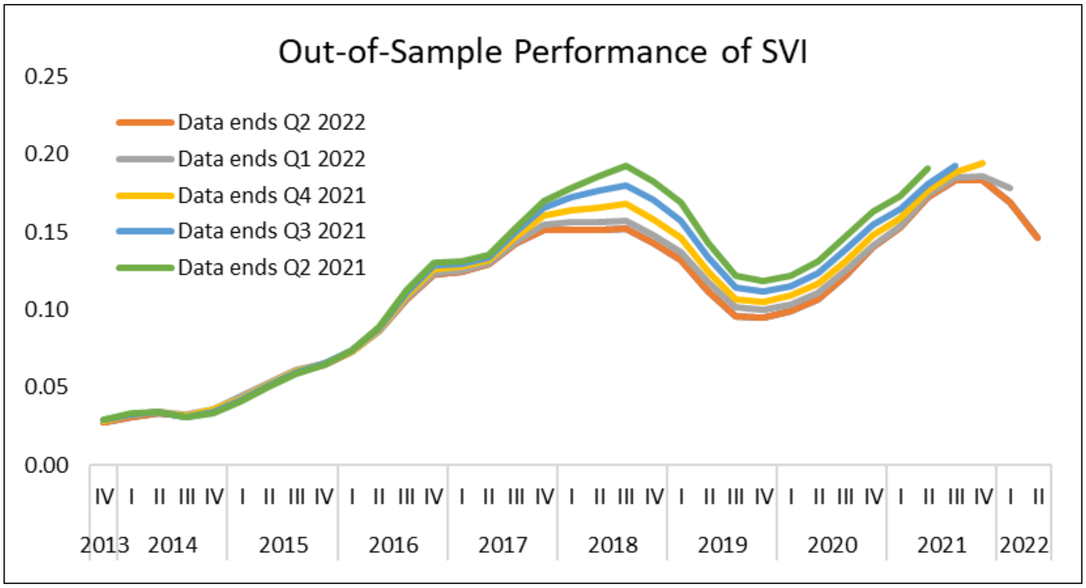
The results again confirm the superior forecasting power of the SVI specification. The SVI-based Kalman model achieves an out-of-sample RMSE of 0.1, while the Credit-gap-based Kalman model records a higher RMSE of 0.4. A DM test comparing the squared forecast errors between the two Kalman models yielded a statistically significant result (t = -2.7, p = 0.02), confirming that the SVI-based model provides more accurate predictions even when accounting for evolving dynamics (Annex III, Figure 2). These findings further reinforce the BMA results and highlight the robustness of the SVI as a leading indicator of NPL risk across both static and time-varying model frameworks.

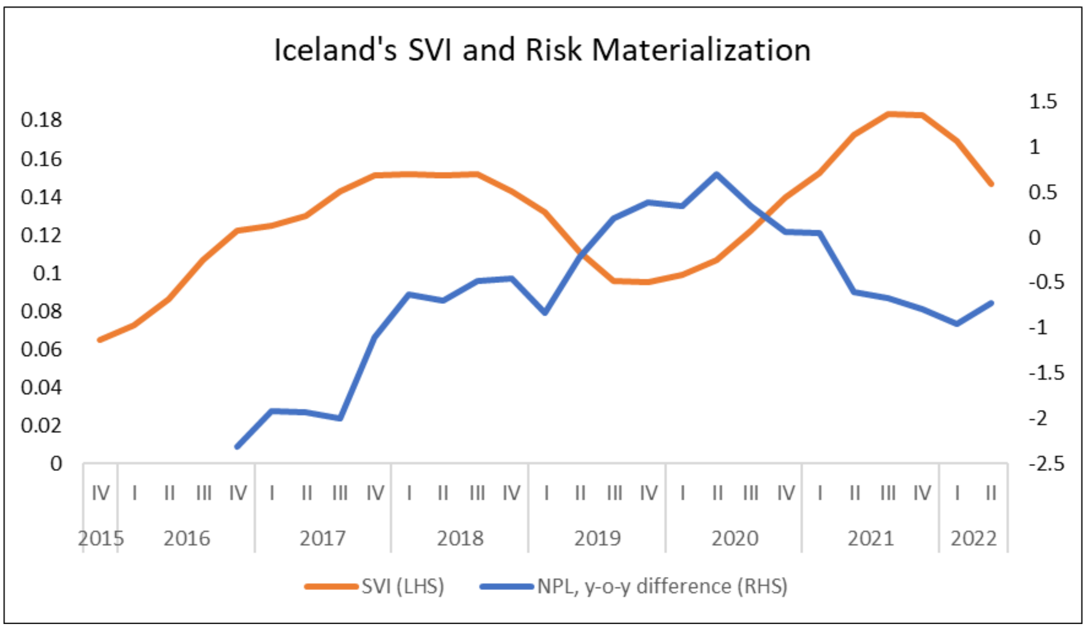
Annex III Figure 2. Kalman NPL Forecast: SVI vs Credit Gap



Sources: IMF Financial Soundness Indicators and authors' calculations.

Annex IV. Out-of-Sample Performance of the SVI and Risk Materialization for Iceland

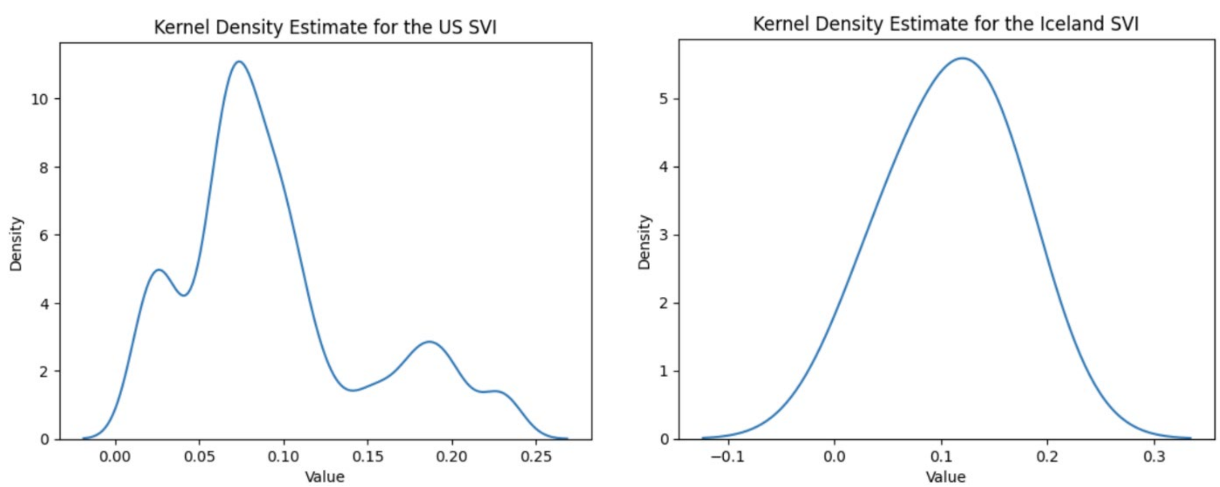




Source: Authors' calculations.

Annex V. Kernel Density Estimates

A Kernel Density Estimate (KDE) was applied to define the risk-free thresholds for the Systemic Vulnerability Indices (SVIs), with optimal bandwidths for each country determined through cross-validation. Cross-validation, a technique for assessing the performance of statistical models, was used to select the bandwidth that minimizes the difference between the estimated and true data distribution. In cross-validation, the data is divided into several subsets. The KDE model is trained on one subset, and then tested on the remaining subsets. This process is repeated multiple times, ensuring that the selected bandwidth performs well across all subsets and generalizes effectively to new, unseen data. This helps in choosing the bandwidth that gives the most accurate estimate of the data's density. The mode of the estimated US SVI distribution was found to be 0.07, while for Iceland, it was 0.12, both corresponding to the values with the highest density and signifying the most probable values within their respective datasets. These estimated modes closely mimic the historical medians of each country's SVI.



Source: Authors' calculations.

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