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Cyclical Patterns of Systemic Risk Metrics: Cross-Country Analysis

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Cyclical Patterns of Systemic Risk Metrics: Cross-Country Analysis [1]

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Abstract

We analyze a range of macrofinancial indicators to extract signals about cyclical systemic risk across 107 economies over 1995–2020. We construct composite indices of underlying liquidity, solvency and mispricing risks and analyze their patterns over the financial cycle. We find that liquidity and solvency risk indicators tend to be counter-cyclical, whereas mispricing risk ones are procyclical, and they all lead the credit cycle. Our results lend support to high-level accounts that risks were underestimated by stress indicators in the run-up to the 2008 global financial crisis. The policy implications of conflicting risk signals would depend on the phase of the credit cycle.

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I. Overview

Modern approaches to financial system oversight aim to contain systemic risk, but their practice is complicated by lack of consensus on how to quantify such risks. At conceptual level, systemic risk is the risk of disruptions in the provision of financial services, caused by financial system impairment, that creates serious negative effects on the real sector (IMF, FSB, and BIS, 2009). Defined in this way, it is clear that systemic risk is multidimensional—reflecting the complexity of the financial system—and its intensity is directly observable, only when risks materialize, in the size of the resultant financial and real sector losses. There are many empirical approaches for measuring systemic risk, but an industry standard or set of best practices are yet to emerge (see Bisias and others (2012) and Blancher and others (2013) for surveys of the field). The focus of this paper is on macro-level approaches for measuring systemic risk that provide a lay-of-the-land snapshot of risks across time and countries. Macro-level approaches rely on analyzing the dynamics of sectoral and market aggregates, and as such are not well suited to capture the early stages of a build-up of risks in individual financial institutions and market participants. It is also difficult to capture with aggregate indices risks arising from interconnectedness of financial institutions and market participants, weaknesses in financial supervision, financial integrity, financial market infrastructure, and so on in a timely and consistent manner. A comprehensive analysis of these pertinent issues requires stress testing and other in-depth tools, such as those used in the Financial Sector Assessment Program (IMF and WB, 2005[2]).

Existing macro-level approaches for measuring systemic risk can be classified in two broad categories: "bottom-up" or indicator-based and "top-down" or model-based. Bottom-up approaches proxy systemic risk by vulnerabilities of the financial sector and asset markets that are more directly measurable. The degree of risk is then judged by the distribution of its proxy metrics across time and potentially across peer countries. In contrast, top-down methods estimate empirical models, in which the dependent variable is the incidence or magnitude of a financial system disruption that affects negatively the real sector. The fitted values of the model over a given time horizon or their change over time are then used as measures of systemic risk. Bottom-up approaches are typically feasible even with sparse data and are capable of revealing new risk patterns. On the downside, they do not control for mitigating factors—as extreme values always raise red flags—and involve a higher degree of subjectivity in interpreting risk signals to arrive at a bottom-line assessment. Top-down approaches seek to redress these issues, but are prone to overfitting—as models are selected for their ability to match historical risk patterns—and could be very data intensive. Examples of top-down and bottom-up approaches are, respectively, the Growth-at-Risk model (Adrian, Grinberg, Liang, and Malik, 2018) and the Financial Stability Monitoring Framework (Adrian, He, Liang, and Natalucci, 2019) used in the IMF's Global Financial Stability Report (GFSR).

[2] See www.imf.org/en/Publications/fssa for an up-to-date information on FSAP country and policy documents.

In this paper, we present a streamlined, bottom-up approach for measuring cyclical systemic risks with macroeconomic data, applicable across a diverse set of economies and geared to a broad audience. Our approach builds upon similar frameworks used in the U.S. Office of Financial Research (OFR) Financial System Vulnerabilities Monitor (OFR, 2020), the European Financial Stability Board Risk Dashboard (ESRB, 2020), and the GFSR's Financial Stability Monitoring Framework. Whereas existing approaches tend to apply different risk concepts to different sectors of the economy,[3] we propose a streamlined risk nomenclature—*liquidity*, *solvency*, and *mispricing* risks—that can be used uniformly, as applicable, across all sectors of the economy. The concept of mispricing risk—which aims at capturing possible asset-price misalignments or weakening credit standards—is related to Adrian, Covitz, and Liang (2015) notion of pricing of risk, and extends it further to economic agents' choice of balance-sheet exposures. Adopting a streamlined bottom-up approach allows us to apply a harmonized analytical framework to a bigger and more diverse set of countries, as we can select risk proxies on a case-by-case basis, depending on data availability.

In the empirical part of the paper, we construct indices of *liquidity*, *solvency* and *mispricing* risks for 107 countries and analyze their patterns over the financial cycle. Our objective is to identify combinations of *liquidity*, *solvency,* and *mispricing* risk metrics typical for various phases of the financial cycle that can be used to inform policy responses.

We contribute to the existing literature by using macro-level risk metrics for a bigger and more diverse set of countries and analyzing their evolution over the credit cycle at different leads/lags. The interest in this topic has been primarily driven by bank regulators' and international financial institutions' efforts to document financial system developments that led to the 2008 Global Financial Crisis (GFC). A key takeaway from this literature is that risks were underestimated in the run-up to the crisis, with risk-based solvency indicators remaining broadly stable or modestly improving (BIS, 2009; Shin, 2014) and measures of market risk falling through mid-2006 (Shin, 2014). The sparse empirical literature on the topic supports the countercyclicality and leading behavior of market risk metrics over the financial cycle (e.g., Aikman, Lehnert, Liang, and Modungno, 2020), but finds that bank-level, solvency indicators also tend to be countercyclical (i.e., they tend to decrease in the upswing phase of the business/credit cycle and increase in downturns) (Brei and Gambacorta, 2016; Montagnoli, Mouratidis, and Whyte, 2020). However, existing studies focus only on the contemporaneous link between solvency and business/credit cycle indicators, leaving open the possibility that the interrelation between them can be of different sign and strength at different lags/leads. We contribute to the literature by using macro-level risk metrics (instead of bank-level data for individual indicators) for a bigger and more diverse set

[3] The OFR monitor follows solvency/leverage and liquidity/funding risks in the financial system, and market and credit risks originating in the rest of the economy. The ESRB risk dashboard examines solvency and profitability and liquidity/funding risks in the financial system, and market and credit risks originating in the rest of the economy. The GFSR monitoring framework tracks asset price valuations and liquidity in financial markets and financial vulnerabilities in the rest of the economy.

countries and applying statistical techniques capable of analyzing cyclicality at different leads/lags.

The paper is organized as follows. Section II presents the analytical underpinnings of the proposed disaggregation of cyclical systemic risk into underlying *liquidity, solvency,* and *mispricing* risks. Section III presents the dataset of macrofinancial indicators used to extract signals about underlying risks. These indicators are then used to construct economy-wide risk indices for 107 countries since 1995 that are then optimized. In Section IV, we analyze the cyclicality patterns of our preferred indices of *liquidity*, *solvency*, and *mispricing* risk, using Stock and Watson (1999) cyclicality analysis and an event study of their behavior around systemic bank crises. In Section V, we interpret the identified patterns of the optimized economy-wide risk indices over the financial cycle from a policymaker's point of view. Section VI concludes with a summary of our main findings.

II. Analytical Framework

Systemic risk is the risk of disruptions in the provision of financial services, caused by impairment of all or parts of the financial system with serious negative effects for the real sector (IMF, FSB, and BIS, 2009). The definition of the financial system potentially encompasses all financial institutions, financial markets, and the financial infrastructure (Houben, Kakes, and Schinasi, 2004). The disruption in the provision of financial services can be triggered by negative shocks originating within the financial system, in the rest of the economy, or from abroad, and manifests itself in: (1) falling asset prices and increased volatility (Eichengreen and Portes, 1987; Bordo and Schwartz, 2000; Illing and Liu, 2003); (2) exchange rate depreciation or losses of official foreign reserves (Sachs, Tornell, and Velasco, 1995; Eichengreen, Rose, and Wyplosz, 1996); (3) widespread insolvencies and defaults of borrowers, lenders and market participants (Bordo, Dueker, and Wheelock, 2000; Breuer, 2004; Claessens and Kose, 2014); and (4) rising interest rates or disruption in the provision of credit (IMF, 1998; Kaminsky and Reinhart, 2001).

Financial stability risks capture different aspects of systemic risk. Financial stability refers to the state of the financial system that minimizes the probability of systemic risk materialization.[4] Financial instability is triggered by negative shocks to the financial system that propagate through existing financial vulnerabilities (Adrian, He, Liang, and Natalucci, 2019). The pricing of risk—measured by the slack or tightness of financial conditions[5]—affects economic agents' optimal exposure to financial vulnerabilities and is, itself, impacted

[4] "Financial stability refers to (a) an environment that would prevent a large number of financial institutions from becoming insolvent and failing and (b) conditions that would avoid significant disruptions to the provision of key financial services such as deposits and investments for savers, loans and securities to investors, liquidity and payment services to both, risk diversification and insurance services, monitoring of the users of funds, and shaping of the corporate governance of non-financial firms." (IMF and World Bank, 2005).

[5] "…tighter financial conditions, that is, higher spreads and volatility, lower asset prices, worsening risk sentiment, exchange rate depreciation, and unfavorable commodity price movements." (IMF, 2017b).

by shocks, thus acting as an amplifier of negative shocks in the financial system (Adrian, Covitz, and Liang, 2015). Given the unpredictability of the timing and nature of shocks (IMF, 2019), financial stability risks are typically proxied by metrics of financial vulnerabilities and pricing of risk.

In this paper, we decompose the "time dimension" of systemic risk (IMF, FSB, and BIS, 2016) into three underlying risks—*solvency, liquidity and mispricing risks*. They encompass, respectively, the three categories of risks identified as pertinent to systemic risk analysis in the IMF's *Guidance Note for Surveillance under Article IV Consultation* (IMF, 2015):

- ***Solvency* risk**—refers to the potential inability of economic agents to pay off all of their liabilities to other agents even after liquidating all assets. *Solvency* risk often arises from excessive leverage or exposure to risky assets.

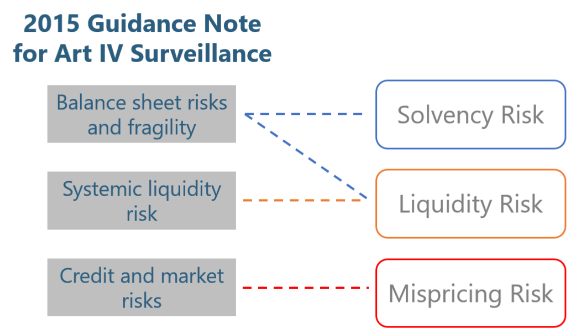
- ***Liquidity* risk**—reflects the potential inability of borrowers to meet their obligations as they fall due, without incurring losses large enough to deplete available liquidity buffers.

- ***Mispricing* risk**—captures the potential for mispricing of risk by economic agents or asset markets. It encompasses both the possibility of under/over-estimation of risk in asset markets—reflected in the slack/tightness of financial conditions[6]—and by economic agents through excessive (de)leveraging and under/over-exposure to specific financial instruments and asset classes:

    - **In asset markets**, underestimation of risk often manifests in protracted risk-on sentiment (in the extreme in irrational exuberance), characterized by loose financial conditions. Trading on market momentum can drive a wedge between asset prices and their fundamental determinants. This, in turn, can give rise to self-reinforcing dynamics/ amplification resulting in boom-bust asset price cycles with associated underestimation/overestimation of risks.

    - **At a sectoral level**, underestimation of risk manifests in loosening of credit standards that often becomes evident only ex-post. This can give rise to overextension (leveraging) of balance sheets of creditors and debtors and concentration of balance-

Mapping of Risks to 2015 Art IV Guidance Note Risk Taxonomy



Source: IMF (2015).
Note: For simplicity, the mapping reflects only the first-round effects of shocks on sectoral balance sheets.

[6] When the price of risk is low/high, the potential for its underestimation/ overestimation is higher/lower.

sheet exposures to specific sectors (such as households) or specific financial instruments (such as unhedged foreign currency loans.) and, through them, to asset prices (such as house prices and exchange rates.). On bank balance sheets, the speed of accumulation[7] and resultant concentration of exposures result in the build-up of credit/market/interest rate risks.

The other dimension of systemic risk—"cross-sectional" or "structural" (IMF, FSB, and BIS, 2016)— arises from interlinkages between economic agents both domestically and cross-border. Interconnectedness risk reflects the potential of spread of *solvency*, *liquidity*, and *mispricing* risks to economic agents other than those, on whose balance sheets the risks originated. Lack of harmonized data across a broad set of countries prevents us from including interconnectedness risk in our analysis.

The above risk taxonomy is a stylized representation of the first-round, differential impact of shocks on the balance sheets of economic sectors. In reality, the three types of risks are interlinked and prone to negative feedback loops.[8] For example, negative real sector shocks carry the potential of eroding the debt servicing capacity of different sectors of the economy, increasing their exposure to debt-related *liquidity* risks. Investors' flight to safety can increase the precautionary demand for liquidity, putting pressure on the price of risky and illiquid assets, and triggering deflation of asset price bubbles and widening of credit risk spreads. The correction in asset markets can overshoot and morph into upside *mispricing* risks (i.e., increased potential for overestimation of risks). Falling asset prices and higher debt service costs erode sectoral net worths, ratcheting economic agents' exposures to *liquidity* and *solvency* risks.

Systemic risk builds up in the expansion and peak phases of the financial cycle and can materialize and subside in its correction/trough phase. The financial cycle captures "*the level and evolution of slack (or excess) in the financial sector*" (IMF, 2015). Systemic risk is procyclical (Caruana, 2010), as by definition when properly identified it should be highest prior to its materialization that manifests in financial retrenchment in the trough of the cycle. At the same time, a central finding of the literature on financial frictions (Brunnermeier, Eisenbach, and Sannikov, 2012) is that they can give rise to feedback loops between asset prices and economic agents' net worths and liquidity spirals. As a result, metrics that serve as proxies for liquidity and solvency risks can exhibit countercyclical behavior, resulting in underestimation of risks and accentuation of the cycle.[9] High-level reviews of financial system developments that led to the 2008 Global Financial Crisis provide empirical support of this conjecture, as risk-based solvency indicators were found to have remained broadly

[7] "Rapid credit growth can compromise credit quality, as banks management and operation processes are progressively strained by the increased volumes of bank business." (Iossifov and Khamis, 2009).

[8] See Section V for a detailed account of the interplay of risks over the financial cycle.

[9] "In this procyclicality dimension, the financial sector endogenously generates systemic risk and this risk can be highest precisely when it looks lowest." (Caruana, 2010).

stable or modestly improved (BIS, 2009; Shin, 2014) and measures of market risk to have fallen through mid-2006 (Shin, 2014).

III. Data Description and Index Construction

A. Data Compilation

The starting point of the analysis is the compilation of data on relevant macrofinancial indicators that can serve as proxies for the three types of risks. The raw dataset consists of quarterly data for 180 plus countries and 48 variables over 1995:Q1-2020:Q3 (Table 1).[10] Data are drawn from publicly available data sources, including various IMF databases,[11] Bloomberg (for financial market data), OECD and Global Property Guide (for housing market data), the Credit Research Initiative (CRI) database of the National University of Singapore's Risk Management Institute (for probabilities-of-default data), and ECB and OECD sectoral accounts data (see Appendices I and II for details). The selection of indicators aims at ensuring maximum country coverage beyond G-20 and OECD countries. Whereas data coverage is uneven both in the time and cross-country dimensions, the sample includes information on more than 15 variables for over 100 countries since 2002.

The selection of indicators is guided by the nature of the risks being proxied, a review of the empirical financial crisis literature, and the goal of maximizing country coverage:

- ***Solvency* risk** is proxied by measures of the adequacy and resilience of sectoral capital buffers;
- ***Liquidity* risk** is proxied by measures of the adequacy and resilience of the debt servicing capacity of borrowers and lenders, as well as signs of funding difficulties;
- ***Mispricing* risk** is proxied by measures of slack/tightness of financial conditions, as reflected in market returns, interest rates and market volatility, and signs of loosening of credit standards, as reflected in the speed of accumulation and resultant concentration of balance-sheet exposures.

Given the link between systemic risk and the financial cycle, the empirical, financial crises literature offers insights on the types of variables that can signal financial stress either ahead of time or in the credit cycle downturn. A review of the literature validates the focus on sectoral financial vulnerabilities and signs of excess in financial markets, as their proxies

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[10] Missing quarterly data are interpolated from annual data by attributing annual ratios to each quarter of the year or assuming constant quarter-on-quarter growth rate of variables in levels.

[11] International Financial Statistics, Financial Soundness Indicators, Balance of Payments and International Investment Position Statistics, the Information Notification System, the World Economic Outlook, and the Joint BIS-IMF-OECD World Bank External Debt Statistics.

frequently appear as explanatory variables in regression models of financial crises (Appendix III).

Table 1 presents the initial set of indicators used in the analysis. Risk indicators that meet the above criteria are grouped by sector of the economy. In our analysis, we use data only for the private sector and limit the analysis of the financial sector to banks, due to the sparse data availability for the non-bank financial sector. Where necessary, variables are transformed, so that higher values correspond to heightened underlying risks. This is achieved by taking the absolute value of indicators, for which extreme values in both directions could constitute a risk, as well as taking the inverse of ratios and multiplying growth rates by minus one for indicators, for which low raw values signal the buildup of risk. The performed transformations are noted in brackets in the last column of Table 1.

The distribution of indicators across time provides a measure of the relative intensity of underlying risks in individual countries. The data for each variable are transformed into percentile ranks,[12] based on the distribution of its values over the entire time span for each individual country. The percentile ranks can be, alternatively, calculated across countries at similar level of economic development over time. Basing the analysis on country-specific percentile ranks allows us to control more granularly for idiosyncratic characteristics of the sample countries not captured by their level of development. Expressed in percentile ranks, the macrofinancial indicators can be interpreted as risk metrics, the extreme values of which raise red flags. Higher values of *liquidity* and *solvency* risk metrics signal build-up of risks (either intrinsic in balance-sheet weaknesses or sentiment-driven). Higher values of the *mispricing* risk metrics reflect heightened risk of financial excess (e.g., high market returns and low volatility) or loosening of credit standards (e.g., overextension of balance sheets of creditors and debtors and concentration of balance-sheet exposures to specific sectors or specific financial instruments.

As noted in the overview section, indicator-based risk monitoring frameworks, such as ours, extract signals from data without attempting to single out deviations from fundamentals or control for policies. As all extreme values of risk proxy indicators raise red flags, the extracted signals may be noisy at times, especially when it comes to asset price-based indicators that are highly sensitive to shocks and changes in the real economy. In analyzing risk signals from *mispricing* risk indicators, in particular, care should be taken not to interpret them literally as an accurate measure of asset-price misalignments, but rather as a signal that misalignment could be developing or worsening. Indicator-based risk metrics can be used in second-stage analysis by country experts to control for fundamentals, policies and special circumstances in individual countries.

[12] The percentile rank shows the percentage of realizations of a given variable in the full sample that fall below its value in a given country and time period.

Table 1. Initial Set of Indicators for Construction of Aggregate Risk Metrics

Sector	Risk Type	Indicator (transformation in brackets)
Economy-wide	…	Real growth of private sector debt
Banking sector	Solvency risk	Regulatory capital-to-risk-weighted assets ratio (inverse)
		Capital-to-assets ratio (inverse)
		NPLs net of provisions-to-capital ratio
		Net open FX position-to-capital ratio (absolute value)
		3-year ahead cummulative probability of default of listed banks (Median; bps)
	Liquidity risk	Return on assets * (-1)
		Liquid assets-to-short-term liabilities ratio (inverse)
		Loans-to-deposits ratio
		Real overnight interbank rate
		Libor-OIS Spread (3-month)
	Mispricing risk	Share of household loans in total bank claims to domestic non-fin. sector
		Share of public sector claims in total bank claims to domestic non-fin. sector
		NPLs share in total gross loans (inverse)
		FX share in total bank liabilities
		FX share in total bank loans
Equity market	Mispricing risk	Real stock market returns
		Stock market volatility * (-1)
Bond market	Mispricing risk	Real domestic government bond yield * (-1)
		Domestic government bond yield volatility * (-1)
		Sovereign FX debt spread * (-1)
Foreign exchange market	Mispricing risk	Growth of REER (+ = appreciation)
		FX market volatility * (-1)
Housing market	Mispricing risk	Real house price growth
		House price-to-rent ratio
		House price-to-income ratio
Households	Solvency risk	Debt-to-financial net worth ratio
		Bank loans to households-to-GDP ratio
		Other financial institutions loans to households-to-GDP ratio
	Liquidity risk	Debt-to-income ratio of households
		Interest payments-to-income ratio of households
	Mispricing risk	Real growth of bank loans to households
		Interest rate – income growth differential of households * (-1)
		FX share in bank loans to households
Corporates	Solvency risk	Debt-to-equity ratio of corporates
		Bank loans to corporates-to-GDP ratio
		Other financial institutions loans to corporates-to-GDP ratio
		External debt of corporates-to-GDP ratio
		3-year ahead cummulative probability of default of listed corporates (Median; bps)
	Liquidity risk	Debt-to-income ratio of corporates
		Interest payments-to-income ratio of corporates
		Share of short-term debt in external debt of corporates
		Corporate external debt amortization-to-GDP ratio
		BOP other inv. (net) to non-official, non-bank sector-to-GDP ratio * (-1)
	Mispricing risk	Real growth of bank loans to corporates
		Interest rate-income growth differential of corporates * (-1)
		Real growth of external debt of corporates
		FX share in bank loans to corporates

Note: Internally at the IMF, the compiled data are housed in the Systemic Risk Tracker, developed by staff of the Strategy, Policy, and Review Department as a central repository of macrofinancial indicators that can be used as proxies of different aspects of systemic risk.

The composite risk metrics, constructed from percentile ranks of the indicators shown in Table 1, would generally move in the opposite direction of untransformed indicators used in the received literature. This is due to the transformations we carry out, so that higher percentile rank corresponds to heightened underlying risk (in the case of mispricing risk: heightened risk of financial excess). Existing studies generally analyze untransformed individual indicators, high values of which indicate low degree of risk (in the case of mispricing risk: low risk of financial excess). For example, Brei and Gambacorta (2016) and Montagnoli, Mouratidis, and Whyte (2020) examine solvency indicators, in which bank capital is in the nominator. High values of such indicators are then associated with low solvency risk. Similarly, Shin (2014) discusses CDS spreads, which when high would indicate low risk of financial excess.

We use the credit cycle as a stand-in for the broader financial cycle, leveraging on Schularick and Taylor (2012) influential finding that "*financial crises throughout modern history can be viewed as credit booms gone wrong*". Following Claessens, Kose, and Terrones (2012), we use the dynamics of the real growth of private debt to capture the credit cycle. We choose a measure of credit dynamics that is not conditioned on the notion of long-term trend relative to real sector developments, in order to avoid the well-known beginning and end-point measurement problems in calculating other widely used measures, such as the credit-to-GDP gap.[13]

B. Construction of Composite Risk Metrics

Raw indices of underlying risks can be constructed by averaging of the percentile ranks of all available indicators. However, despite the conceptual appeal of the initial set of indicators (Table 1), the quality of their empirical signals may differ due to issues such as measurement errors and reporting delays.

We enhance the signal-to-noise ratio of our composite risk metrics, using the Cronbach's Alpha methodology and Stock and Watson cyclicality analysis on individual indicators:

- **We first narrow down the list of indicators, based on the Cronbach's Alpha estimate of the reliability, with which they proxy the same economy-wide risk concept when taken as a group (OECD, 2008).** The square root of the Cronbach's Alpha can be interpreted as providing an estimate of the correlation of a composite metric—called "test scale" and constructed by summing up the standardized values of individual risk metrics— with an underlying factor—in this case economy-wide *solvency, liquidity or mispricing* risk (StataCorp, 2019b).

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[13] Drehmann and Tsatsaronis (2014) provide a summary of measurement problems of the credit-to-GDP gap, while arguing that they do not have a large impact on its properties of early warning indicator of banking crises.

- **We then weed out indicators that behave differently over the financial cycle than the majority of proxies for the same type of risk.** As noted above, we use the credit cycle—as captured by the dynamics of real growth of private debt—as a stand-in for the broader financial cycle. Using Stock and Watson (1999) cyclicality analysis, we drop indicators that exhibit markedly different intertemporal correlation patterns with real growth of private debt—used to capture the credit cycle— than those of the majority of proxies for the same type of risk for a given sector of the economy. This is necessary because we later aggregate the signals from individual indicators using arithmetic averages. Doing so with series that behave differently over the financial cycle would tend to reduce the signal-to-noise ratio of our composite risk metrics.

The two techniques are chosen for their flexibility in handling missing values, which are a prominent feature of our dataset, and empirical tractability and replicability.

Cronbach's Alpha

The Cronbach's Alpha ("C-alpha") is given by the following expression (OECD, 2008):

$$\alpha_c = \frac{k}{k-1}\left(1 - \frac{\sum_{j=1}^{k} \sigma_{x_j}^2}{\sigma_{x_0}^2}\right)$$

k – number of items x ;

$\sigma_{x_j}^2$ – variance of item x_j;

$x_0 = \sum_{j=1}^{k} x_j$ – test scale.

"C-alpha measures the portion of total variability of the sample of individual indicators due to the correlation of indicators. It increases with the number of individual indicators and with the covariance of each pair." (OECD, 2008, p. 72). We apply the C-alpha analysis on the individual risk metrics, the values of which are transformed, where needed, in the way noted in the last column of Table 1 and then expressed in percentile ranks. The percentile transformation ensures that all variables are of the same scale, which makes further standardization—prior to combining them into the test scale—unnecessary. The C-alpha is especially well suited for the purposes of our analysis, as the sequentially optimized *test scale* is constructed in the same way as both the raw composite sector risk metrics and the preferred, economy-wide, risk indices, derived as an outcome of the analysis in this section.[14] In practice, the values of the calculated C-alpha should be seen as indicative, as its theoretical properties depend on the absence of missing values (SAS Institute Inc, 2016), whereas the latter are allowed in its empirical implementation (StataCorp, 2019b).

[14] "A score is created for every observation for which there is a response to at least one item (one variable in varlist is not missing). The summative score is divided by the number of items over which the sum is calculated." (StataCorp, 2019b, p. 11).

Table 2 presents the narrowed down list of indicators obtained from the application of the Cronbach's Alpha methodology. Cronbach's Alpha analysis of the initial set of indicators suggests that the reliability of the three economy-wide scales, constructed from available indicators of *solvency, liquidity and mispricing* risks, can be improved by dropping indicators that are weakly correlated with other proxies of the same type of risk (Appendix Table 1). We proceed to drop items with negative or positive but low correlation with a scale constructed from all items except the one under consideration (see item-rest correlations in Column 5 of Appendix Table 1). The resulting sub-set of risk proxies proxy more reliably underlying risks with estimated Cronbach's Alpha coefficients in the second-stage of the analysis (Table 2) within the 0.6-0.8 range commonly considered acceptable (OECD, 2005; Goforth, 2015). Several of the remaining indicators are less correlated with other proxies of the same type of risk (Column 5 of Table 2), but dropping them would not improve significantly the Cronbach's Alpha coefficients (see last column of Table 2), which is why we keep them at this stage.

Table 2. Cronbach's Alpha Analysis of Narrowed-Down Set of Indicators of Economy-Wide Risks

Risk Metrics (Items and Test Scale)	Obs.	Sign	Item-Test Correlation	Item-Rest Correlation	Inter-Item Covariance (xcl. one item at time)	Cronbach's alpha (xcl. one item at time)
Liquidity risk						
Libor-OIS Spread (3-month)	1,163	+	0.70	0.26	160	0.62
Loans-to-deposits ratio	5,738	+	0.68	0.17	172	0.64
Return on assets * (-1)	6,565	+	0.68	0.15	188	0.67
Corporate external debt amortization-to-GDP ratio	6,989	+	0.87	0.24	163	0.63
Debt-to-income ratio of corporates	2,493	+	0.70	0.42	154	0.61
Interest payments-to-income ratio of corporates	1,543	+	0.54	0.21	169	0.64
Debt-to-income ratio of households	2,682	+	0.68	0.38	156	0.61
Interest payments-to-income ratio of households	1,721	+	0.62	0.30	159	0.62
Test scale (mean of standardized items)					*165*	***0.66***
Solvency risk						
Regulatory capital-to-risk-weighted assets ratio (inverse)	6,502	+	0.69	0.45	194	0.71
Capital-to-assets ratio (inverse)	6,174	+	0.61	0.34	208	0.72
3-year ahead cumm. prob. of default of banks (Median)	6,981	+	0.65	0.37	204	0.72
Bank loans to corporates-to-GDP ratio	11,265	+	0.76	0.49	179	0.68
Debt-to-equity ratio of corporates	2,872	+	0.74	0.57	186	0.69
External debt of corporates-to-GDP ratio	4,533	+	0.46	0.17	227	0.75
3-year ahead cumm. prob. of default of corporates (Median)	7,681	+	0.62	0.32	216	0.73
Bank loans to households-to-GDP ratio	11,312	+	0.70	0.42	208	0.72
Debt-to-financial net worth ratio	2,836	+	0.72	0.53	189	0.70
Test scale (mean of standardized items)					*201*	***0.74***
Mispricing risk						
NPLs share in total gross loans (inverse)	6,439	+	0.61	0.34	111	0.68
Real growth of bank loans to corporates	10,576	+	0.60	0.26	111	0.68
Real growth of external debt of corporates	4,157	+	0.37	0.16	121	0.70
Int. rate-income growth differential of corporates*(-1)	2,373	+	0.41	0.23	116	0.69
Real growth of bank loans to households	10,620	+	0.63	0.29	109	0.67
Int. rate–income growth differential of households*(-1)	2,529	+	0.53	0.32	111	0.68
Stock market volatility*(-1)	8,331	+	0.43	0.15	123	0.70
Real stock market returns	7,677	+	0.45	0.18	123	0.70
Real domestic government bond yield*(-1)	3,992	+	0.48	0.30	115	0.69
Sovereign FX debt spread*(-1)	6,375	+	0.63	0.39	103	0.66
Domestic government bond yield volatility*(-1)	5,905	+	0.43	0.14	120	0.70
FX market volatility*(-1)	18,277	+	0.65	0.12	124	0.71
Price-to-income ratio	5,072	+	0.43	0.22	118	0.70
Price-to-rent ratio	4,597	+	0.55	0.38	110	0.68
Real house price growth	4,796	+	0.52	0.34	112	0.68
Test scale (mean of standardized items)					*115*	***0.70***

Source: Authors' estimates using StataCorp (2019a).

Stock and Watson (1999) cyclicality analysis

We use the Stock and Watson (1999) methodology to analyze the behavior of the indicators shown in Table 2 over the credit cycle, with the view of optimizing further the signal-to-noise ratio of aggregate risk metrics derived from them. Appendix Figure 2 presents the distributions across sample countries of the cross-correlations of individual indicators, grouped by sector and underlying risk, with leads and lags of real growth of private debt (expressed in percentile ranks over the entire time span for each individual country). The cross-country distributions of these cross-correlations provide an indication of the statistical significance of the observed common patterns in the data. Following Stock and Watson (1999), if the highest correlation is with one of the lags of real growth of private debt, we conclude that the risk metric follows the credit cycle with a delay. Alternatively, if the highest correlation is with a given lead of the variable, we determine that the risk metric leads the credit cycle. If the maximum correlation is positive, the risk metric is procyclical, whereas if it is negative, it is countercyclical vis-à-vis private sector debt.

We proceed to drop indicators, which intertemporal correlation patterns with real growth of private debt deviate significantly from the common patterns by sector/risk or are available only for a small number of countries. We first drop from the list the real growth rates of sub-components of private debt, used to capture different aspects of *mispricing* risk, in order to avoid mechanical correlation patterns.[15] As seen in Appendix Figure 2, the real growth rates of bank loans to households and bank loans and external debt of corporates are contemporaneously correlated with real growth of private debt, of which they are sub-components. Next, we exclude from the list the real domestic government bond yield and house price-to-income and house price-to-rent ratios, as their median sample correlations are clustered around zero for all leads and lags of real growth of private debt. We also drop the LIBOR-OIS spread and interest payments-to-income ratios for households and corporates from the preferred list, as they are available only for a small number of countries (see Table 2). Finally, we remove from the list the share of non-performing loans in total bank loans and interest payments-to-income ratios for households and corporates, as in contrast with the other risk metrics, they lag rather than lead the credit cycle.[16]

Preferred composite risk metrics

Table 3 presents the preferred set of 20 indicators, obtained from applying the Cronbach's Alpha and Stock and Watson (1999) cyclicality analyses on the initial set of

[15] We retain other indicators constructed as ratios of sub-components of private debt to sectoral net worths (i.e., debt-to-income and debt-to-equity ratios), as they are less prone to such trivial correlation patterns—both conceptually (given feedback loops between credit, asset prices, and economic agents' income and net worth) and in practice, as they are countercyclical and lead the credit cycle (Appendix Figure 1).

[16] As noted above, this is necessary because in the next section we aggregate the signals from individual indicators using arithmetic averages. Averaging across series that behave differently over the financial cycle would tend to reduce the signal-to-noise ratio of the composite risk metrics.

indicators. The remaining *solvency* and *liquidity* risk metrics cover the banking, corporate, and household sectors, whereas the selected *mispricing* risk metrics are only asset price-based (Table 3). A number of these or derivative indicators have also been found to be useful predictors of financial crises (Appendix III). Examples include capital-to-assets ratio and return-on-equity (Jordà and others, 2017), loan-to-deposit ratio (Navajas, 2013), real stock market returns (Schularick and Taylor, 2012), housing price growth (Babecky and others, 2014), private sector debt service ratio (Drehmann and Juselius, 2014) and bank loans to households-to-GDP ratio (Alessi and Detken, 2018).

Table 3. Preferred Set of Indicators for Construction of Aggregate Risk Metrics by Sector/Market

Risk Type	Sector	Indicator (transformation in brackets)
Liquidity risk	Banking sector	Loans-to-deposits ratio
		Return on assets * (-1)
	Corporates	Corporate external debt amortization-to-GDP ratio
		Debt-to-income ratio of corporates
	Households	Debt-to-income ratio of households
Solvency risk	Banking sector	Regulatory capital-to-risk-weighted assets ratio (inverse)
		Capital-to-assets ratio (inverse)
		3-year ahead cummulative probability of default of listed banks (Median; bps)
	Corporates	Bank loans to corporates-to-GDP ratio
		Debt-to-equity ratio of corporates
		External debt of corporates-to-GDP ratio
		3-year ahead cummulative probability of default of listed corporates (Median; bps)
	Households	Bank loans to households-to-GDP ratio
		Debt-to-financial net worth ratio
Mispricing risk	Equity market	Real stock market returns
		Stock market volatility * (-1)
	Bond market	Domestic government bond yield volatility * (-1)
		Sovereign FX debt spread * (-1)
	FX market	FX market volatility * (-1)
	Housing market	Real house price growth

We use the preferred set of 20 indicators to construct economy-wide indices of underlying risks for 107 countries over the period 1995:Q1-2020:Q3. For each type of risk, the economy-wide index is calculated by averaging the percentile ranks of the indicators first by sector/market and then across sectors, effectively giving each sector/market equal weight in the resultant economy-wide risk index. As noted above, expressed in percentile ranks, the preferred indicators can be interpreted as risk metrics, the extreme values of which raise red flags. We opt for simple averages to enhance the transparency of the constructed risk indices. In the case of *mispricing* risk, we calculate the index only if it is based on information on more than one financial market.

IV. EMPIRICAL ANALYSIS

We analyze the patterns of the constructed economy-wide indices of *liquidity*, *solvency*, and *mispricing* risk over the financial cycle, using Stock and Watson (1999) cyclicality analysis and an event study of their behavior around systemic bank crises.[17] As in the index-construction stage of the analysis, we use the credit cycle—as captured by the dynamics of real growth of private debt—as a stand-in for the broader financial cycle.

A. Stock and Watson (1999) Cyclicality Analysis

Analysis of cyclicality patterns shows that *liquidity* and *solvency* risk indices are counter-cyclical, whereas the *mispricing* one is procyclical, and they all lead the credit cycle. Figure 1 presents the distributions across sample countries of the cross-correlations of economy-wide risk indices with leads and lags of real growth of private debt (expressed in percentile ranks over the entire time span for each individual country). Results suggest that *liquidity* and *solvency* risk indices are counter-cyclical in levels, whereas the *mispricing* one is procyclical, and they all lead the credit cycle by at least four quarters. Across sample countries, the intertemporal correlation between the real growth of private debt and the economy-wide *liquidity* and *solvency* risk indices peaks in negative territory around the fourth lead of real growth of private debt. The opposite holds for the economy-wide, asset price-based *mispricing* risk index. Its intertemporal correlation with real growth of private debt peaks in positive territory around the fourth lead of real growth of private debt. Box 1 presents a case study that illustrates the main findings from our cross-country analysis with the experience of Denmark in the run-up and aftermath of the 2008 Global Financial Crisis.

The economy-wide indices of underlying risks cannot be combined directly in an overall index of systemic risk. This is because the metrics of *mispricing* risk do not co-move with *liquidity* and *solvency* risk metrics over the credit cycle (Figure 1).[18]

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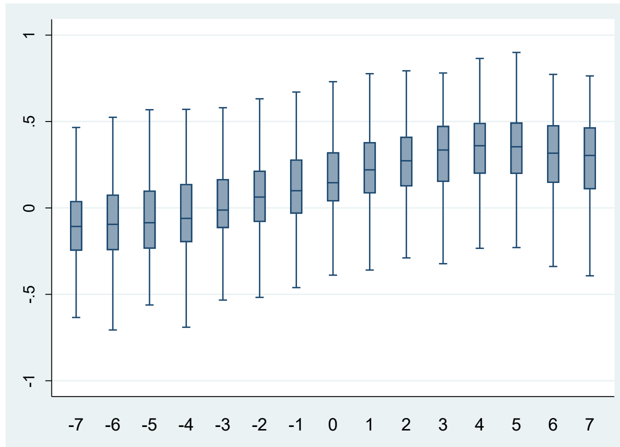
[17] Systemic bank crises typically occur in extreme cases of systemic risk materialization in the correction phase of the credit cycle.

[18] Similar results are obtained, when the cross-correlations are estimated with the credit-to-GDP gap from one-sided Hodrick-Prescott trend (with smoothing parameter of 400,000) as an alternative measure of the credit cycle.

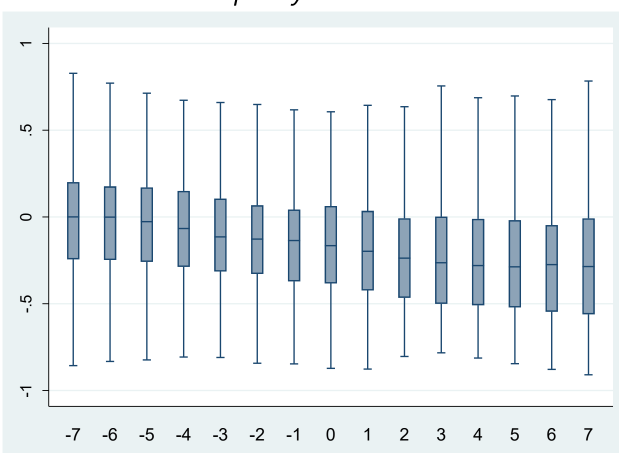
Figure 1. Sample Distribution of Cross-Correlograms of Preferred Economy-Wide Risk Indices and Real Growth of Private Debt

(Correlation Coefficients of Variables Expressed in Percentile Ranks within Countries' Own History)

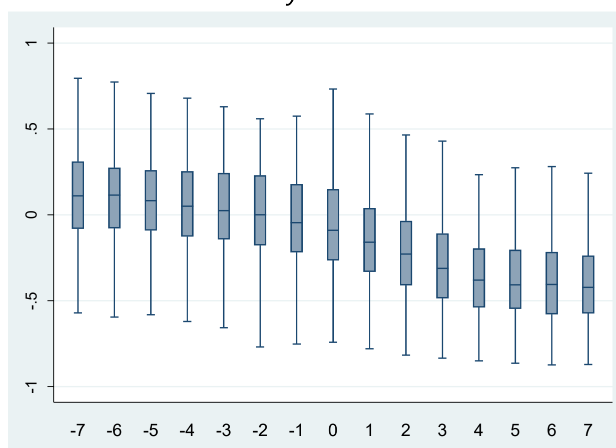
Mispricing risk index



Liquidity risk index



Solvency risk index



Notes: The box plots show, on the vertical axis, the distribution of individual country correlation coefficients of preferred economy-wide risk indices with different leads and lags of real growth of private debt. All variables are expressed in percentile ranks over the entire time span for each individual country. The leads and lags are shown on the horizontal axis; In box plots, the lower and upper hinges of each box show the 25th and 75th percentiles of the distribution, the line in the box indicates the median, and the end-points of whiskers mark next adjacent values. Following Stock and Watson (1999), a large positive correlation at k=0 indicates that the two series co-move in the same direction; a large negative correlation at k=0 shows that the two series move in opposite directions; a maximum correlation at negative k (e.g., k=-1) indicates that the risk metric follows developments in real credit growth with a lag of k quarters; a maximum correlation at positive k (e.g., k=1) indicates that the risk metric leads developments in real credit growth with a lead of k quarters.

Box 1. Denmark: Systemic Risk Patterns over a Full Credit Cycle

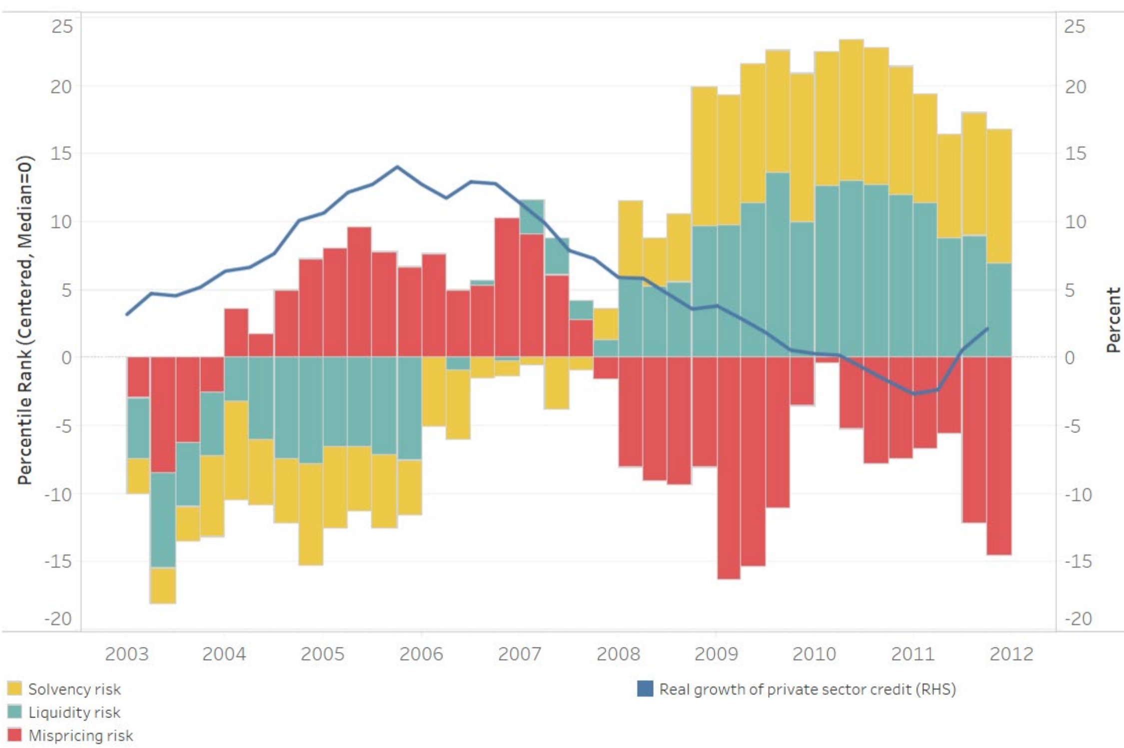
Over the period 2003-11, the Danish economy witnessed all phases of the credit cycle, in parallel with a house prices boom/bust cycle accompanied by a secular increase in household leverage. The figure below shows the growth of real private debt alongside the economy-wide risk indices, which are centered around their medians and expressed as contributions to an aggregate index, in which they enter with equal weights of one-third.

The dynamics of the different indices of underlying risks are consistent with the findings outlined above:

- *Liquidity* and *solvency* risk metrics are countercyclical and lead the cycle, progressively falling below their medians in the upswing of the credit cycle before reversing course close to its peak and swinging into positive territory in the downturn and trough phases of the credit cycle.

- The *mispricing* risk index is, on the other hand, pro-cyclical, and also leads the credit cycle. It signals rising potential for *underestimation of risks* in the upswing and peak phases of the credit cycle, before receding and starting to flag a growing potential for *overestimation of risks* in the downturn and trough phases.

Denmark: Evolution of Underlying Risks Over the Credit Cycle, 2003–11

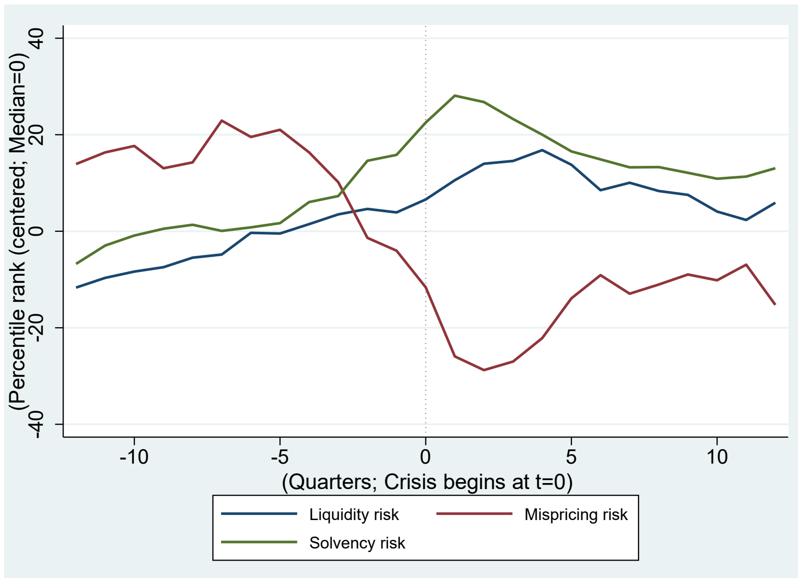


Source: Authors' estimates.
Note: The economy-wide risk indices are in percentile ranks centered around the median (50th percentile rank = 0) and are expressed as contributions to an aggregate index, in which they enter with equal weights of one-third.

B. Event Analysis around Systemic Banking Crises

Systemic bank crises are extreme cases of systemic risk materialization in the correction phase of the credit cycle. Real growth of private debt typically peaks in the year prior to a systemic bank crisis and then steeply declines as the crisis unfolds, bottoming out two years after its start (Appendix Table 2). Taking a closer look at risk patterns at the extreme can bring out salient features of the data that would otherwise remain hidden.

Figure 2. Evolution of Preferred Economy-Wide Risk Indices around Systemic Banking Crises



Source: Authors' estimates.
Notes: Shown are averages of indices in levels (centered around their medians) across 65 systemic banking crises since 1995.

An event study of the behavior of economy-wide risk indices around systemic bank crises reaffirms the findings from the cyclicality analysis and provides further insights of their potential to act as early warning indicators. Figure 2 presents the average values of the economy-wide indices of *liquidity*, *solvency* and *mispricing* risks in levels around 65 systemic banking crises since 1995. The timing of systemic bank crises is taken from Laeven and Valencia (2018). The chart shows the average within-country percentile ranks of these indices, centered around their medians, 12 quarters before and after a systemic banking crisis that occurs in period t=0. Results show that the *mispricing risk* index is procyclical vis-à-vis the credit cycle and is near its peak two to three years ahead of a systemic banking crisis. It builds and remains above its median in the upswing phase of credit cycles that end with a banking crisis, plateaus and then recedes in the year leading up to the downturn phase, and bottoms out below its median in the trough phase of the cycle. *Liquidity* and *solvency* risk indices are, on the other hand, countercyclical in levels—they tend to be lower in the upswing phase than in the downturn phase of credit cycles that end with a banking crisis. At the same time, they do build up in the year leading up to the downturn (moving in the opposite direction of mispricing risk metrics), peaking above their medians in the trough phase of the cycle, before gradually tapering off.

V. Interpretation of Findings

Our main finding—that economy-wide *liquidity* and *solvency* risk metrics are countercyclical, whereas the *mispricing* ones are procyclical, and they all lead the credit cycle—provide a blueprint of expected patterns of risks and their proxy metrics over the phases of the financial cycle:[19]

- ***Build-up phase* that in the extreme can give rise to financial manias, credit booms, or asset price bubbles.** *Solvency, liquidity, and mispricing* risks are initially generally benign in both the financial and real sectors of the economy. Over time, the virtuous cycle of financial deepening and real growth acceleration can morph in a self-perpetuating cycle of credit expansion, unsustainable pace of income growth, and asset price inflation. The resulting build-up of *downside mispricing* risk (i.e., increased potential for underestimation of risks) is characterized by high rates of return, low volatility, compressed risk premia, and rapid credit growth. Rising asset prices increase collateral valuations, making existing loans appear increasingly better provisioned, and encouraging banks and their clients to take more risk (*solvency* risk is initially *underestimated* by its proxy metrics). Higher net worths and faster income growth compress risk premia, which alongside greater credit availability, initially mask *liquidity* risk as captured by its proxy metrics. Risk management can become laxer, further amplifying *downside mispricing* risks, as financial market participants increasingly trade on market momentum and financial institutions' management and operation processes become progressively strained by the increased volumes of business. As leverage of debtors and creditors rises, their sensitivity to abrupt changes in incomes, interest rates, and—where credit is extended in foreign currency—exchange rate shocks, making it more likely that rising *solvency* and *liquidity* risks are registered by their proxy metrics.

- ***Correction* phase that in the extreme can turn into financial market crashes, financial sector panics, or credit crunches**. Excessive risk-taking during the build-up phase make the economy vulnerable to negative external and internal shocks, increasing the likelihood of "hard landing", as these shocks erode the debt servicing capacity of different sectors of the economy. Investors' flight-to-safety increases the precautionary demand for liquidity, putting pressure on the price of risky and illiquid assets, triggering deflation of asset price bubbles and widening of credit risk spreads. The correction of *mispricing* risks can overshoot and morph into *upside mispricing* risks (i.e., increased potential for *overestimation of risks*), characterized by negative rates of return, high

[19] See for example Claessens and Kose (2014) for a description of risk dynamics in the correction phase of the cycle.

volatility, large risk premia, increase of non-performing loans in banks' portfolios, and credit crunch. Falling asset prices and higher debt service costs erode sectoral net worths, ratcheting economic agents' exposure to *liquidity* and *solvency* risks and raising the potential for *overestimation* by their proxy metrics. These can be further magnified by changes in investor sentiment and herding behavior. The decline of collateral valuations and the heightened *liquidity* and *solvency* risks could trigger a tightening of credit underwriting standards, further ratcheting upside *mispricing* risks and draining liquidity from the financial system. *Solvency* and *liquidity* risks, as captured by their proxy metrics, may initially continue to rise before subsiding, as incomes and net worths can fall faster than the pace of deleveraging, giving rise to Fisherian debt deflation spiral (Fisher, 1933).

- ***Peak and trough phases*****—characterized by inflection points in the level or change of intensity of underlying risks.** In the peak phase, the self-reinforcing dynamics of *downside mispricing* risk stall, making it even more likely for *solvency* and *liquidity* risk metrics to register rising risks and give impetus for a negative feedback loop between rising *solvency* and *liquidity* risk and falling *mispricing* risk metrics. In the trough phase, the process of repair of overleveraged balance sheets eventually improves the creditworthiness of borrowers, restores the capacity of creditors to underwrite risks, and rebuilds investor confidence, setting the stage for a new systemic risk cycle.

Our results suggest that low values of *liquidity, solvency,* and *mispricing* risk indices need to be evaluated in reference to the phase of the financial cycle. Low levels of *liquidity* and *solvency* aggregate risk metrics would tend to underestimate risks in the build-up phase of the credit cycle, due to the interplay between liquidity and net worth of creditors/debtors and credit-driven booms of real activity and asset prices. Low values of *mispricing* aggregate risk metrics in the correction phase of the cycle may not be benign, as the correction of financial market excess and concentration of balance-sheet exposures may overshoot, potentially spreading *solvency*, *liquidity*, and *mispricing* risks to otherwise sound parts of the financial system and the real economy.

Economy-wide risk indices have the potential to serve as early warning indicators of banking crises. The event study suggests that *mispricing* risk metrics in levels provide useful early warning signals two to three years ahead of banking crisis. Increases in *liquidity* and *solvency* risk indices, especially when they occur alongside downward correction in mispricing risk metrics can provide additional early warning signals of banking crises, albeit with shorter lead time of about a year.

VI. CONCLUSION

In this paper, we advance the literature on indicator-based metrics of systemic risk by proposing a harmonized risk taxonomy across sectors and applying it to a bigger and more diverse set of countries. We group systemic risk metrics into proxies for *liquidity*, *solvency*, and *mispricing* risks. The first two risks are standard in the literature. *Mispricing* risk aims at capturing possible asset-price misalignments or weakening credit standards. We then use macrofinancial indicators to construct optimized, economy-wide risk indices for 107 countries over 1995–2020 . We use them to show that *liquidity* and *solvency* risk metrics are countercyclical, whereas the *mispricing* one is procyclical. All risk metrics lead the credit cycle by at least a year, pointing to their potential to act as early-warning indicators of banking crises.

In contrast to evidence from bank-level studies of solvency dynamics, our results lend support to high-level accounts that risks were underestimated by stress indicators in the run-up to the 2008 GFC. When comparing our findings to those in the received literature, one needs to take into account that high values of our composite risk metrics indicate heightened underlying risks (in the case of *mispricing* risk: higher risk of financial excess). As a result, the *solvency* risk index would move in the opposite direction of ratios, such as the leverage ratio and the capital-to-risk weighted assets ratio, in which capital buffers are in the nominator. In the same vein, the composite *mispricing* risk index would move in the opposite direction of financial price indicators that capture financial stress (for example, CDS spreads). With this in mind, our results strongly support high-level accounts that risks were underestimated by stress indicators in the run-up to the 2008 GFC. In our view, conflicting evidence from existing bank-level studies of bank solvency dynamics can be explained by the studies' focus on their contemporaneous link with the business/credit cycle.

The relative importance assigned to signals from the various risk metrics would depend on the relevant time horizon for policy action. In the correction and trough phases of the cycle, the focus of the policy response is on contemporaneous prevention of risk spillovers. The need for and design of policies to engineer a soft-landing of the economy and crisis response policies (for example, relaxation of the macroprudential regime, liquidity and equity support for businesses, bank recapitalization) can then be informed by high levels of *solvency* and *liquidity* risk indices and low values of the *mispricing* risk metrics. In the build-up and peak phases of the cycle, policy response should, instead, be forward-looking, aiming to stem risks before they appear on sectoral balance sheets and in asset valuations. Tightening of macroprudential policies aimed at containment of systemic risk can then be informed by high levels of *mispricing* risk indices and rising *solvency* and *liquidity* risk metrics.

Areas for future research include testing the early-warning indicator properties of risk indices and reconciliation of the findings from macro and micro-level empirical studies. With respect to the latter, our finding that all three, economy-wide risk indices lead the credit cycle points to the need for further research of the interrelation between bank-level solvency indicators and the business/credit cycle at different lags/leads.

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APPENDIX I. DEFINITIONS OF MACROFINANCIAL INDICATORS USED IN ANALYSIS

Sector	Risk Type	Indicator	Variable description	Data Source
Economy-wide	…	Real growth of credit to private sector	Growth (y-o-y) of ratio of private sector debt to CPI index [private sector credit: bank loans (domestic and where available external) and externally-held debt securities (where available)]	IMF IFS/ BIS TCS
Banking sector	Solvency risk	Regulatory capital-to-risk-weighted assets ratio (inverse)	Deposit Takers: Regulatory Capital to Risk-weighted Assets (EOP, %)	IMF FSI
		Capital-to-assets ratio (inverse)	Deposit Takers: Capital to Asset Ratio (EOP, %) (Inversed)	IMF FSI
		NPLs net of provisions-to-capital ratio	Deposit Takers: Non-Performing Loans Net of Provisions to Capital (EOP, %)	IMF FSI
		Net open FX position-to-capital ratio (percentile based on absolute values)	Deposit Takers: Sensitivity to Mrkt Risk: Net Open Position in FX to Capital (EOP,%)	IMF FSI
		3-year ahead cummulative probability of default of listed banks (Median; bps)	3-year ahead cummulative probability of default of bank sector generated by BuDA model (Median; bps)	CRI
	Liquidity risk	Return on assets * (-1)	Deposit Takers: Earnings & Profitability: Return on Assets (EOP, %)	IMF FSI
		Liquid assets-to-short-term liabilities ratio	Deposit Takers: Liquid Assets to Short Term Liabilities (EOP, %)	IMF FSI
		Loans-to-deposits ratio	Deposit Takers: Total [Non-Interbank] Loans to Customer Deposits (EOP, %)	IMF FSI
		Real overnight interbank rate	Overnight Interbank Rate minus CPI yoy growth rate	Bloomberg
		Libor-OIS Spread (3-month)	3-month Interbank Rate minus 3-month OIS Swap Rate	Bloomberg
	Mispricing risk	Share of household loans in total bank claims to domestic non-fin. sector	Numerator: Other Depository Corporations loans to Other Resident Sectors; Denominator: Sum of Other Depository Corporations loans to Private Sector (Other Non-financial Corporations, Other Resident Sectors) and claims (loans and securities) on Public Sector (Loans to Public Non-financial Corporations, Claims on Central Government, and Claims on State and Local Government)	IMF IFS
		Share of public sector claims in total bank claims to domestic non-fin. sector	Numerator: Other Depository Corporations claims (loans and securities) on Public Sector (Loans to Public Non-financial Corporations, Claims on Central Government, and Claims on State and Local Government), Denominator: Sum of Other Depository Corporations loans to Private Sector (Other Non-financial Corporations, Other Resident Sectors) and claims (loans and securities) on Public Sector (Loans to Public Non-financial Corporations, Claims on Central Government, and Claims on State and Local Government)	IMF IFS
		NPLs share in total gross loans (inverse)	Deposit Takers: Asset Quality: NPL to Total Gross Loans (EOP, %)	IMF FSI
		FX share in total bank liabilities	Deposit Takers: FX-Denominated Liabilities to Total Liabilities (EOP,%)	IMF FSI
		FX share in total bank loans	Deposit Takers: FX-Denominated Loans to Total Loans (EOP, %)	IMF FSI
Equity market	Mispricing risk	Real stock market returns	Growth (y-o-y) of ratio of stock market index to CPI index	Bloomberg
		Stock market volatility * (-1)	Rolling standard deviation (over 60 working days) of daily annualized stock market returns (pct pts)	Bloomberg
Bond market	Mispricing risk	Real domestic government bond yield * (-1)	10-year generic government bond yield minus CPI yoy growth rate	Bloomberg
		Domestic government bond yield volatility * (-1)	Rolling daily annualized standard deviation (over 60 working days) of government bond yield (bps) (see financetrain.com/how-to-calculate-interest-rate-volatility/)	Bloomberg
		Sovereign FX debt spread * (-1)	Emerging markets: Stripped spreads between the return on countries' U.S. dollar-denominated foreign debt and that of U.S. government securities (EMBIG) (bps); Advanced and non-EMBIG emerging and developing countries: Five-year credit default swap spreads (bps)	Bloomberg
Foreign exchange market	Mispricing risk	Growth of REER (+ = appreciation)	Real Effective Exchange Rate, based on Consumer Price Index, yoy growth (+ = appreciation)	IMF IFS
		FX market volatility * (-1)	Rolling standard deviation (over 60 working days) of daily annualized FX market returns (Dom. Curr./1 USD; pct pts)	Bloomberg
Housing market	Mispricing risk	Real house price growth	Growth (y-o-y) of ratio of nominal house price index (2015=100) to CPI index (2015=100)	BIS/GPG
		House price-to-rent ratio	Ratio of nominal house price index (2015=100) to CPI housing sub-component index (2015=100)	BIS/GPG/Haver
		House price-to-income ratio	Ratio of nominal house price index (2015=100) to per capita nominal GDP index (2015=100)	BIS/GPG/WEO

(Continued)

(Continued)

Sector	Risk Type	Indicator	Variable Transformation	
Households	Solvency risk	Debt-to-financial net worth ratio of households	Total Debt (Loans and Debt Securities) of Households & NPISH over Financial Net	OECD/ECB
		Bank loans to households-to-GDP ratio	Other Depository Corporations Loans to Other Resident Sectors, ratio to GDP	IMF IFS
		Other financial institutions loans to households-to-GDP ratio	Other Financial Corporations Loans to Other Resident Sectors, ratio to GDP	IMF IFS
	Liquidity risk	Debt-to-income ratio of households	Total Debt (Loans and Debt Securities) of Households & NPISH over Implicit Interest rates on total debt	OECD/ECB
		Interest payments-to-income ratio of households	Interest Before FISIM Allocation over Augmented, adjusted gross disposable income	OECD/ECB
	Mispricing risk	Real growth of bank loans to households	Growth (y-o-y) of ratio of Other Depository Corporations Loans to Other Resident Sectors to CPI index	IMF IFS
		Interest rate – income growth differential of households * (-1)	Implicit Interest rates on total debt minus yoy growth rate of Augmented, adjusted gross disposable income	OECD/ECB
		FX share in bank loans to households	Share of Foreign-Currency Loans in Other Depository Corporations Loans to Other Resident Sectors	IMF IFS
Corporates	Solvency risk	Debt-to-equity ratio of corporates	Total debt (loans and debt securities) of Non Financial Corporations to Equity & Invest Fund Shares	OECD/ECB
		Bank loans to corporates-to-GDP ratio	Other Depository Corporations Loans to Other Non-financial Corporations, ratio to GDP	IMF IFS
		Other financial institutions loans to corporates-to-GDP ratio	Other Financial Corporations Loans to Other Non-financial Corporations, ratio to GDP	IMF IFS
		External debt of corporates-to-GDP ratio	Gross External Debt (Loans and Securities), Other Sectors, ratio of GDP	BIS-IMF-WB
		3-year ahead cummulative probability of default of listed corporates (Median; bps)	3-year ahead cummulative probability of default of non-financial sector, excluding basic materials, energy and utilities, generated by BuDA model (Median; bps)	CRI
	Liquidity risk	Debt-to-income ratio of corporates	Total debt (loans and debt securities) of Non Financial Corporations over Augmented gross disposable income	OECD/Eurostat
		Interest payments-to-income ratio of corporates	Interest Before FISIM Allocation over Augmented gross disposable income, Non-Financial Corporations	OECD/Eurostat
		Share of short-term debt in external debt of corporates	Share of Short-term Debt in Gross External Debt (Loans and Securities): Other Sectors	BIS-IMF-WB
		Corporate external debt amortization-to-GDP ratio	Total debt service paid, Amortization, paid - Official amortization paid (principal only), percent of GDP	IMF WEO
		BOP other inv. (net) to non-official, non-bank sector-to-GDP ratio * (-1)	Net Other inflows to nonofficial non-bank sector, percent of GDP in U.S. dollars	IMF IFS
	Mispricing risk	Real growth of bank loans to corporates	Growth (y-o-y) of ratio of Other Depository Corporations Loans to Other Non-financial Corporations to CPI index	IMF IFS
		Interest rate-income growth differential of corporates * (-1)	Implicit Interest Rates on total debt minus yoy growth of Augmented gross disposable income, Non-Financial Corporations	OECD/ECB
		Real growth of external debt of corporates	Growth (y-o-y) of ratio of Gross External Debt: Other Sectors (Loans and Securities) to CPI index	BIS-IMF-WB
		FX share in bank loans to corporates	Share of Foreign-Currency Loans in Other Depository Corporations Loans to Other Non-financial Corporations	IMF IFS

Notes:

BIS TCS - Bank for International Settlements Total Credit Statistics;
BIS PP - Bank for International Settlements Property Prices Statistics;
BIS-IMF-WB - Joint BIS-IMF-OECD World Bank External Debt Statistics;
CRI - Credit Research Initiative (CRI) database of the National University of Singapore's Risk Management Institute;
Eurostat - Eurostat Institutional Sector Accounts database;
GPG - Global Property Guide;
IMF FSI- IMF Financial Soundness Indicators database;
IMF IFS- IMF International Financial Statistics database;
IMF WEO - IMF World Economic Outlook database;
OECD- Organization for Economic Cooperation and Development Sectoral Accounts database.

APPENDIX II. DEFINITIONS OF MACROFINANCIAL INDICATORS DERIVED FROM SECTORAL ACCOUNTS

The 2008 System of National Accounts (SNA) contains standards for data collection at the level of sectors of the economy. It classifies all agents in the domestic economy in four institutional sectors—households, non-financial corporations, financial corporations (including the central bank) and general government. *"The sectoral accounts present the accounts of institutional sectors in a coherent and integrated way, linking – similar to the way in which profit and loss, cash flows and balance sheet statements are linked in business accounting– uses/expenditure, resources/revenue, financial flows and their accumulation into balance sheets from one period to the next. ... Accordingly, the sectoral accounts present the data with three constraints: each sector must be in balance vertically (e.g. the excess of expenditure on revenue must be equal to financing); all sectors must add up horizontally (e.g. all wages paid by sectors must be earned by households); and transactions in assets/ liabilities plus holding gains/losses and other changes in the volume of assets/liabilities must be consistent with changes in balance sheets (stock-flow consistency).*" (ECB, 2011, p. 103).

The debt stock includes the outstanding amounts of loans and debt securities on the liability side of sectoral balance sheets. In line with the approach taken by the European Commission under the Macroeconomic Imbalance Procedure (MIP), the definition excludes financial derivatives, trade credit, and other accounts payable (EC, 2012a). Data are unconsolidated within each sector (i.e., transactions between constituents of the same sector are recorded in gross terms, rather than netting them out), except in the case of the general government, for which only consolidated data are published. We rely on unconsolidated financial accounts data for the private sector, as this information is used in ratios that involve non-consolidated data from non-financial accounts for all domestic sectors, except the general government.

The two *liquidity risk* metrics are constructed as the ratios of the stock of debt and interest payments to the augmented gross disposable income of the various sectors. The resulting two metrics are the *debt-to-income* and *interest payments-to-income ratios*. In constructing the former, the stock of debt is used as a proxy for the relative size of principal debt repayments (data on which are not available) over time, as well as across countries under the implicit assumption of similar maturity structures. In SNA, the interest payments made by borrowers are split between "SNA interest" and a financial intermediation service charge indirectly measured (FISIM). Only "SNA interest" is recorded as interest revenues and expenditures in the non-financial accounts, whereas FISIM is classified mostly under final consumption—in the case of households and government—and intermediate consumption, in the case of financial and non-financial corporations.[20] In order to reconstruct the total interest payments made by sectors, we calculate interest payments as the sum of "SNA interest" and FISIM (see also Lahnsteiner, 2013). We proxy the debt servicing capacity of each sector of the economy by its gross disposable income (GDI) taken before interest payments and, in the case of banks and corporates, also before payments to shareholders (i.e., reinvested earning on FDI and distributed income of corporations)

[20] FISIM is also added to the government intermediate consumption, which increases the government contribution to economy's output. See Chapter 14 in EU (2013) for more details.

(augmented gross disposable income).[21,22] The adjustments are required because: (1) money spent on interest payments is part of sectors' debt servicing capacity; and (2) bond holders have priority over shareholders in the distribution of profits.

The *solvency risk* metric (or *leverage ratio*) is constructed as the ratio of the stock of debt to firms' capital/households' net worth.[23] The capital of non-financial and financial corporations and households' net worth are defined as the difference between the respective sector's assets (both financial and non-financial) and liabilities other than equity.[24] However, many countries do not publish data on non-financial assets, which prevents us from constructing precise measures of firms' capital/households' net worth comparable across countries. Instead, we follow the existing literature by proxying households' net worth by the difference between financial assets and liabilities; and financial and non-financial corporations' capital—by the value of "Shares and Other Equity". In the case of firms, our metric will be a close approximation of firms' capital, if the "Tobin's Q" is equal to one.[25]

Sectoral *interest rate – income growth differentials* are used as proxies for *mispricing risk.* The implicit interest rate is calculated as the ratio of interest payments (including both "SNA interest" and FISIM) over the average of beginning and end-period stock of debt of each sector, except for financial corporations. The calculation cannot be performed for financial corporations, because their interest payments also include the payment of interest on deposits, which are not included in the definition of debt in the denominator of the ratio. The definition of the augmented gross disposable income of all sectors is the same as the one used in the construction of the *liquidity risk* metric.

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[21] In national accounts, gross disposable income is defined as the sum of final consumption and savings and as such is net of interest payments and payments to shareholders. In the case of the general government, gross disposable income is equal to total revenues minus social benefits other than social transfers in kind.

[22] In carrying out the adjustment, we augment the gross disposable income of all sectors by the "ESA interest" paid, but in order to avoid double-counting, FISIM is added back only in the case of financial and non-financial corporations.

[23] "*Given that the financial accounts are based on the market valuation principle, fluctuations in leverage can either be a reflection of transactions in the form of net equity issuance and changes in debt financing, or they can stem from valuation effects on the outstanding amount of debt and/or equity (holding gains or losses owing to changes in market prices or other changes, e.g. write-downs in debt positions)*." (ECB, 2013; p. 34).

[24] Any equity recorded on the liability side of households and non-profit institutions serving households accounts belongs to unincorporated enterprises (proprietors) and the non-profit institutions serving households.

[25] The values of firm's capital and equity are closely linked through the "Tobin's Q", which equals the ratio of the market value of the firm to the replacement cost of its assets.

APPENDIX III. LITERATURE REVIEW OF EMPIRICAL STUDIES OF FINANCIAL CRISES

	Alessi & Detken 2018	Borio 2002	Eichengreen 2000	Frankel 2010	Hermansen 2015	Holopainen & Sarlin 2017	Jorda 2011	Jorda 2017	Manasse 2013	Manasse 2016	Navajas 2013	Schularick 2012	Schularick 2017
Dependent Variable	Crisis	Crisis	Crisis	Cont.	Crisis	Crisis	Crisis	Crisis	Crisis	Crisis	Crisis	Crisis	Bad boom dum. at peak
Horizon	4 years	t+1 to t+3	t+3	t+1 to t+2	t+1	5-12 quarters	t+1	t+1	t+1	1-2 years	t+1	t+1	t+1 to t+3
Method	Random forest	Signal extr.	Probit	OLS	Signal extr.	KNN	Logit	Logit	CARGGING	CRAGGING	Logit	Logit	Logit
Country Size	28	34 OECD	75 EMs	60+	34 OECD	15	14	17	85 EM	85	80	12	17
Time	1970Q1-2012Q4	1960-99	1975-1997	2008-09	1970-2014	1976Q1-2014Q3	140 years	140 years	1980-2010	1980-2010	2005-12	140 years	150 years
Power	Missed crisis 54.5%, False Alarms 10%					Missed crisis 0%, False Alarms 11%	AUC = 0.73	AUC = 0.85				AUC = 0.65	AUC = 0.78
Sample in/out	Out				Out	Out	In	In	Out		In	Out	In
Macro													
Real Credit Boom (de-trend)											●		●
Change of Credit/GDP Ratio									●●				
Credit/GDP Gap (deviation from trend)	●●●	●●●(>4%)			●●●(>10%)	●●●							
Credit to GDP Level	●●●					●●●						●	
Change in Loans/GDP				●●●			●●●						
CA/GDP (level or change)	●●●			●●●		●●●	●●●						●●
GDP per Capita growth				●●●			●●●						
Real GDP growth						●●●							
Real Loan Growth, Deflated by GDP			●●●(+)									●●●	
Investment									●●				
Gross fixed investment/GDP										●●●			
Inflation						●●●							
M3 growth	●●●												
M3 gap	●●●												
Credit Growth	●●●					●●●				●●●			
Balance sheet													
Loan growth								●●●					
CAR								●●●			●●●		●●
Loans-to-deposits ratio								●●●					●●●
Non-core funding ratio								●●●					
ROE											●●		
Net Accumulation of foreign asset/liability									●●				
Bank NFA /GDP										●●●			
Bank foreign liability/GDP										●●●			
Financial													
Stock price (real growth)	●●●					●●●						●●●	
Stock price real gap (deviation from trend)		●●●(>40%)			●●●(>20%)								
House price (real)	●●●					●●●							
Real house price gap (deviation from 5-y MA)	●●●				●●●(>10%)	●●●							●●●
House price-to-rent (deviation from 5-y MA)	●●●				●●●(>5%)								
House price/income	●●●					●●●							
Deposit interest rate									●●	●●●			
Long-term real interest rate growth (10y)	●●●												
Short-term real interest rate growth (3m)	●●●												
Long-term bond yield						●●●							
External													
Reserves (% GDP)				●●●									
M2/reserves			●●●										
Short-term debt (% of reserves)				●●●									
REER (Deviation from 5 or 10-yr MA)				●●●	●●●(>20%)								
Real exchange rate	●●●												
External debt/service ratio	●●●												
Fiscal													
Gov debt/GDP	●●●					●●●							
Household													
Credit to household /GDP	●●●												
Credit to household growth	●●●												
Household loan/income						●●●							
Household debt service ratio	●●●					●●●							
Real credit to household	●●●												

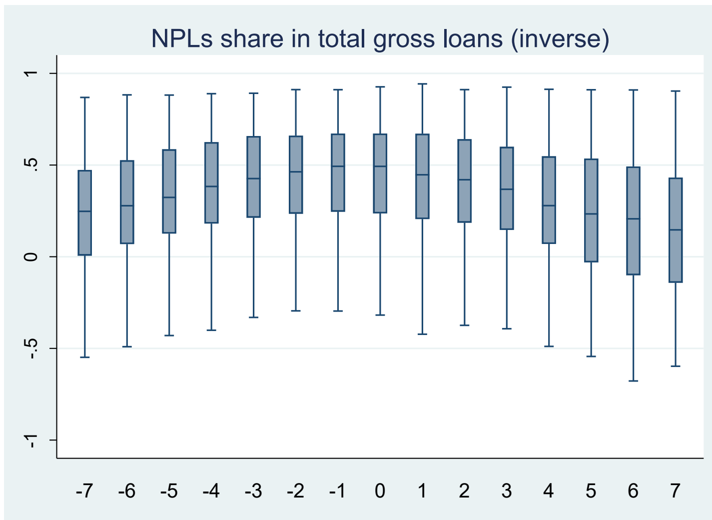
Legend: Confidence levels:
●●● - 99 percent
●● - 95 percent
● - 90 percent

APPENDIX IV. ADDITIONAL STATISTICAL OUTPUT

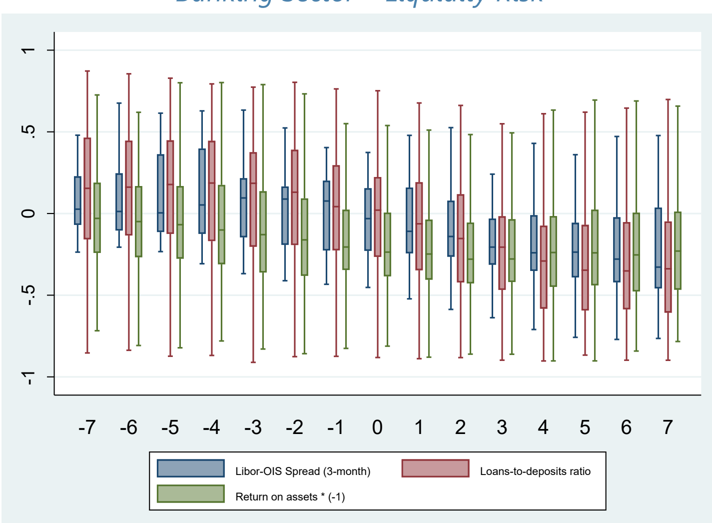
Appendix Figure 1. Sample Distribution of Cross-Correlograms of Risk Metrics from Narrowed-Down List and Real Growth of Private Debt [1/] [2/]

(Correlation Coefficients)

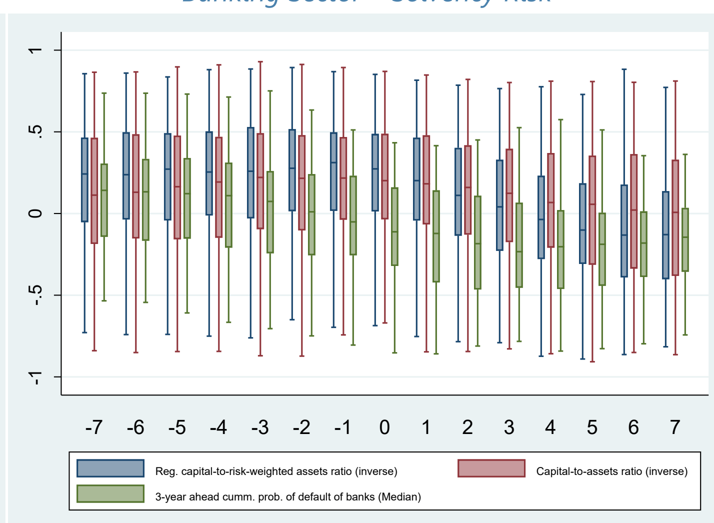
Banking Sector – Mispricing Risk



Banking Sector – Liquidity Risk



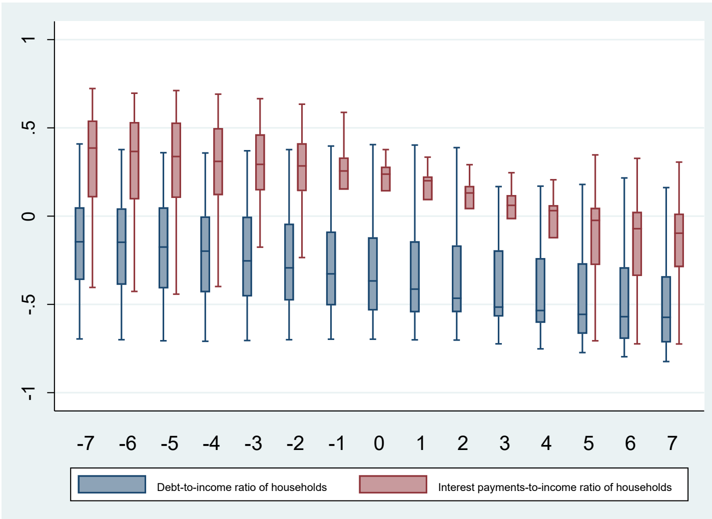
Banking Sector – Solvency Risk



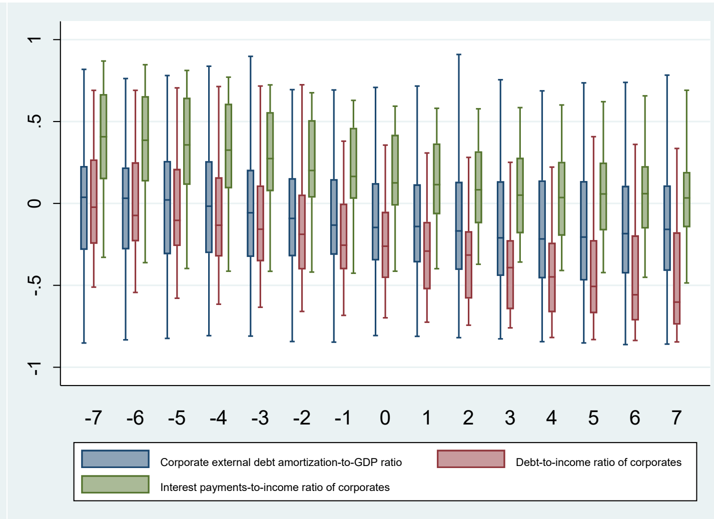
(Continued)

Appendix Figure 1. (Continued)

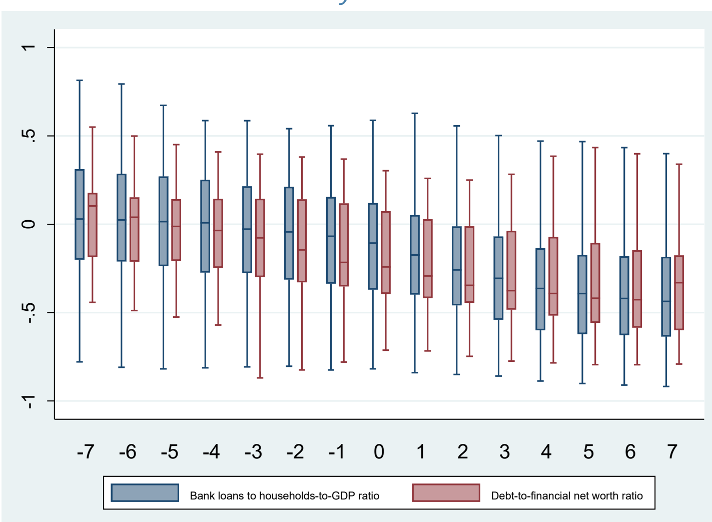
Households Sector – Liquidity Risk



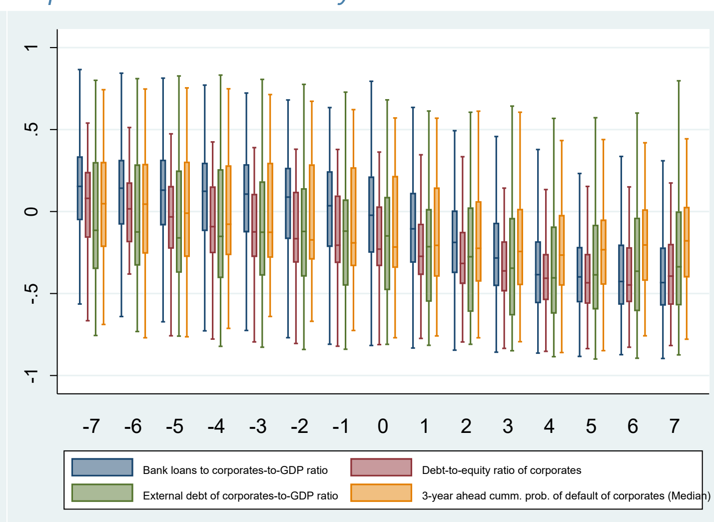
Corporates Sector – Liquidity Risk



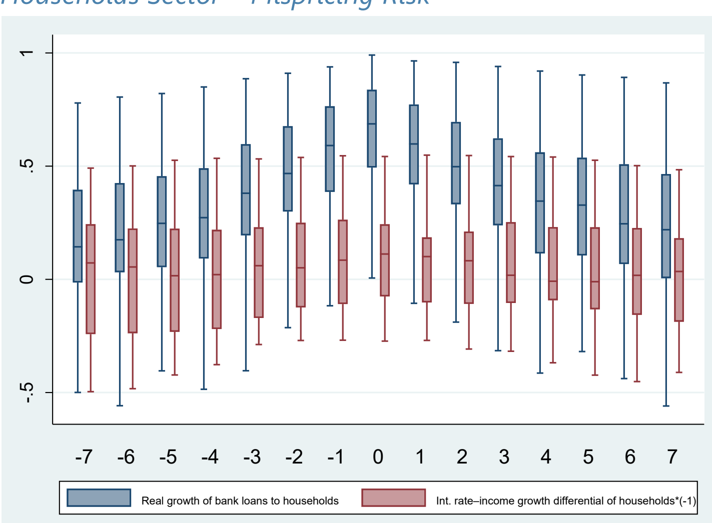
Households Sector – Solvency Risk



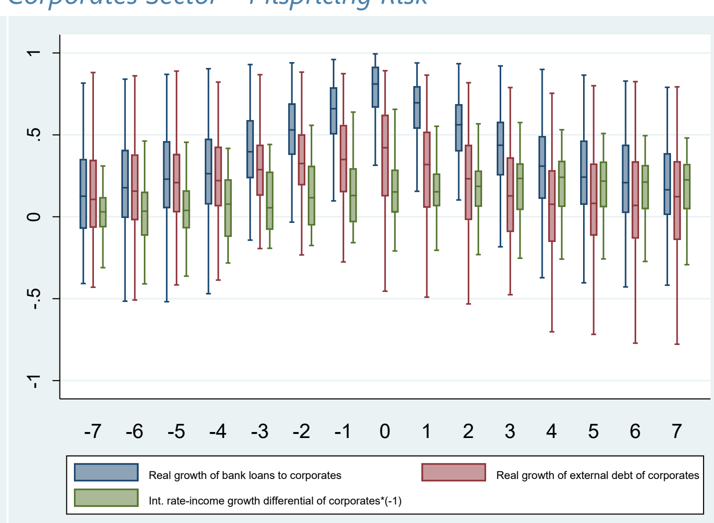
Corporates Sector – Solvency Risk



Households Sector – Mispricing Risk



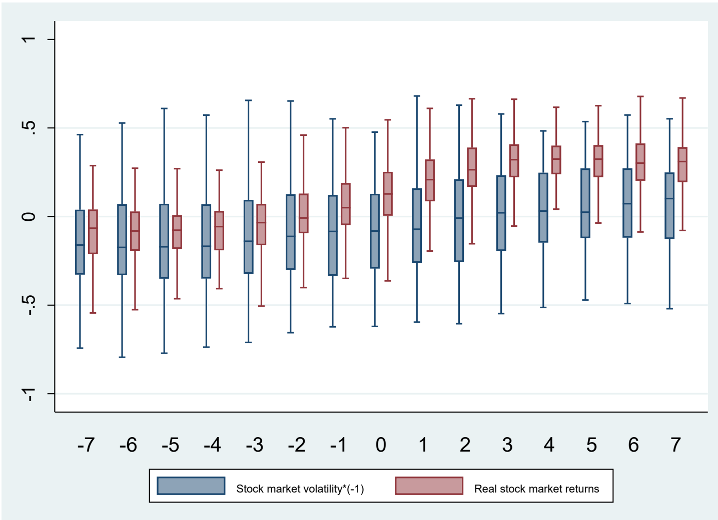
Corporates Sector – Mispricing Risk



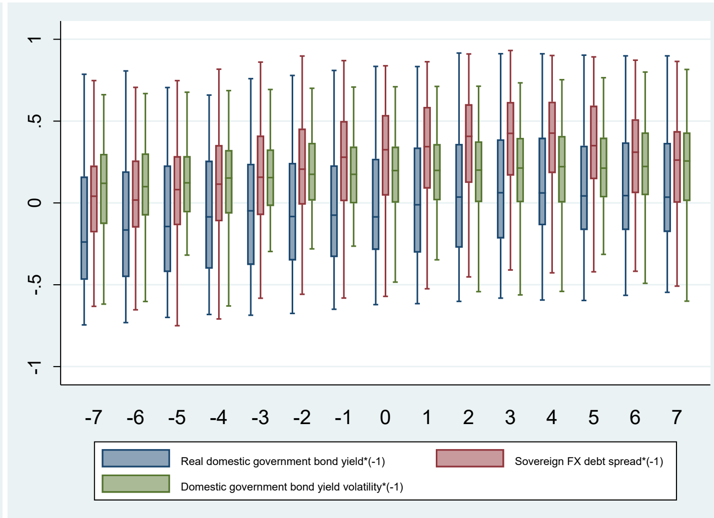
(Continued)

Appendix Figure 1. (Continued)

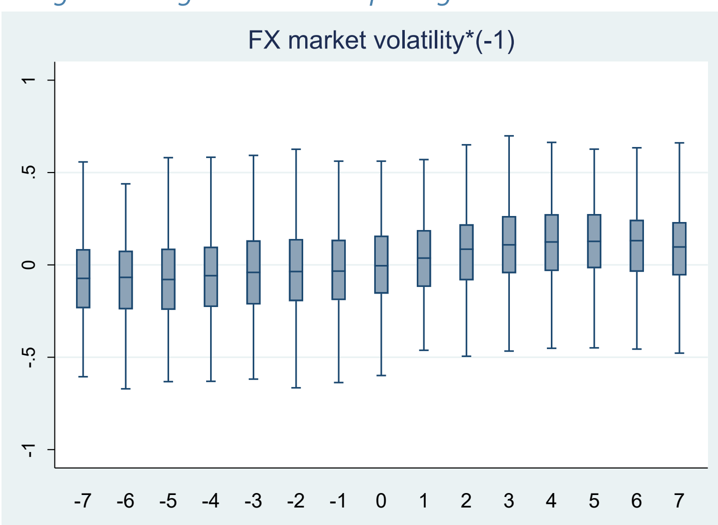
Equity Market – Mispricing Risk



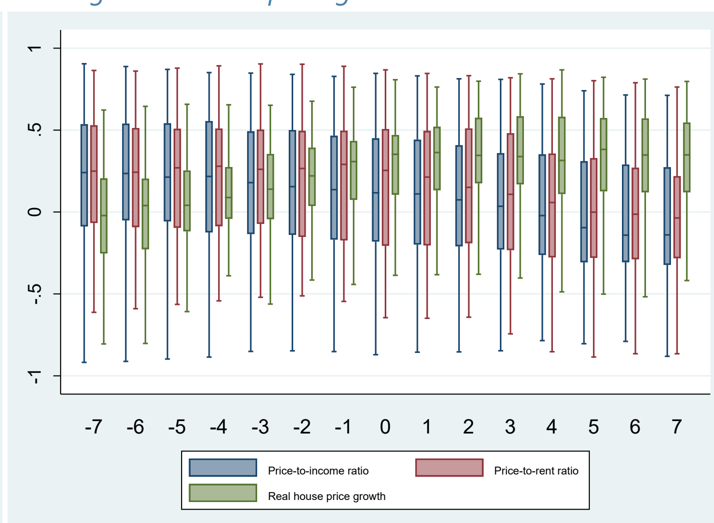
Bond Market – Mispricing Risk



Foreign Exchange Market – Mispricing Risk



Housing Market – Mispricing Risk



Notes: 1/ A large positive correlation at k=0 indicates that the two series co-move in the same direction; a large negative correlation at k=0 shows that the two series move in opposite directions; a maximum correlation at negative k (e.g., k=-1) indicates that the risk proxy follows developments in real credit growth with a lag of k quarters; a maximum correlation at positive k (e.g., k=1) indicates that the risk proxy leads developments in real credit growth with a lead of k quarters (Stock and Watson, 1999).
2/ In box plots, the lower and upper hinges of each box show the 25th and 75th percentiles of the distribution, the line in the box indicates the median, and the end-points of whiskers mark next adjacent values.

Appendix Table 1. Cronbach's Alpha Analysis of Initial Set of Indicators of Economy-Wide Risks

***Risk* Metrics (Items and Test Scale)**	**Obs.**	**Sign**	**Item-Test Correlation**	**Item-Rest Correlation**	**Inter-Item Covariance (xcl. one item at time)**	**Cronbach's alpha (xcl. one item at time)**
Liquidity risk						
Libor-OIS Spread (3-month)	1,163	+	0.49	0.11	62	0.46
Liquid assets-to-short-term liabilities ratio (inverse)	6,096	+	0.51	0.14	68	0.49
Loans-to-deposits ratio	5,738	+	0.60	0.24	48	0.40
Real overnight interbank rate	5,677	+	0.50	0.02	76	0.52
Return on assets * (-1)	6,565	+	0.51	0.12	62	0.46
BOP other inv. (net) to non-official, non-bank sector to GDP*(-1)	7,819	+	0.52	0.05	76	0.52
Corporate external debt amortization-to-GDP ratio	6,989	+	0.76	0.17	55	0.44
Debt-to-income ratio of corporates	2,493	+	0.55	0.29	58	0.45
Share of short-term debt in external debt of corporates	4,538	+	0.39	0.00	79	0.53
Interest payments-to-income ratio of corporates	1,543	+	0.59	0.33	55	0.43
Debt-to-income ratio of households	2,682	+	0.55	0.27	57	0.44
Interest payments-to-income ratio of households	1,721	+	0.61	0.35	53	0.42
Test scale (mean of standardized items)					62	**0.49**
Solvency risk						
Regulatory capital-to-risk-weighted assets ratio (inverse)	6,502	+	0.60	0.37	125	0.67
Net open FX position-to-capital ratio (pctl based on abs values)	4,979	+	0.34	0.07	147	0.72
Capital-to-assets ratio (inverse)	6,174	+	0.54	0.29	133	0.69
NPLs net of provisions-to-capital ratio	6,469	+	0.37	0.09	150	0.72
3-year ahead cumm. prob. of default of banks (Median)	6,981	+	0.62	0.36	125	0.67
Bank loans to corporates-to-GDP ratio	11,265	+	0.73	0.47	113	0.65
Debt-to-equity ratio of corporates	2,872	+	0.74	0.57	117	0.66
External debt of corporates-to-GDP ratio	4,533	+	0.44	0.18	139	0.70
OFIs loans to corporates-to-GDP ratio	2,602	+	0.45	0.13	138	0.70
3-year ahead cumm. prob. of default of corporates (Median)	7,681	+	0.61	0.33	130	0.68
Bank loans to households-to-GDP ratio	11,312	+	0.68	0.42	128	0.68
Debt-to-financial net worth ratio	2,836	+	0.71	0.52	120	0.66
OFIs loans to households-to-GDP ratio	2,849	+	0.35	0.01	142	0.71
Test scale (mean of standardized items)					131	**0.70**
Mispricing risk						
Share of household loans in total bank claims	11,297	+	0.22	-0.09	49	0.57
Share of public sector claims in total bank claims	11,471	+	0.04	-0.25	60	0.62
FX share in total bank liabilities	4,971	+	0.34	0.10	43	0.53
FX share in total bank loans	5,090	+	0.38	0.15	43	0.53
NPLs share in total gross loans (inverse)	6,439	+	0.48	0.25	38	0.50
FX share in bank loans to corporates	7,971	+	0.33	0.08	45	0.54
Real growth of bank loans to corporates	10,576	+	0.42	0.13	40	0.51
Real growth of external debt of corporates	4,157	+	0.33	0.14	42	0.52
Int. rate-income growth differential of corporates*(-1)	2,373	+	0.41	0.23	41	0.52
FX share in bank loans to households	7,237	+	0.32	0.07	46	0.55
Real growth of bank loans to households	10,620	+	0.49	0.21	38	0.50
Int. rate–income growth differential of households*(-1)	2,529	+	0.48	0.27	39	0.51
Stock market volatility*(-1)	8,331	+	0.40	0.14	41	0.52
Real stock market returns	7,677	+	0.40	0.15	41	0.52
Real domestic government bond yield*(-1)	3,992	+	0.43	0.24	40	0.51
Sovereign FX debt spread*(-1)	6,375	+	0.53	0.29	36	0.48
Domestic government bond yield volatility*(-1)	5,905	+	0.43	0.16	40	0.51
FX market volatility*(-1)	18,277	+	0.55	0.13	41	0.52
Growth of REER (+ = appreciation)	17,784	+	0.45	0.05	47	0.56
Price-to-income ratio	5,072	+	0.42	0.22	39	0.51
Price-to-rent ratio	4,597	+	0.52	0.36	37	0.49
Real house price growth	4,796	+	0.47	0.29	38	0.50
Test scale (mean of standardized items)					42	**0.54**

Source: Authors' estimates using StataCorp (2019a).

Appendix Figure 2. Evolution of Real Growth of Private Debt around Systemic Banking Crises

Source: Authors' estimates.
Notes: Shown are averages of indices in levels (centered around their medians) across 65 systemic banking crises since 1995.