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The effect of structural risks on financial downturns

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Abstract

We investigate the extent to which various structural risks exacerbate the materialization of cyclical risk. We use a large database covering all sorts of cyclical and structural features of the financial sector and the real economy for a panel of 30 countries over the period 2006Q1–2019Q4. We show that elevated levels of structural risks may have an important role in explaining the severity of cyclical and credit risk materialization during financial cycle contractions. Among these risks, private and public sector indebtedness, banking sector resilience and concentration of real estate exposures stand out. Moreover, we show that the elevated levels of some of the structural risks identified may be related to long-standing accommodative economic policy. Our evidence implies a stronger role for macroprudential policy, especially in countries with higher levels of structural risks.

JEL Codes: E32, G15, G21, G28

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1 Introduction

Over the past two decades, financial markets have slowly gained prominence as a key factor driving real economic activity around the world. During the "Great Moderation" of 2003–2007, the global economy recorded its best performance of the past 50 years. However, this episode of record economic growth, accompanied by booms in the credit and housing markets, ended with the deepest financial crisis since the Great Depression. One of the buzzwords that emerged following the outbreak and propagation of the Global Financial Crisis (GFC) was the *financial cycle*. Since then, numerous studies have attempted to understand how the financial cycle affects the real economy (Borio 2014), as well as to measure it (Drehmann et al. 2012) and control it (Galati & Moessner 2013). Another buzzword that moved (back) into the limelight with the emergence of the 2007–2009 crisis was *systemic risk*, which has since become an important research topic (Hellwig 2009, Haldane & May 2011, Acharya et al. 2017).

Many policies have been put forward by academics, central banks, regulators and other policy makers in response to the GFC. One of the newly emphasized ones is macroprudential policy, which is tasked with increasing and maintaining the resilience of the banking sector, preventing build-ups of systemic risk and reducing the likelihood of crises and mitigating their impacts on the financial sector and the economy as a whole. At its core, macroprudential policy responds to developments in systemic risk in the financial sector. Systemic risk itself has two basic components recognised by the current literature: cyclical and structural risks. The cyclical component of systemic risk is related to the dynamic evolution of the financial cycle and can be represented, for example, by the credit-to-GDP gap (the "Basel gap"; Borio & Lowe 2002, Borio & Drehmann 2009, Detken et al. 2014). The structural component of systemic risk is related to the distribution of risks in the financial sector and has the potential to amplify adverse economic shocks. It is represented by various structural features of the financial sector and the real economy in general, such as the resilience and asset quality of the financial sector and the indebtedness of sectors of the real economy.

In this paper, we provide a comprehensive empirical overview of the relationship between financial downturns and the structural characteristics of the financial sector and the real economy. Specifically, we investigate the extent to which various structural risks could exacerbate the materialization of credit risk (as seen through increase in non-performing loans to total loans ratio, NPL) during a financial cycle downturn. We begin by assembling a large database covering all sorts of cyclical risks and various structural features of the financial sector and the real economy for a panel of 30 countries over the period 2006Q1–2019Q4. In our exploration, we concentrate on the period surrounding and following the outbreak of the GFC, which also encompasses the eurozone debt crisis and other, more minor events. We take advantage of the endogenous nature of the financial and debt crises as well as benefiting from improved international data coverage over the past ten years.

We proceed by conducting a turning point analysis in which we identify turning points of the financial cycle (from peak to trough) for our sample of countries. In the process, we account for the intensity and length of the recessionary phase of the cycle. We then match the initial levels of various structural risks in the periods preceding peaks of the financial cycle to the extent of cyclical and credit risk materialization. The turning point analysis highlights several possibly stylized facts. Among other, we find that countries with low resilience of banking sector (low liquidity, profitability and leverage ratio) in the pre-crisis period experienced greater cyclical and credit risk materialization. We also find that the pre-crisis level of government debt is positively correlated with cyclical and credit risk materialization. Last, we find that countries with low interest rates in periods preceding to the financial cycle downturns were also more indebted and had less resilient financial sectors.

These results set the stage for a more formal empirical analysis of the relationship between the credit risk materialization and structural features of systemic risk. We employ panel regression models to analyse the importance of structural risks in explaining the degree of credit risk materialization. We primarily find that the extent of credit risk materialization is significantly associated with the indebtedness of sectors of the real economy, the concentration of real estate exposures (as measured by the share of real estate loans in total loans) and the resilience of the banking sector and the structure of the financial sector (bank-based vs. market-based). To account for the strength of the link between structural risks and credit risk materialization, we divide our sample of countries into high and low structural risk countries. We show that countries with above-median level of various structural risks record stronger link between structural risks and credit risk materialization.

We contribute to several different strands of literature. First, we extend the literature on financial cycles along a few dimensions. We provide the first detailed, cross-country empirical analysis of the interplay between the extent of credit risk materialization (financial cycle downturns) and numerous structural risks. While some studies recognise that the course of financial crises is directly affected by certain structural characteristics of the financial sector or the economy in general (Allen et al. 2012, Langfield & Pagano 2016, Bats & Houben 2020), we consider a more comprehensive sample of structural risks than is common in the existing literature. Furthermore, since we employ quarterly data rather than the annual data typically used in other cross-country studies (Bats & Houben 2020, Ari et al. 2020), we can better identify and document the properties of systemic risk and its two components – cyclical and structural. Last, we take advantage of our large dataset and use a time-series approach on top of the regularly employed frequency and turning-point based methods in studying the financial cycle (Stremmel & Zsámboki 2015, Claessens et al. 2011, 2012). Second, we contribute to the literature studying the structure of the financial system and its implications for lending and economic growth (Langfield & Pagano 2016, Bats & Houben 2020). We enrich the analytical considerations of the role of the structure of the financial system with other characteristics that might be of importance, such as real estate exposure concentration, the level of indebtedness or the banking sector profitability and leverage ratio. Third, we also contribute to the ongoing and vast analytical work on the macroprudential policy framework. Existing studies typically deal with the appropriate configuration of macroprudential policy tools (Hanson et al. 2011, Malherbe 2020, Ambrocio et al. 2020, Pfeifer & Hodula 2021) and the early warning properties of different financial cycle indicators (Drehmann & Juselius 2014, Babecký et al. 2014). Our empirical evidence allows us to draw relevant policy conclusions with regard to the design and implementation of macroprudential policy measures.

The remainder of this paper is structured as follows. Section 2 presents an overview of the literature on cyclical and structural systemic risks and discusses their interaction. Section 3 presents the data employed in the analyses. Section 4 gives the results of our turning point analysis and Section 5 introduces the results of our panel regression approach. The final Section 6 concludes.

2 Systemic Risk: An Overview

Increases in systemic risk in the financial system give rise to a threat to financial stability. Systemic risk is generally defined as the risk of a serious failure occurring in the entire financial system or a part thereof, with undesirable impacts on the current and future development of the economy as a whole. In other words, growth in systemic risk implies an increase in the vulnerability of the entire financial system. It has two components - a cyclical one and a structural one. The cyclical dimension is concerned with the build-up of macro-financial imbalances over the financial cycle, while the structural (cross-sectional) dimension is concerned with the build-up of systemic risk due to changes in the financial system.

In what follows, we describe each of the two parts of systemic risk in more detail, aiming to summarize the advances made in research in this area, to establish where our work fits into the literature and to highlight our contribution.

2.1 Cyclical Risk

There is an emerging consensus in the academic literature that cyclical risk tends to build up gradually, well in advance of financial crises. It is thus associated with the financial cycle and the cyclicality of the financial system in general (see, for example, Minsky 1982, Kindleberger et al. 1996). Typically, studies find that the average length of (financial) cycles arising from credit and asset prices is around 15–20 years (Aikman et al. 2015, Schularick & Taylor 2012, Lang et al. 2019, Mandler & Scharnagl 2021). In an upward phase of the financial cycle, credit growth and prices of financial assets and property rise sharply, against a backdrop of very relaxed financial conditions. In turn, the elevated asset prices increase the value of collateral and thus the amount of credit the private sector can obtain, until, at some point, the process goes into reverse. Unsurprisingly, peaks of financial cycles have historically tended to cause serious macroeconomic dislocations (Jordà et al. 2013, Mian et al. 2017). Claessens et al. (2012) show that recessions coupled with financial imbalances are lengthier and deeper than normal business cycle contractions.

Credit and house price indicators are among the oldest and most widely used indicators (Borio & Zhu 2012, Aikman et al. 2015, BIS 2017). A challenge in exploring the recurrent nature of the financial cycle is that each cycle differs noticeably over time (Figure A1). Furthermore, when looking at the longer time scale, one must not forget other structural changes in the economy, such as changes made to exchange rate, monetary, fiscal and regulatory regimes. Burnside et al. (2016) show that periods of financial repression, for example, have tended to influence the shape of the financial cycle. And while recurrent long swings in financial forces are evident, it might be tricky to compare financial cycles. For instance, Albuquerque et al. (2015) show that it might be better to focus on episodic, not conventional time series. This is the path we take in our paper, in which we concentrate on the period surrounding and following the Global Financial Crisis of 2007–2009.

2.2 Structural Risks

A general feature of structural risks is their potential to amplify the impact of adverse economic shocks. As research indicates, the origins and depth of financial crises differ significantly, but they primarily reflect interactions between build-ups of cyclical imbalances and underlying structural risks (Liang 2013). In what follows, we divide structural risks into two broad categories: (i) risks stemming from the structural characteristics of the banking sector and (ii) risks to the banking sector stemming from the real economy. A detailed breakdown of structural risks is provided in Table 1, which is based partly on the ESRB (2014) approach. [1] The amplification channels of listed structural risks are established, for example, through direct linkages between financial institutions, common exposures, similar business models, low resilience, vulnerability of the private sector and pro-cyclical financial regulation (Gorton & Metrick 2012, Liang 2013, Aldasoro et al. 2017). Increased structural risks may contribute to deleveraging of the private sector, triggering a downward spiral of falling asset values and bank defaults through these channels during financial cycle contractions.

The literature often focuses on the risk of high private or public indebtedness (or, in dynamic terms, underlying rapid credit growth) and shows that high debt can increase systemic risk and the likelihood of a financial crisis. Previous empirical studies have examined government debt crises and their relation to banking crises (Borio & Lowe 2002) or financial crises in general (Manasse et al. 2003, Rose & Spiegel 2012, Dawood et al. 2017). Hunt et al. (2015) shows that high and rapidly rising levels of household debt can be risky because they increase the sensitivity of households to a negative shock to their income or balance sheet. During periods of financial stress, highly indebted households tend to cut their spending more than their less-indebted peers. This is the amplification mechanism of cyclical risk materialization and explains the deep fall in GDP seen during the 2007–2009 crisis and the subsequent slow recovery. It should also be noted that higher indebtedness and a lower share of liquid assets change the sensitivity of the response of households to monetary policy. Gelos et al. (2019) show that households with higher debt levels and lower shares of liquid assets are actually the most responsive to monetary policy.

Studies generally recognise that the course of financial crises is directly affected by certain structural characteristics of the financial sector or the economy in general. Allen et al. (2012) show that bank-based financial systems need more time to recover from an economic downturn following a financial crisis. Langfield & Pagano (2016) find that countries with bank-based financial systems exhibit higher systemic risk and lower economic growth, particularly during housing market crises. Bats & Houben (2020) reach a similar conclusion that bank-based financial structures are associated with higher systemic risk than market-based ones.

[1] In addition, ESRB (2014) considers risks stemming from the propagation and amplification of shocks within the financial system. However, this is an inherent feature of all structural risks.

Table 1: Mnemonics and Description of Our Variables

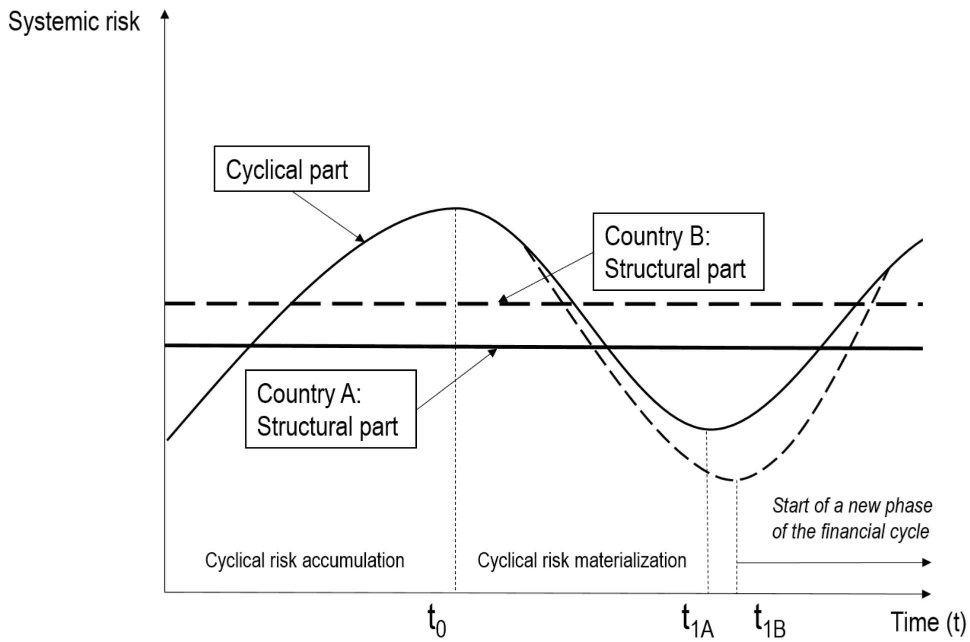
Type of risk	Mnemonics (in regression)	Description	Source
Structural risks stemming from the characteristics of the banking sector	Assets/GDP	Total assets of the banking sector to GDP, per cent	FSI*
	FinOpen	The Chinn-Ito index (KAOPEN) measuring a country's degree of capital account openness	Chinn & Ito (2006)
	bank x market	Bank credit to private sector as ratio of GDP over sum of ratio of total non-financial sector debt market capitalization to GDP and ratio of stock market capitalization to GDP	WB(GFDD) and BIS
	REL/L	Residential real estate loans to total loans, per cent	FSI
	LR	Tier 1 leverage ratio defined as bank's core capital relative to its total assets, per cent.	FSI
	ROA	Return on assets, per cent	FSI
	Liq/Assets	Liquid assets to total assets (liquidity ratio), per cent	FSI
	DSTI	Debt service to total income, per cent	FSI
	C RWA	Regulatory capital to risk-weighted assets, per cent	FSI
	RW	Risk-weighted exposures to total exposures	FSI
	3M IR	3-month interbank interest rate	OECD database
Structural risks stemming from the characteristics of the real economy	Debt NFS	Debt of non-financial sector to GDP, per cent	BIS statistical warehouse
	Debt HH	Debt of households to GDP, per cent	BIS statistical warehouse
	Debt GOV	Debt of government to GDP, per cent	BIS statistical warehouse
	Debt PNS	Debt of private non-financial sector, per cent	BIS statistical warehouse
	Exp/GDP	Exports to GDP, per cent	WB database
	FCL/L	Foreign currency loans to total loans, per cent	FSI
	GDP growth	Real GDP growth, per cent	OECD database
Cyclical risks	NPL/L	Non-performing loans to total loans, per cent	FSI
	FCI	Financial cycle indicator	Aldasoro et al. (2020)
	d-SRI	Domestic systemic risk indicator	Lang et al. (2019)
	FinCyc	Financial cycle index	own calculation

Current research points to the existence of certain structural risk thresholds above which the economy is more vulnerable. This issue is best described in relation to the level of indebtedness, both public and private. For example, Reinhart & Rogoff (2010) and Reinhart et al. (2012) suggest that there is a threshold effect whereby debt above 90% of GDP is associated with worse growth outcomes. Lombardi et al. (2017) suggest that there are negative long-run effects of debt on consumption and that these effects tend to intensify as the household debt-to-GDP ratio exceeds 60%. On the other hand, Pescatori et al. (2014) argue there is no simple debt ratio threshold above which medium-term growth prospects are severely undermined. Identifying a debt threshold has the advantage of giving policymakers a single number to benchmark against. However, it effectively abstracts from a comprehensive assessment of structural risks and their relationship with cyclical economic developments. Structural risks are not likely to develop in isolation but can create clusters of related structural risks that can jointly amplify an adverse shock. In our paper, we focus on an extensive dataset covering all sorts of structural risks.

2.3 Interaction of Structural and Cyclical Risks

Structural and cyclical risks are not independent, and the nature of their interaction may change over the course of the financial cycle. This interplay can take several forms, the most important of which points to the importance of structural risks for the accumulation and subsequent materialization of cyclical risk. Shin (2010) states that increased systemic risk from interconnectedness of banks is a corollary of excessive asset growth. On the other hand, Stremmel & Zsámboki (2015) show that some structural characteristics of the banking sector (structural risks) have an impact on the amplitude of the financial cycle. We show this relationship in a stylized setting in Figure 1, where a higher level of structural risks links to more pronounced materialization of the cyclical part of systemic risk.

Figure 1: Stylized Interplay Between the Cyclical and the Structural Part of Systemic Risk



Note: Own processing.

Empirical studies on the interplay between cyclical and structural risks are scarce and usually consider no more than one structural feature at a time, leaving the rest of the financial sector or real economy characteristics constant. To our knowledge, there are only two other papers on this topic. Stremmel & Zsámboki (2015) study the empirical relationship between cyclical features of the banking sector and a set of structural characteristics. They find that the concentration of the banking sector, the share of foreign banks, the size and stability of financial institutions, the share of foreign currency loans and financial interlinkages contribute to the amplitude of the financial cycle and hence to the variability of financial cycles. Ari et al. (2020) identify key risk factors that increase the severity of the rapid growth of non-performing loans during banking crises. Those factors include high credit growth, high government debt and high corporate debt with short maturity.

We use the analyses of Stremmel & Zsámboki (2015) and Ari et al. (2020) as a starting point and modify them in several ways. First of all, unlike Stremmel & Zsámboki (2015), we focus on the materialization of cyclical risk, i.e. on the descending phase of the financial cycle, similarly to Ari et al. (2020). We use a broader set of structural risks than both of the aforementioned papers. Finally, we substantially extend the analysis of the relationship between cyclical and structural risks. We consider an event-study approach similarly to both papers, but we further propose a simple regression approach using panel data, which allows us to control for a much higher number of confounders. In this approach, we use several alternatives to capture the downward phase of the cycle and a broad set of structural risks.

3 Data on Cyclical, Credit and Structural Risks

We use quarterly country-level data from 30 advanced countries to examine the relationship between cyclical (credit) risk and structural features of the financial system and the real economy. Our data span a maximum period of 2006Q1–2019Q4. The sample period is determined primarily by data availability of detailed structural risks indicators in quarterly frequency. We deliberately restrict our sample to end in 2019Q4 to avoid the Covid crisis, which is beyond the scope of this study.

We rely on three types of data. First, we require a measure of cyclical and credit risk. We use cyclical risk measure to identify periods of financial downturns when risk tend to materialize. For this purpose, we collect data on the stock of private credit and house prices and use them to craft a composite financial cycle measure. Our main analyses will focus on relationship between structural risks and a subset of cyclical risk - the credit risk. To capture country's credit risk, we use the non-performing loans to total loans (NPL) ratio. Second, we construct an extensive dataset covering all sorts of structural risks. Third, we collect several macroeconomic controls from numerous data sources.

3.1 How To Measure Cyclical and Credit Risk

Since the GFC, the literature has focused on defining and measuring risks stemming from the course of the financial cycle. Although some studies tend to favour a parsimonious description of the financial cycle defined in terms of only one variable (Schularick & Taylor 2012, Aikman et al. 2015),[2] various composite indicators of the financial cycle have grown in popularity (Drehmann et al. 2012, Hollo et al. 2012). The latter stream of literature builds on the premise that relevant features of the financial cycle are reflected in multiple

[2]In such studies, the financial cycle is expected to be driven predominantly by credit and to some extent by asset prices.

indicators, and considering them all together allows for more precise measurement. Hence, studies began to combine information from multiple time series into a single representative measure of the financial cycle.

A composite financial cycle indicator should be more successful than a single measure in reducing the uncertainty arising from the unclear definition of the financial cycle. In this respect, we follow Drehmann et al. (2012) and Borio (2014) in combining the information contained in credit aggregates and property prices into a single measure of the financial cycle. As noted by Borio (2014), credit and property prices represent analytically the smallest set needed to replicate the mutually reinforcing interaction between financing constraints (as represented by the credit-to-GDP ratio) and perceptions of asset prices (as represented by property prices).[3]

Although the literature has provided valuable insights into the measurement of the financial cycle, it has fallen short of developing a widely accepted construction technique for deriving a financial cycle indicator. In our exploration, we require a financial cycle measure to identify periods of financial cycle downturns. To derive a financial cycle measure, we use a frequency-based filter to extract the cyclical component from the three time series under consideration: the credit-to-GDP ratio, the house price index and private sector credit growth.[4] Specifically, we use the band-pass filter developed in Christiano & Fitzgerald (2003), although the choice of filtration method does not seem to drive the estimation output.[5] We then use principal component analysis (PCA) to extract the first common component of the series under consideration. PCA has been used extensively in the literature for developing various financial stress measures (Illing & Liu 2006, Hakkio et al. 2009, Cevik et al. 2013). The variables are normalized prior to entering the PCA. We estimate the common factor for each of the 30 advanced countries that form our sample.[6]

Figure 2 offers a cross-country perspective of the estimated common factor and its evolution around systemic events. The mean of the indicator starts to increase four years before the outbreak of the GFC. If we set the value of the indicator in "normal times" to zero, the graph clearly shows a build-up of imbalances before the crisis, followed by a sharp decline as the crisis starts and the cyclical risk materializes.

We consider two alternative composite measure of financial cycle, namely the composite financial cycle index developed in Drehmann et al. (2012) and the the domestic cyclical systemic risk indicator introduced in Lang et al. (2019). These indicators were kindly provided to us by the authors of the respective papers.

[3]Clearly, these two variables represent a compromise with regard to the ideal set of information for measuring the financial cycle. Our choice of variables was primarily data-driven. For example, it would be preferable to include key systemic risk propagation mechanisms such as actual leverage and maturity mismatch, but long country-level time series are too scarce in these cases for our international sample.

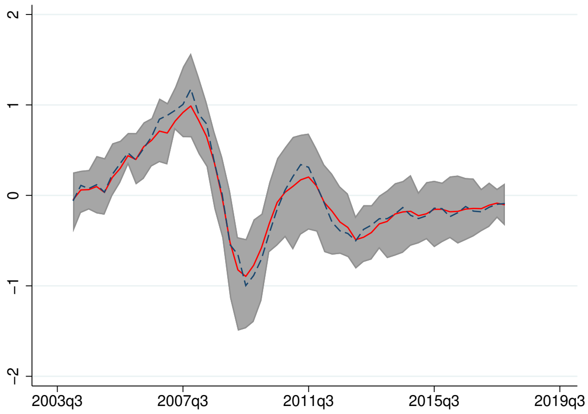
[4]We follow Stremmel & Zsámboki (2015) in considering the duration of a financial cycle to span from 32 to 120 quarters (or 8 to 30 years).

[5]A two-sided Hodrick-Prescott filter with lambda equal to 400,000 delivers roughly the same estimate for the 2003Q1–2017Q4 period.

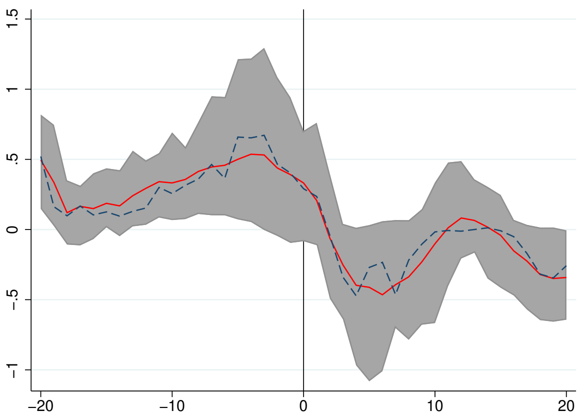
[6]The cumulative percentage of the variance explained by the first principal factor ranges from 48 to 86 in the sample of countries. By using two measures of credit and only one measure of asset (house) prices, the factor loads more on the credit dynamics. The focus on credit dynamics is justified by the well documented fact that credit booms typically precede crises (Jordà et al. 2011, Schularick & Taylor 2012).

Figure 2: Cross-country Distribution of the Estimated Financial Cycle Index

(A) Composite Financial Cycle Indicator



(B) Evolution Around Systemic Financial Crises



Note: Panel A: The shaded region marks the area between the first and third quartile of the cross-country distribution. The solid red line denotes the mean and the dashed blue line the median. The sample size is 30 countries. Panel B: the x-axis depicts the number of quarters before/after systemic financial crises. $t = 0$ marks the beginning of a crisis any time during the 2004Q1–2019Q4 time span according to the ECB/ESRB crises database described in Lo Duca et al. (2017).
Source: Own computation based on various data sources.

While the distinction between cyclical and structural risk factors seems clear in theory, some structural variables can also have a cyclical component. This mostly concerns credit aggregates and debt-related indicators and it might signal the risk of endogenenity in the analyses to come. However, this concern is not valid for credit risk. Structural variables do not contain a credit risk component, as may be the case with cyclical variables, and so there is no trivial two-way relationship between the level of structural risks and the level of credit risk materialisation. Furthermore, the materialization of credit risk determines the depth of the financial downturn. Therefore, we can safely examine whether structural risks relate to the extent of credit risk materialization without the risk of reverse causality or simultaneity. The NPL ratio is well-suited for the analysis of credit risk evolution and the indicator has been used extensively in the literature (Babihuga 2007, Festić et al. 2011, Fungáčová & Poghosyan 2011, Ari et al. 2020).

3.2 Forming the Dataset on Structural Risks

We use two approaches (turning point analysis and panel regression) to clarify the relationship between credit risk materialization and structural risks. Both of these approaches require a comprehensive dataset on various structural risks. We construct an extensive dataset that contains 16 types of structural risks based on our categorization (see Table 1). The data covers the period 2006Q1–2019Q4 and is obtained from several statistical databases and previous empirical studies. For the vast majority of the structural risks covered, we have more than 1,000 observations available to create a rich database that ensures sufficient robustness of the results. Basic descriptive statistics for the variables are then shown in Table A1 in Appendix A.[7] The relations between the structural risk variables are described in a correlation matrix (Figure A2). The correlation matrix illustrates potential clusters of structural risks associated with low resilience (capital ratio

[7]Note that cyclical risks are also listed at the bottom of these tables.

and profitability), high vulnerability (indebtedness and debt service) and the importance of the banking sector to the economy (assets to GDP, bank-based financial system and financial openness).

4 Turning Point Analysis

Using a simple event-study framework, we take a first look at the relationship between financial downturns, credit risk materialization and structural risks using the set of indicators defined above. Being aware of the challenges inherent to exploring the financial cycle's recurrent nature, we adopt a phase-centric approach originally proposed for analysis of the business cycle (Burns & Mitchell 1946). Using this approach, we define units of cyclical time as a sequence of phase turning points. In our application, we focus on the recessionary phase of the financial cycle (from peak to trough), which constitutes one unit of cyclical time (regardless of the elapsed calendar time). We then summarize the changes in both cyclical and structural risks in each of the phase-based time units and assess the co-movements.

We focus on the period surrounding and following the outbreak of the GFC which among other, includes the eurozone sovereign debt crisis. This period has several favourable properties. First, the GFC itself was a textbook example of a crisis created by endogenously accumulating imbalances in the financial sector (similarly to the eurozone debt crisis that followed). As pointed out by Claessens et al. (2011) and Filardo et al. (2018), not all financial cycles are the same (although they do share some commonalities), so focusing on a narrower time span might yield more precise estimates. Second, we benefit from the improved data coverage in the IMF FSI database following the related 2006 initiative and the latest 2019 update.

4.1 Methodology

Our specific methodology for identifying turning points is based on Harding & Pagan (2002), which is an extension of the BB algorithm developed by Bry & Boschan (1971). The algorithm is meant to identify turning points in the logarithm of a series.[8] Hence, we focus on changes in the levels of the variables. This is of utmost importance given the focus of our paper on both the cyclical and structural features of systemic risk. Using the algorithm, we search for local maxima and minima of our handcrafted financial cycle indicator(FinCyc, see Table 1), while imposing certain rules. Specifically, we require the duration of the materialization phase to be at least four quarters ($d \geq 4$). The break between individual financial cycle downturns is set to be at least four consecutive quarters of growth. d is set in a way that allows us to encompass the materialization of cyclical risk during a shallow recession or an economic slowdown, when loan defaults are not on a scale that leads to systemic losses and the risks diminish mainly through loan repayment and the application of more stringent credit standards to refinancing and new lending.

The peaks (local maxima) and troughs (local minima), i.e. our turning points, are defined using the following rules.

A cyclical risk peak as depicted by the financial cycle indicator (f) occurs at time t if:

[8] Applications of the BB algorithm include, but are not limited to, business cycle research (King & Plosser 1994, Watson 1994) and research concerning the cyclical movements of equity and housing prices (Pagan & Sossounov 2003, Bracke 2013).

$$\{[(f_t - f_{t-d}) > 0, (f_t - f_{t-1}) > 0] \wedge [(f_{t+d} - f_t) < 0, (f_{t+1} - f_t) < 0]\}, where\ d \geq 4. \quad (1)$$

A cyclical risk trough occurs at time t if:

$$\{[(f_t - f_{t-d}) < 0, (f_t - f_{t-1}) < 0] \wedge [(f_{t+d} - f_t) > 0, (f_{t+1} - f_t) > 0]\}, where\ d \geq 4. \quad (2)$$

Having specified the turning points, we proceed by computing the amplitude of cyclical risk materialization for each country in our sample. The amplitude measures the change in f_t from a local maximum (f_{max}) to the nearest local minimum (f_{min}) multiplied by the duration (d) to account for the intensity and length of the materialization of cyclical risk:[9]

$$A_m = (f_{max} - f_{min}) \times d. \quad (3)$$

We identify 69 phases of cyclical risk materialization in our sample of countries over the period 2006Q1–2019Q4. A quick overview is available in Table 2. A majority of the countries in the sample experienced at least two episodes of cyclical risk materialization, lasting from six to nine quarters on average. The first amplitude identified was the most intense. This is not surprising, as for most countries it is linked to the period surrounding the GFC. The second amplitude captures the period of the eurozone sovereign debt crisis. The third amplitude is mostly country specific, without a clear common denominator. According to the mean of the amplitude, the most severe materialization phase was identified in the cases of Greece, the United States, Portugal and Italy (Table A2 in Appendix A).

Table 2: Amplitudes of Cyclical Risk Materialization: Summary Statistics

Amplitude	Mean	Median	Min	Max	Standard deviation	No. of countries	Average duration
1	14.21	13.36	1.32	42.75	9.15	30	8
2	11.25	9.02	1.64	60.37	11.63	29	9
3	6.51	5.55	2.37	13.24	3.22	10	6

Note: Table A2 in Appendix A shows the estimated amplitude and duration values for individual countries.

To demonstrate the validity of our identification approach, we plot credit and house prices during a five-year window around the starting date (t=0) of the first amplitude identified (Figure 3). This point reflects the peak of the cycle and the starting point of cyclical risk materialization. The graphs show a gradually increasing rate of credit growth and considerable growth of house prices in the period preceding the starting date. They also nicely depict the fall in the growth rates of both credit and house prices right after the peak point. Note that house price growth starts to slow approximately six quarters before the identified peak point. This is not surprising given previous research showing that property prices peak well ahead of crises (Drehmann & Juselius 2014). In a similar fashion, we plot real GDP growth and the unemployment rate around the start

[9] In fact, the length of the materialization of cyclical risk is likely to be a very important dimension for countries with a high and persistent level of structural risks.

of the cyclical risk materialization phase (Figure A3). This reveals that in our sample of countries, real GDP growth dropped by approximately 6 percentage points (pp) around the start of the first amplitude, bottoming around six to eight quarters past the peak point. In addition, the unemployment rate increased by around 2 pp on average in the two years following the start of a crisis.

Figure 3: Cross-country Distribution of Credit and House Price Growth Around the Start of the Cyclical Risk Materialization Phase

Note: The shaded region marks the area between the first and third quantile of the cross-country distribution. The solid red line denotes the mean and the dashed blue line the median.
Source: Own computation.

4.2 Correlation Analysis

In what follows, we match the identified amplitudes of cyclical risk materialization with the levels of individual structural risks to shed some light on their mutually reinforcing relationship. First, we consider the level of the structural indicator at the start of the materialization phase.[10] By doing so, we are able to assess (albeit indirectly) whether the initial level of structural risks could have determined the extent to which cyclical risk materialized. We mark this approach with the prefix *START* in the following analysis. Second, we calculate the difference between the values of the structural indicator at the start and the end of the cyclical risk materialization phase.[11] This approach allows us to check how structural risks evolved over the whole course of cyclical risk materialization.

[10]For instance, if f_t marks the start of the first financial cycle materialization phase at 2008Q3 and the end at 2010Q4, we pair the A_m value [(2008Q3 value – 2010Q4 value) times 10] with the level of the structural risk indicator at 2008Q3.

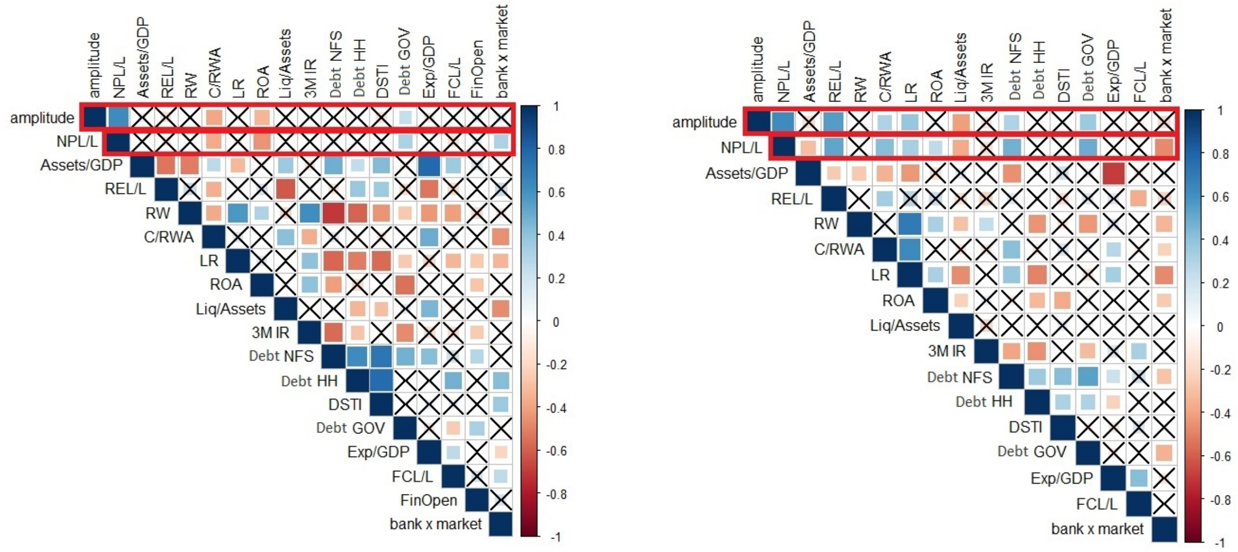
[11]Under this approach, we pair the cyclical risk materialization amplitude (A_m) with the difference between the level of the structural risk indicator at the end and the start date of the cyclical risk materialization phase.

This approach is marked as *END–START*. Using the two approaches, we obtain a comprehensive story of the interaction of structural and cyclical risks during financial cycle contractions.

Next, we run a correlation analysis using the *START* and *END–START* approaches. In the correlation matrices, our main variable of interest is the calculated cyclical risk materialization amplitude and its correlation with various structural risks. The correlation matrices are shown in Figure 4. The left-hand panel A is the correlation outcome of the amplitude (A_m) and the structural risk values at the start of the cyclical risk materialization phase. The right-hand panel B shows the correlations of A_m and the difference in the structural risk values between the end and the start of the cyclical risk materialization phase. We also check the consistency of the correlations by considering the change in the NPL ratio (considered to be a credit risk materialization) during the periods that were identified by the turning point analysis. We expect cyclical risk materialization (A_m) and credit risk materialization (NPL/L) to be highly correlated, as credit risk is a subset of cyclical risk.

Figure 4: Correlation Matrices for Financial Cycle Amplitude and Individual Structural Risks

(A) *START* (B) *END–START*



Note: Crossed fields denote a statistically insignificant correlation coefficient at the 5% level as evidenced by t-statistics. The mnemonics are as follows: amplitude = cyclical risk materialization amplitude, NPL/L = non-performing loans to total loans, Assets/GDP = total banking sector assets to GDP, REL/L = residential real estate loans to total loans, RW = risk-weighted exposures to total exposures, C/RWA = regulatory capital to risk-weighted assets, LR = leverage ratio, ROA = return on assets, Liq/Assets = liquid assets to total assets, 3M IR = three-month interbank rate, Debt NFS = Debt non-financial sector to GDP, Debt HH = Debt of households to GDP, DSTI = debt-service to total income, Debt GOV = Debt of government to GDP, Exp/GDP = exports to GDP, FCL/L = foreign currency loans to total loans, FinOpen = financial openness index, bank x market = bank to market ratio.
Source: Own computation.

The correlation pairs for the *START* specification point to several possibly stylized facts. They show that countries with a low initial (pre-crisis) level of banking sector resilience (a low capital ratio and low profitability) experienced greater and longer materialization of cyclical and credit risk. Thakor (2014) documents that lower bank capital leads to higher systemic risk and a higher probability of a government-funded bailout that may elevate government debt and trigger a sovereign debt crisis. We find that the starting level of government debt is also positively correlated with cyclical and credit risk materialization. A high level of government debt has been found to be detrimental for the aftermath of crises (Cecchetti et al. 2011, Romer & Romer 2018).[12] The correlation analysis provides solid ground for additional analysis using panel data regressions, which allow us to determine whether the simple bivariate correlations can survive increasingly demanding statistical tests.

Considering the *END–START* specification reveals additional interesting patterns in the data. Not surprisingly, we find that more severe cyclical risk materialization is associated with larger materialization of credit risk (i.e. an increase in the NPL ratio). Furthermore, we find that countries which experienced greater cyclical or credit risk materialization also recorded a bigger increase in the capital ratio. This coincides with the conclusion reached by the 2018 report of the Committee on the Global Financial System (CGFS 2018) that, following the GFC, banks enhanced their resilience to future risks by substantially building up capital buffers. At the same time, countries with deeper financial cycle contractions experienced a more severe deterioration in the liquidity position of the banking sector. Further, higher cyclical and credit risk materialization coincides with faster growth of private and public debt. The recession that went hand in hand with the last period of financial distress led to a decrease in sales, which resulted in a greater need of non-financial corporations to turn to debt financing. Longer and deeper financial cycle contractions also necessitated higher government support, reflected in an increased level of public debt. In a related study, Ari et al. (2020) find that countries that resolve their NPLs rapidly tend to have less depressed output and a faster economic recovery following a banking crisis. This last piece of evidence echoes the literature discussing the cleansing effect of recessions (Schumpeter 1939, 1942) and the "unfinished recession" phenomenon. The latter – coined in Drehmann et al. (2012) – broadly describes an "overreaction" by policymakers to unfavourable short-term developments, eventually leading to even bigger market frictions in the future.

We detect other interesting patterns outside our focal point that warrant comment. For the START specification, various correlations with the interbank rate, which serves as our monetary policy proxy, suggest that countries with an initially low interest rate (i.e. a low value at the start of each cyclical risk materialization period) also had a high level of private and government sector indebtedness. At the same time, a low interest rate was significantly correlated with a low leverage ratio, a low return on equity and a worse liquidity position, which signals lower resilience of the financial sector to adverse market shocks. Considering the END–START specification further shows that the post-crisis easing of monetary policy was correlated with substantial increases in both private and public sector indebtedness. This also links to the "overreaction" of policymakers to short-term disturbances mentioned earlier.

On the one hand, monetary policy easing increases the resilience of the financial system in the short term via better access to funding and improved borrower creditworthiness, supporting the creation of bank capital and reducing bankruptcies (Gertler et al. 2013, Kiyotaki & Moore 2019). This is also apparent from our correlation matrix, where lower interest rates are correlated with lower risk weights (risk-weighted exposures to total exposures) in the banking sector. On the other hand, a prolonged period of low interest rates can increase financial vulnerabilities (Adrian & Liang 2018), depressing the profitability of financial institutions (Altavilla et al. 2018) and consequently reduc-

[12]Similar evidence can be found in the case of private debt (Mian et al. 2017).

ing their capitalization. Furthermore, Borio & Zhu (2012) and Bonfim & Soares (2018) provide evidence for the existence of a risk-taking channel of monetary policy. This is particularly the case when the low interest rate environment lasts for an extended period of time, referred to as "too low for too long" (ESRB 2021). However, low interest rates, as a structural risk, also affect valuations, incomes and cash flows, which in turn can modify how banks measure risk (Gambacorta 2009).[13]

As a robustness check, we consider the identified financial cycle amplitudes separately. Specifically, we focus the correlation analysis on the first and the second amplitudes identified, which for most countries link to the GFC and the eurozone debt crisis respectively. Given the narrow gap between the occurrence of these two crises, we only consider the START specification. The correlation matrices are given in Figure A4 in Appendix A. The extent of both cyclical and credit risk materialization related to the occurrence of the GFC was negatively correlated with interest rates and banking sector resilience (ROA and regulatory capital ratio) which is largely in line with (Iacoviello 2015). The amplitude related to the eurozone debt crisis further highlights the important role of government debt, which is not surprising given the source of the crisis.

5 Panel Regression Approach

In the panel regression approach, we use an unbalanced cross-country time series dataset comprising 30 OECD countries over the period 2008Q3–2019Q4. The following equation describes our empirical approach:

$$Credit\ Risk_{it}^{mat} = \beta Structural_{it-4}^{'} + \gamma \mathbf{X}_{it-4}^{'} + \mu_i + \tau_t + \epsilon_{it}, \tag{4}$$

where the dependent variable $Credit\ Risk_{it}^{mat}$ represents the materialization phase of our credit risk indicator, $Structural_{it-4}^{'}$ is a row vector of structural risks, $\mathbf{X}_{it-4}^{'}$ is a row vector of macro controls, μ_i captures unobserved country-specific effects, τ_t captures time-specific effects and ϵ_{it} is the error term. The main parameter of interest is β, which captures the elasticity between cyclical risk materialization and structural risks.

Our panel-data units (countries) probably differ systematically from one another in unobserved ways that affect the outcome of interest. We therefore use unit fixed effects, since they eliminate all between-unit variation, producing an estimate of a variable's average effect within units over time (see, for example, Allison 2009, Wooldridge 2010). We also use time fixed effects, since the variables of interest exhibit substantial variability over time. We expect that our dataset contains period-to-period shocks to the outcome variables that apply to all units of the analysis equally. By employing time fixed effects, we deal with time-variant unobservables that are not unit specific. Still, our model shows the individual time trends of our variables, but only using the variations that are not common to all units.

Generally, we aim to adjust our model for unobserved, unit-specific and time-invariant confounders when estimating causal effects from our data. Through this process, we aim to reduce selection bias in the estimation of causal effects by eliminating large portions of variation thought to contain confounding factors.

When considering left-hand side variables, we are driven by the following economic intuition. In general, the nature of any financial cycle downturn can be of two forms:

[13] For a comprehensive summary and discussion of the benefits and costs of a low interest rate period, see also Malovana et al. (2020).

(i) a shallow recession or an economic slowdown, when loan defaults are not on a scale that leads to systemic losses and the risks diminish mainly through loan repayment and the application of more stringent credit standards to refinancing and new lending, and (ii) materialization during a severe recession (or even a financial crisis), when loan defaults caused by the highly adverse economic developments are on a scale that leads to systemic losses. These forms of financial downturns can overlap and their relative significance will differ depending on the intensity and length of the recessionary phase of the cycle. This boils down to several indicators (considered one-by-one) that should be successful in capturing both a shallow recession and severe materialization of credit risk: (i) the NPL ratio, which proxies the credit losses of the banking sector and hence represents a subset of cyclical risk – credit risk, and (ii) various composite indicators of cyclical systemic risk. Since the structural risk indicators can, in theory, contain cyclical components of their own, we focus mainly on the link between structural risks and the credit risk (NPL ratio). Structural variables do not contain a credit risk component, as may be the case with composite indicators of cyclical systemic risk, and so there is no trivial two-way relationship between the level of structural risks and the NPL ratio. Nevertheless, we also estimate the relationship between composite indicators of cyclical systemic risk and structural risks, but treat it as a robustness check.

Given our focus on the credit risk materialization during financial downturns, we select only those periods for which the first difference of the the NPL ratio is above zero ($NPL_{it} - NPL_{it-1} > 0$). These periods are then matched with the corresponding values of structural risks and other right-hand side controls. Our models are estimated using the ordinary least squares estimator with heteroscedasticity-corrected standard errors. We also perform robustness checks with respect to the estimation method, where we use the Driscoll & Kraay (1998) estimator with Driscoll-Kraay standard errors, which are well calibrated when cross-sectional dependence is present (Hoechle 2007). For country-specific dependence, we include country dummies, but we also try clustering the standard errors by country. These estimates are available from the authors upon request.

A note on the endogeneity issue. Examining the role of structural risks in explaining the extent to which credit or cyclical risks materialize is a complicated task that needs to be handled with care. The difficulties stem from the risk of not sufficiently addressing multiple endogeneity issues, in our case *reverse causality and simultaneity bias* and *omitted-variable bias*. As regards reverse causality and simultaneity, a possible concern could be that during a financial downturn, structural risks tend to increase as a result of, for example, government support of the economy. If left uncorrected, this bias could somewhat inflate our estimated parameters, making them the upper bound of the true relationship. The same applies to the fact that cyclical risk measures can contain structural components. To cater for this possibility, we lag the structural risk indicators and other control variables by one year (four quarters). We also try to split our sample into two groups based on the level of structural risks. We formally examine the causal relationship between cyclical risk materialization and structural risks by employing panel Granger causality tests. In the Granger causality analysis, we deliberately use our hand-crafted financial cycle indicator in order to test whether its alleged cyclical component in our structural risks indicators is strong enough to induce two-way running causality. The test results are presented in Table B1 in Appendix B. The tests reject the null hypothesis that structural risks do not Granger-cause cyclical risk materialization for all of the panel units. For a majority of the structural risks, the causality runs in only one direction. The use of relatively high-frequency quarterly data should also be helpful in mitigating the endogeneity concerns stemming from reverse causality and simultaneity. Omitted-variable bias is of less concern, as we consider multiple right-hand side controls and country-fixed effects that account for changes within groups across time.

5.1 Do Structural Risks Explain Periods of Credit Risk Materialization?

In this section, we describe the main findings stemming from our exploration of the relationship between structural risks and credit risk materialization. We consider the impact of structural risks on banking sector losses (captured by the NPL ratio).

We consider different model specifications based on the selection of structural risks in the vector $Structural'_{it-4}$. We start by regressing period-to-period increases of NPL ratio on those structural risks which were identified as significant in the correlation analysis in the previous section. We deliberately omit some of the previously considered structural risks due to endogeneity issues (the asset-to-GDP ratio), an insufficient number of observations (the ratio of foreign currency loans to total loans) or a lack of any time variation (financial openness). Our final specifications are also respectful of the presence of multicollinearity between pairs (groups) of structural risks. For instance, we do not consider the leverage ratio, bank risk weights and the capital ratio in the same specification. We formally check for multicollinearity in our regressions by calculating the variance inflation factor and assessing its value for individual variables.

The estimates, given in Table 3, show that the extent of credit risk materialization is positively correlated with private and public sector indebtedness (private, government, households, non-financial sector debt), real estate exposure, the bank-to-market ratio and bank risk weights (risk exposures to total exposures), and negatively correlated with financial sector resilience indicators (the regulatory capital ratio and the leverage ratio) and the interest rate. These empirical facts appear to correctly describe the structural sources of the financial imbalances during the period under review. The estimated parameters are robust to changes in the empirical specification and the use of composite cyclical risk indicators as the dependent variable (Table C1) instead of NPLs.

The estimated parameters can be interpreted as the mean elasticity between credit risk materialization and past realizations of structural risks in the sample of countries. As the estimated effect shows, 10 pp higher private and public sector indebtedness is associated with a 0.8 pp and 1.1 pp higher NPL ratio respectively. We have an average NPL ratio of 4.3% in our sample, so the estimated effect is economically significant. Analogously, 10 pp higher concentration of real estate exposures would be associated (on average) with a 1.6 pp higher NPL ratio. Another finding worth noting is that countries with a larger role of the banking sector in financial intermediation (bank-to-market ratio) experienced higher credit risk materialization on average. Early literature (Levine 2002) suggests that the overall performance of the economy (in terms of GDP growth) depends not on the financial structure (bank based vs. market based), but rather on the quality of the financial services produced by the entire financial system. On the other hand, recent literature (Langfield & Pagano 2016, Bats & Houben 2020) shows that bank-based financial structures are associated with higher systemic risk than market-based ones. In more bank-based financial structures, bank financing is found to increase systemic risk and market financing to reduce it. This seems to be in line with our results.[14] We also

[14]The post-GFC literature warns about certain aspects of market-based financing (Adrian & Shin

find that countries with higher trade openness experienced more pronounced credit risk materialization.

Table 3: Structural Risks and Credit Risk Materialization

Dep. var.: NPL/L	(1)	(2)	(3)	(4)
Debt PNS	0.080***	0.081***		
	(0.018)	(0.020)		
Debt GOV	0.105***	0.153***	0.166***	0.153***
	(0.021)	(0.028)	(0.028)	(0.028)
Debt HH			0.172***	
			(0.041)	
Debt NFS				0.061**
				(0.027)
REL/L (real est. exp.)	0.145**	0.166**	0.119*	0.152**
	(0.058)	(0.068)	(0.067)	(0.069)
Liq/Assets (liq. ratio)	-0.084***	-0.082***	-0.082***	-0.091***
	(0.025)	(0.021)	(0.021)	(0.021)
bank x market	0.130**	0.116*	0.118*	0.184**
	(0.051)	(0.066)	(0.065)	(0.069)
C RWA (reg. cap. ratio)	-0.193**			
	(0.085)			
LR (leverage ratio)		-1.104***	-1.200***	-1.058***
		(0.266)	(0.271)	(0.264)
RW (risk weights)		0.190***	0.185***	0.189***
		(0.054)	(0.054)	(0.054)
3M IR (interest rate)	-0.362*	-0.229*	-0.345*	-0.117
	(0.214)	(0.150)	(0.154)	(0.151)
Exp/GDP (openess)	0.083***	0.075***	0.079***	0.068**
	(0.024)	(0.027)	(0.025)	(0.028)
Macro controls	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	800	622	622	622
adj. R^2	0.514	0.516	0.517	0.508
F-test	22.651	19.630	19.731	19.039
	0.000***	0.000***	0.000***	0.000***

Note: The dependent variable is the ratio of non-performing loans to total loans expressed as the period-to-period increases over the period 2008Q3–2019Q4. Robust standard errors in parenthesis. The constant was estimated but is not reported. Macro controls include real GDP growth and the rate of inflation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A higher regulatory capital ratio, a higher liquidity ratio and a higher leverage ratio (all lagged by four periods) are linked with a smaller increase of the NPL ratio. Overall, the resilience of the banking sector, represented by these three indicators, is found to be negatively associated with credit risk materialization as seen through growth in the NPL ratio. These estimates retain significance across the different specifications. When we consider the relationship between the reported bank risk weights (risk exposures to total exposures) and NPL ratios, the parameter estimates come in positive, in line with the previous set of results. A higher aggregate risk weight indicates a riskier portfolio, as evidenced by the results – 10 pp higher risk weights are associated with a 1.9 pp higher NPL ratio. Lower interest rates appear to be associated with a higher NPL ratio as well. A 1 pp drop in the level of interest rates relates to a 0.3 pp increase in the NPL ratio.

Overall, we identify a potentially non-negligible role for structural risks in explaining the degree of credit risk materialization. However, the estimated elasticities so far represent the *average* effect. We will further test whether the strength of the relationship changes once the structural risks pass a certain *threshold*.

2010) that are generally perceived as risky, such as the non-bank financial intermediation (Cizel et al. 2019, Hodula et al. 2020, Irani et al. 2021).

5.2 Considering the Thresholds of Structural Risks

We divide our sample of 30 OECD countries into two sub-samples according to the pre-crisis values of structural risks. As a threshold for the sample split, we consider above and below-median values of the following structural risks: real estate exposure concentration (REL_L), the leverage ratio (LR), private sector indebtedness (DEBT) and interest rates (IR). Specifically, we consider above-median values of real estate exposure concentration and indebtedness and below-median values of the leverage ratio and interest rates as a sign of a country having an above threshold level of structural risk. We calculate the value of structural risks for each country as the average of the given indicator over the three-year window ahead of the start of our sample period in 2008Q3.[15] Detailed results are reported in Table 4 using the NPL ratio as the dependent variable.

Although the setting of the threshold as the median value may seem arbitrary, this will make our two sub-samples relatively comparable in size, which will facilitate our analysis. Moreover, there is no consensus in the current literature on what threshold should apply for which structural risk (see e.g. Pescatori et al. (2014) and section 2 of this paper). However, this does not preclude further research that might attempt to identify these thresholds more precisely in the future.

Columns 1–4 in Table 4 show the regressions for those countries with above threshold values of structural risks prior to the starting date of our sample period. Columns 5–8 then report estimates for countries with below threshold values of structural risks.[16] In other words, we look at whether the relationship between structural risks and credit risk materialization remains the same, as long as some countries have previously above threshold values of structural risks and others have below threshold values. What we expect is greater significance and higher regression coefficients on the left-hand side of the table. Generally speaking, this is indeed the case. Above threshold pre-crisis values of structural risks in the form of higher concentrations of real estate exposures, lower leverage ratios, higher private debt and a lower interest rate environment are generally associated with greater credit risk materialization.

We find the certain threshold of structural risks to be detrimental to the strength of the empirical relationship between credit risk materialization and structural risks. In line with the analytical discussion in the previous section, higher concentration of real estate exposures is found to be associated with an increase in the NPL ratio. This is, however, much more pronounced in countries where structural risks were already high prior to the outbreak of the GFC. On the other hand, the impact of an increase in real estate exposures in countries with low structural risks is found to be statistically insignificant. The same is true for almost all the independent variables, regardless of the structural risk variables according to which the sample of countries is divided. If, on average, real estate exposures increased by 10 pp in a country with low leverage ratio, LR (the second column), the NPL ratio would increase by 5.85 pp. This is approximately three times higher than our baseline estimates, where the threshold of structural risks was not taken into account (see Table 3 and the previous section).

[15] If data are not available for the full three-year window, we use the available data only, but we require at least three quarters ahead of 2008Q3. If we do not have observations for the data before 2008Q3, we exclude them from the analysis. This concerns Israel, Korea and the UK.

[16] Table A3 in Appendix A shows the division of countries according to their values of particular structural risks. In the sample, only Portugal was identified as a high structural risk country using all four criteria. Greece, Norway, Spain and Sweden were identified as high-risk countries in three out of the four criteria.

Further, we find that lower liquidity ratios are associated with higher NPLs, especially in countries with above threshold debt of private nonfinancial sector (private sector indebtedness) prior to the GFC, but we find the relationship to be strong regardless of which structural risk is used as the splitting criterion. Higher risk weights (risk-weighted exposures to total exposures) are found to be associated with higher NPLs, especially for countries with high concentrations of real estate exposures and low leverage ratios. Similarly, above threshold government debts are associated with a higher NPL ratio, especially for countries with lower capitalization.

Last, we find an important role of the interest rate environment for the relationship between credit risk materialization and structural risks. We find that a decrease in interest rates in a country with unfavourable structural characteristics is found to be associated with a substantially higher NPL ratio. In another words, the evidence shows that post-crisis easing of monetary policy was less effective in reducing the default rate in countries with above threshold values of structural risks.

Table 4: Empirical Link Between an Increasing NPL Ratio and the above and below threshold values of Structural Risks

Dependent variable: NPL ratio (upturns)	Above threshold structural risks				Below threshold structural risks			
Split by	REL/L (1)	LR (2)	Debt PNS (3)	3M IR (4)	REL/L (5)	LR (6)	Debt PNS (7)	3M IR (8)
Debt PNS	0.034***	0.112**	0.038	0.073***	0.061***	0.032***	0.053***	0.045***
	(0.008)	(0.053)	(0.028)	(0.025)	(0.016)	(0.008)	(0.009)	(0.007)
Debt GOV	0.123**	0.201***	0.132***	0.093**	0.065***	0.037***	-0.004	-0.015
	(0.050)	(0.046)	(0.043)	(0.047)	(0.024)	(0.014)	(0.012)	(0.010)
REL/L (real est. exp.)	0.343***	0.585***	0.491***	0.420***	0.005	0.010	-0.012	-0.005
	(0.102)	(0.222)	(0.132)	(0.085)	(0.044)	(0.025)	(0.020)	(0.031)
Liq/Assets (liq. ratio)	-0.103***	-0.089	-0.168***	-0.154***	-0.037	0.007	-0.001	0.024
	(0.033)	(0.241)	(0.045)	(0.032)	(0.042)	(0.013)	(0.011)	(0.026)
bank x market	0.346***	0.313***	0.305***	0.318***	-0.040	-0.052*	-0.082**	-0.023
	(0.070)	(0.094)	(0.101)	(0.084)	(0.043)	(0.030)	(0.033)	(0.024)
LR (leverage ratio)	-0.880	-0.777	0.019	-0.009	0.101	-0.513***	0.119	0.023
	(0.992)	(0.768)	(0.952)	(0.810)	(0.185)	(0.197)	(0.198)	(0.136)
RW (risk weights)	0.308**	0.317**	0.194**	0.138**	0.019	0.056*	0.032	0.069*
	(0.120)	(0.151)	(0.097)	(0.064)	(0.029)	(0.032)	(0.031)	(0.029)
3M IR (interest rate)	-0.415***	-0.384***	-0.398***	-0.590***	-0.053	-0.033	-0.083	0.045
	(0.112)	(0.109)	(0.157)	(0.064)	(0.104)	(0.098)	(0.120)	(0.077)
Exp/GDP (openess)	0.251***	0.245***	0.205***	0.223***	0.053	0.033	0.083	0.045
	(0.063)	(0.055)	(0.045)	(0.066)	(0.067)	(0.088)	(0.076)	(0.071)
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	413	295	378	463	436	440	435	418
adj. R^2	0.528	0.536	0.508	0.515	0.370	0.237	0.325	0.353
F-test	15.226	13.524	17.677	14.818	11.304	10.278	12.597	12.913
	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***

Note: The dependent variable is the ratio of non-performing loans to total loans expressed as the period-to-period increases over the period 2008Q3–2019Q4. We consider four structural risk indicators used as a basis for splitting the sample: REL/L = real estate concentration exposure, LR = leverage ratio, Debt PNS = private non-financial sector debt, 3M IR = interest rates. Robust standard errors in parenthesis. The constant was estimated but is not reported. Macro controls include real GDP growth and the rate of inflation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

What is particularly interesting is the effect of the low interest rates seen before 2008 on the relationship between credit risk materialization and structural risks. Based on the emerging literature on the topic, we assume that low interest rates may amplify the negative impact of structural risks on credit risk (Bikker & Vervliet 2018, Malovana et al. 2020, ESRB 2021).

Columns 4 and 8 of Table 4 show the relationship between the individual structural risks and growth in the NPL ratio for countries with low and high pre-2008 interest rates. Generally, we find a positive correlation between structural risks and NPLs in countries with lower interest rates. In this respect, we confirm that higher indebtedness (private debt and government debt) and real estate exposure concentration and lower liquidity ratio are associated with a higher NPL ratio, even more so in countries that kept their interest rates low before the GFC. A 10 pp increase in private debt is found to be associated with a 0.7 increase in the NPL ratio if rates were kept low, as compared to a 0.45 increase in the case of higher interest rates. In fact, we may expect the estimated coefficients to be quantitatively underestimated. The low-rate countries also have systematically higher levels of private debt (284% of GDP), so the unit change in private indebtedness is lower in low-rate countries than in high-rate ones (where private debt scales to only 193% of GDP).

6 Conclusion

The accumulation of structural risks is a phenomenon which, for a long time, was not a subject of general economic interest. Yet structural risks are an inherent part of systemic risk, alongside cyclical risk (Borio 2003). In this paper, we collect a comprehensive set of various structural characteristics of the banking sector and the real economy for 30 advanced economies over the period 2006–2019 and investigate their relation to credit risk materialization during financial cycle downturns. To identify financial downturns, we handcraft our own financial cycle indicator allowing for cross-country comparison.

We use our rich dataset to empirically analyse the relationship between the extent of credit risk materialization and various structural risks. To account for the fact that individual financial cycles differ greatly, we focus on a narrow historical episode comprising a financial cycle peak and a subsequent bust. The period surrounding and following the Global Financial Crisis of 2007–2009 is a great candidate for empirical exploration. Using a turning point analysis, we first show that elevated levels of structural risks prior to the outbreak of a crisis are strongly correlated with the extent to which credit and cyclical risk materialize. Specifically, we unravel that countries with low regulatory capital ratio, low profitability (return on assets) and high (private and government) indebtedness experienced greater and longer materialization of credit and cyclical risk. Second, we estimate a series of panel regressions that allow us to make causal conclusions on the relationship between credit risk materialization and structural risks. We specify our regressions in such a way as to reduce any endogeneity concerns, in particular reverse causality, which may be present.

We show that past accumulation of structural risks may influence the extent to which credit risk materialize during financial cycle downturns. Among these risks, private and public sector indebtedness, banking sector leverage ratio, liquidity and concentration of real estate exposures stand out. Our estimates are robust to changes of the empirical specification and the choice of proxy variables. Furthermore, we show that above threshold levels of structural risks prior to financial cycle contractions substantially amplify the materialization of credit risks and the financial cycle contraction itself. These results provide evidence of a fundamental property of some structural risks related to their potential to amplify adverse shocks.

We show that the elevated levels of some of the structural risks identified may be related to the long-standing accommodative economic policy, which restricts the natural materialization of accumulated systemic risk during financial cycle contractions. Given that many world economies have operated in such an environment for a prolonged period of time, the role of macroprudential policy can be expected to grow (Malovana et al. 2020, ESRB 2021). In light of our empirical results, countries with high levels of selected structural risks should consider being more proactive in increasing capital buffers during the expansionary phase of the financial cycle. Although these macroprudential policy tools cannot significantly dampen the emergence of systemic risks, they can increase the resilience of the banking sector in situations where previously accumulated credit risks materialize.

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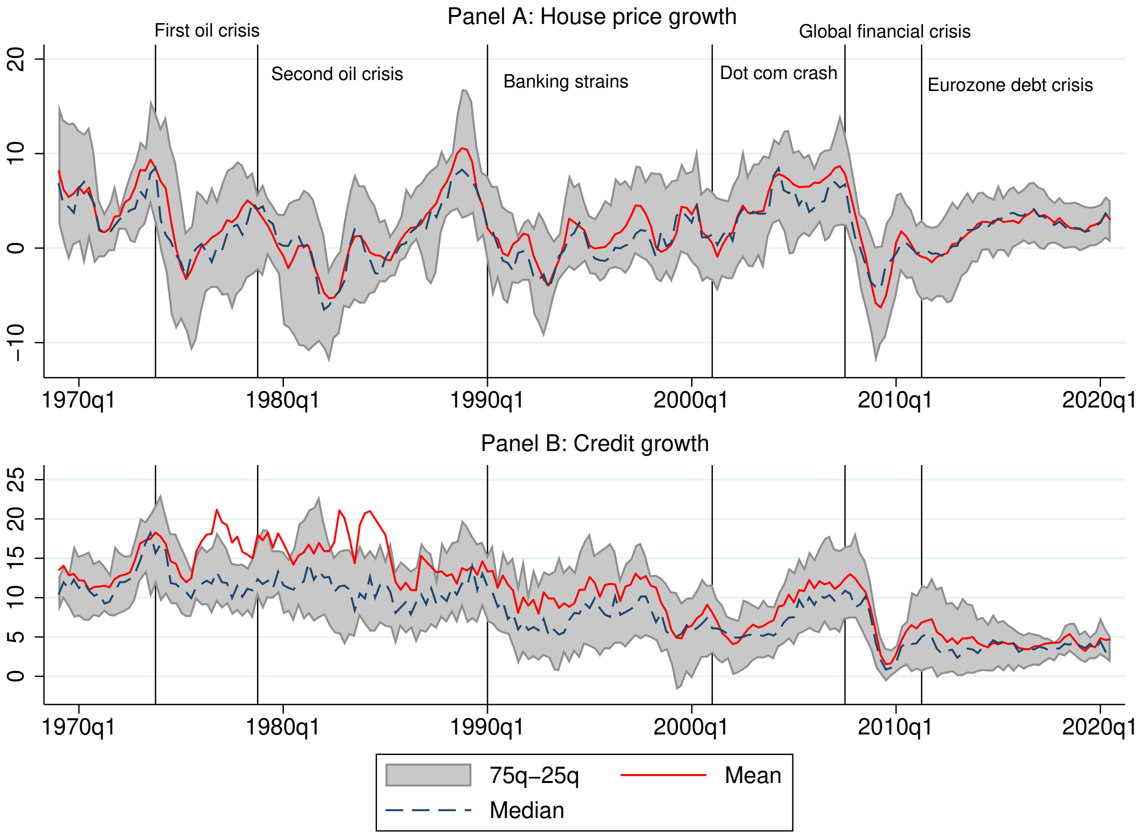
A Details on the Data and the Sample of Countries

Figure A1: A Historical Overview of Cyclical Risks



Note: The underlying data were collected for a sample of 30 advanced economies.
Source: Bank for International Settlements database.

Table A1: Descriptive Statistics of the Full Sample

Variable	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Assets/GDP	1,306	211.855	124.534	0.36.366	80.917	109.542	281.598
FinOpen	1,380	1.633	0.698	−1	2	2	2
bank x market	1,380	0.321	0.108	0.031	0.246	0.386	0.618
REL/L	1,034	27.354	12.253	2.385	18.684	34.389	63.773
LR	1,033	7.968	3.250	1.372	5.591	10.035	17.512
ROA	1,333	9.216	9.999	−85.351	3.984	15.445	38.262
Liq/Assets	1,199	24.622	14.590	4.284	13.862	30.360	84.247
DSTI	1,058	16.860	6.516	3.300	12.900	20.800	32.700
C RWA	1,335	16.137	3.271	8.093	13.940	17.975	27.493
RW	1,062	51.903	17.492	15.165	35.546	67.495	94.767
3M IR	1,334	1.387	1.918	−0.839	0.049	2.012	10.534
Debt NFS	1,380	241.490	85.634	49.100	188.075	297.225	510.700
Debt HH	1,380	64.986	30.874	12.300	40.800	87.425	137.900
Debt GOV	1,380	68.388	42.018	4.200	35.675	86.725	205.200
Debt PNS	1,380	169.012	75.429	28.700	113.325	215.325	413.500
Exp/GDP	1,380	49.029	38.772	9.791	29.187	57.585	273.907
FCL/L	912	21.196	13.165	0.848	11.097	27.830	61.198
GDP_growth	1,380	1.680	3.174	−12.934	0.555	3.031	28.960
NPL/L	1,320	4.774	6.420	0.146	1.472	4.578	47.196
FCI	1,168	0.010	0.144	−0.358	−0.082	0.096	0.366
d-SRI	570	−0.135	1.307	−6.450	−0.738	0.337	11.211
FinCyc	1,062	−0.016	0.513	−2.234	−0.316	0.258	1.769

Table A2: Materialization Phases of Cyclical Risk Identified

Country/Episode	Materialization episodes					
	1		2		3	
	value	duration	value	duration	value	duration
Australia	8.593	6	12.372	8		
Austria	14.911	15	8.343	7		
Belgium	14.655	7	1.706	5		
Canada	6.261	6	2.152	6	5.198	7
Chile	13.764	9	6.846	9		
Colombia	1.322	7	1.636	12		
Czechia	14.915	16	9.286	10		
Denmark	6.880	6	6.404	6		
Finland	18.702	7	2.880	8	9.529	6
France	19.955	7	11.179	7	5.095	6
Germany	8.918	6	13.051	7		
Greece	11.826	6	60.370	27		
Hungary	3.330	7	1.862	6		
Ireland	8.244	8	2.874	6	4.540	5
Israel	9.157	6	4.682	6	2.373	5
Italy	10.372	6	29.408	14		
Japan	26.682	7	13.222	8		
Korea	14.511	9	10.522	9		
Luxembourg	9.221	5	17.440	20		
Mexico	14.654	7	9.019	6	8.757	5
Netherlands	13.558	7	10.947	8	3.563	4
New Zealand	4.684	6	12.560	11	5.908	6
Norway	4.958	6	2.793	8	6.942	7
Poland	10.334	6				
Portugal	33.770	11	3.796	5		
Spain	13.153	7	21.082	12		
Sweden	21.819	8	21.144	13		
Switzerland	28.401	14	15.608	7	13.236	12
United Kingdom	15.924	7	8.543	7		
United States	42.746	13	4.397	7		
max	**42.746**	**16**	**60.370**	**27**	**13.236**	**12**
min	**1.322**	**5**	**1.636**	**5**	**2.373**	**4**
mean	**14.207**	**7.9**	**11.246**	**9.1**	**6.514**	**6.3**

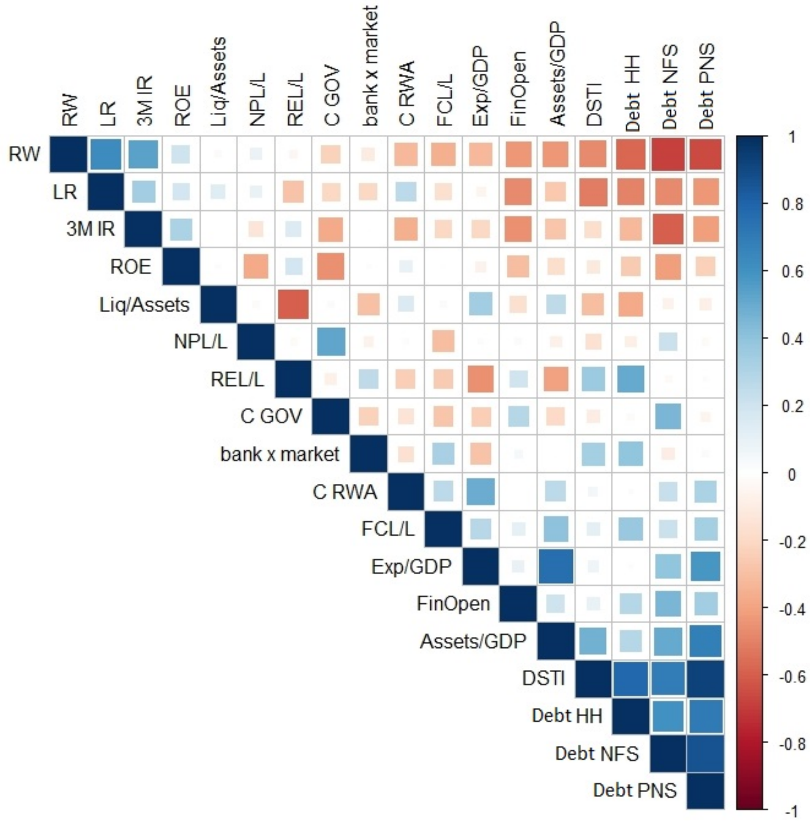
Note: The table shows the estimated amplitude of cyclical risk materialization. The amplitude measures the change in the financial cycle indicator from a local maxima to the nearest local minima multiplied by the number of quarters between the minimum and maximum points (duration). The higher the amplitude, the longer and more intense the cyclical materialization was. We identified a maximum of three cyclical risk materialization episodes per country.

Table A3: Sample Split According to the Level of Individual Structural Risks

Country/Split indicator	REL/L	LR	Debt PNS	3M IR
Australia	x			
Austria		x		x
Belgium			x	x
Canada	x			
Colombia		x		
Czechia	x			x
Denmark	x		x	
Finland	x			x
France			x	x
Germany				x
Greece		x	x	x
Hungary		x		
Chile		x		
Ireland			x	x
Israel				
Italy			x	x
Japan			x	x
Korea				
Luxembourg			x	x
Mexico		x		
Netherlands			x	x
Norway	x	x	x	
Poland	x	x		
Portugal	x	x	x	x
Spain	x		x	x
Sweden	x		x	x
Switzerland			x	x
Turkey		x		
United Kingdom				
United States	x	x		

Note: The table shows how we split the individual countries into two groups – countries with a heightened level of the selected structural risk indicator (above-mean) and the rest. We consider four structural risk indicators used as a basis for splitting the sample: REL/L = real estate concentration exposure, LR = leverage ratio, Debt PNS = private non-financial sector debt, 3M IR = interest rates.

Figure A2: Correlation Matrix for Structural Risks



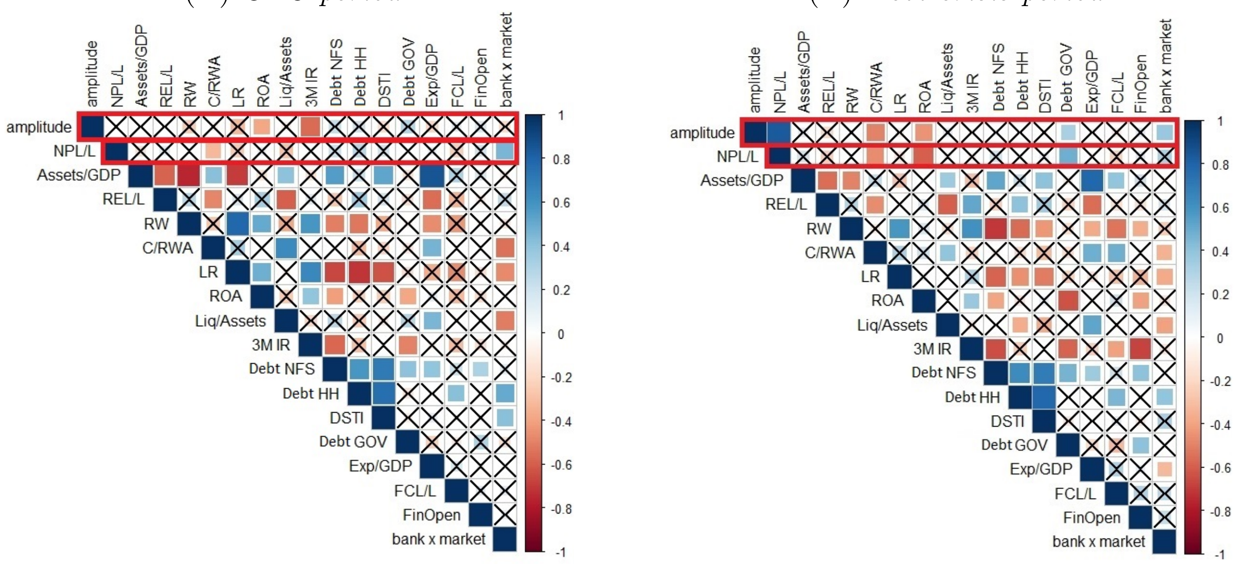
Note: We used the first principal component (FPC) order as the ordering method for the correlation matrix. The matrix should therefore show clusters of structural risks that are similar and emerge together.

Figure A3: Cross-country Distribution of Real GDP Growth and Unemployment Changes Around the Start of the Cyclical Risk Materialization Phase

Note: The shaded region marks the area between the first and third quantile of the cross-country distribution. The solid red line denotes the mean and the dashed blue line the median.
Source: Own computation.

Figure A4: Correlation Matrices for Financial Cycle Amplitude and Individual Structural Risks

(A) *GFC period* (B) *Debt crisis period*



Note: Both correlations are based on the START approach, the same as the correlations in Panel A of Figure 4. Crossed fields denote a statistically insignificant correlation coefficient at the 5% level as evidenced by t-statistics.
Source: Own computation.

B Panel Granger Causality

To detect panel Granger causality, we follow the Dumitrescu & Hurlin (2012) procedure, which consists in estimating the following heterogeneous panel data models:

$$Cyclical_{it}^{mat} = \tau_i + \sum_{j=1}^{p} \gamma_{ij} Cyclical_{it-j}^{mat} + \sum_{j=1}^{p} \lambda_{ij} Structural_{it-j} + \epsilon_{it}, \tag{5}$$

$$Structural_{it} = \tau_i + \sum_{j=1}^{p} \eta_{ij} Structural_{it-j} + \sum_{j=1}^{p} \kappa_{ij} Cyclical_{it-j}^{mat} + \mu_{it}, \tag{6}$$

where $Structural_{it-j}$ indicates the past values of structural risks, p is the lag order, which is assumed to be identical for all panel units, and η and μ are the error terms, which are assumed to be well-behaved. The test of the null hypothesis that structural risks do not Granger-cause cyclical risk materialization in Eq. 5 and that cyclical risk materialization does not Granger-cause structural risks in Eq. 6 is based on the standardized average Wald statistics proposed by Dumitrescu & Hurlin (2012), denoted as $\bar{Z}$ and $\tilde{Z}$. For a panel with large T and small N, as in our case, $\bar{Z}$ is preferred to $\tilde{Z}$. We set a lag order of four quarters to be consistent with the lag used in the baseline Eq. **??**.

Table B1: Panel Granger Causality

Causality direction	*NPL/L*		*ROA*	
	$\bar{Z}$	$\tilde{Z}$	$\bar{Z}$	$\tilde{Z}$
$REL/L \rightarrow Cyclical_{it}^{mat}$	7.181***	5.809***	0.372	-0.012
$Cyclical_{it}^{mat} \rightarrow$ REL/L	1.847*	1.249	0.034	-0.301
$DebtGOV \rightarrow$ Cyclical$_{it}^{mat}$	6.284***	5.042***	5.012***	3.955***
$Cyclical_{it}^{mat} \rightarrow$ Debt GOV	1.254	0.833	0.301	-0.073
$DebtNFS \rightarrow$ Cyclical$_{it}^{mat}$	2.793***	2.057**	3.266***	2.462**
$Cyclical_{it}^{mat} \rightarrow$ Debt NFS	1.217	0.710	0.575	0.161
$DebtHH \rightarrow$ Cyclical$_{it}^{mat}$	4.932***	3.887***	0.188	-0.169
$Cyclical_{it}^{mat} \rightarrow$ Debt HH	1.296	0.777	0.533	0.124
$DebtPNS \rightarrow$ Cyclical$_{it}^{mat}$	3.700***	2.833**	2.277**	1.616
$Cyclical_{it}^{mat} \rightarrow$ Debt PNS	1.436	0.897	1.557	1.001
$C\_RWA \rightarrow$ Cyclical$_{it}^{mat}$	4.041***	3.124***	2.716***	1.991**
$Cyclical_{it}^{mat} \rightarrow$ C_RWA	3.867***	2.975**	1.132	0.637
$LIQ\_ASSETS \rightarrow$ Cyclical$_{it}^{mat}$	1.777*	1.188	-0.689	-0.920
$Cyclical_{it}^{mat} \rightarrow$ LIQ_ASSETS)	-1.427	-1.551	1.033	0.552
$bankxmarket \rightarrow$ Cyclical$_{it}^{mat}$	5.347***	4.241***	1.979**	1.361
$Cyclical_{it}^{mat} \rightarrow$ bank x market	1.371*	0.551	-0.710	-0.793
$LR \rightarrow$ Cyclical$_{it}^{mat}$	2.261**	1.602	2.248**	1.591
$Cyclical_{it}^{mat} \rightarrow$ LR	2.860**	2.114**	1.886*	1.281
$RW \rightarrow$ Cyclical$_{it}^{mat}$	3.818***	2.934**	3.737***	2.864**
$Cyclical_{it}^{mat} \rightarrow$ RW	0.223	-0.140	-0.162	-0.470

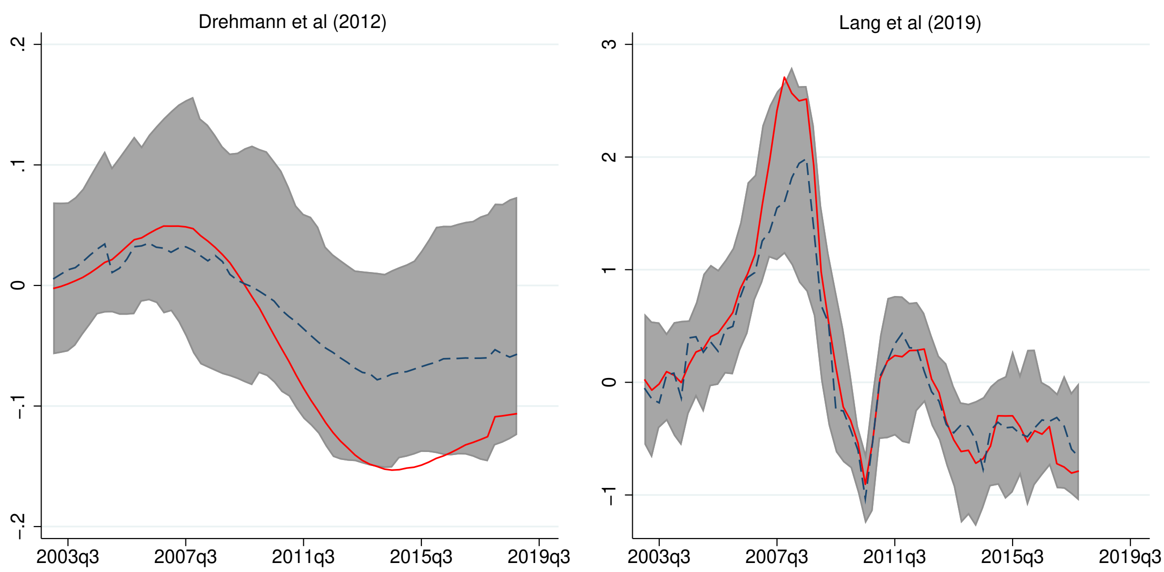
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The test was performed using a lag order of 4. The stationarity of the variables was verified by the Levin-Lin-Chu unit-root test, which is suitable for panels with a substantially larger number of time periods than panel units. For all the variables, the test rejects the null hypothesis that the panels contain unit roots.

C Structural Risks and Cyclical Risk Materialization Captured by Composite Financial Cycle Indexes

We complement the analysis of the relationship between structural risks and the extent of credit risk materialization by focusing on a broader expression of the entire financial cycle. In practise, we regress period-to-period increases of various composite financial cycle indicators on the set of structural risks and the set of controls as specified in eq. 4.

We gradually consider our handcrafted financial cycle indicator (see Section 3 for details on the estimation), the composite financial cycle index developed in Drehmann et al. (2012) and the domestic cyclical systemic risk indicator introduced in Lang et al. (2019). The cross-country distribution of the composite financial cycle index and the domestic cyclical systemic risk indicator is shown in Figure C1.

Figure C1: Alternative Measures of Cyclical Risk



Note: Drehmann et al. (2012) provided us with the Financial Cycle Index and Lang et al. (2019) with the Domestic Cyclical Risk Indicator. The shaded region marks the area between the first and third quantile of the cross-country distribution. The solid red line denotes the mean and the dashed blue line the median.
Source: Aldasoro et al. (2020), Lang et al. (2019), own computation.

In contrast to studying the influence of structural risks on credit risk materialization, the use of composite cyclical risk indicators allows us to encompass different sources of risk. This however comes with the cost of not being able to quantify the magnitude of the relationship between cyclical risk materialization and structural risks.

In Table C1, we regress cyclical risk materialization (as seen through the quarter-on-quarter decreases in the different composite cyclical risk indicators) on individual structural risks and a set of macroeconomic controls. The estimates show that the extent of cyclical risk materialization is negatively correlated with private and public sector indebtedness, real estate exposure, the bank-to-market ratio and bank risk weights, and positively correlated with financial sector resilience indicators (the regulatory capital ratio and the leverage ratio) and the interest rate. The estimates are largely in line with our baseline set of results as shown in Table 3 in the main text.

Table C1: Structural Risks and Cyclical Risk Materialization

Dep. var.:	FCI(own)		FCI(BIS)		FCI(ECB)	
	(1)	(2)	(3)	(4)	(5)	(6)
Debt PNS	-0.031**	-0.036**	-0.025**	-0.008	-0.038**	-0.035***
	(0.012)	(0.018)	(0.012)	(0.037)	(0.016)	(0.010)
Debt GOV	-0.073*	-0.103**	-0.059**	-0.079**	-0.082**	-0.107**
	(0.040)	(0.052)	(0.025)	(0.031)	(0.032)	(0.041)
REL/L (real est. exp.)	-0.118*	-0.260**	-0.247**	-0.385***	-0.161*	-0.320***
	(0.062)	(0.128)	(0.109)	(0.126)	(0.087)	(0.101)
Liq/Assets (liq. ratio)	-0.010	0.003	-0.019	-0.012	-0.032	0.024
	(0.043)	(0.058)	(0.043)	(0.057)	(0.034)	(0.046)
bank x market	-0.517***	-0.569***	-0.316***	-0.445***	-0.271***	-0.322***
	(0.094)	(0.123)	(0.095)	(0.121)	(0.076)	(0.098)
C RWA (reg. cap. ratio)	0.359**		0.457**		0.281*	
	(0.180)		(0.182)		(0.145)	
LR (leverage ratio)		2.967***		2.988***		2.379***
		(0.501)		(0.493)		(0.397)
RW (risk weights)		-0.264***		-0.335***		-0.230***
		(0.101)		(0.099)		(0.080)
3M IR (interest rate)	0.556	1.160**	1.019**	1.531***	0.539*	0.774**
	(0.393)	(0.468)	(0.398)	(0.461)	(0.317)	(0.371)
Exp/GDP (openess)	-0.067*	-0.047	-0.019	0.004	-0.141***	-0.108***
	(0.041)	(0.050)	(0.041)	(0.049)	(0.033)	(0.040)
N	628	476	688	519	375	268
adj. R^2	0.239	0.267	0.285	0.342	0.203	0.244
F-test	7.534	7.434	9.286	10.215	6.312	6.702
	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variables are the period-to-period decreases of the individual cyclical risk indicators over the period 2008Q3–2019Q4. FCI(own) denotes the handcrafted composite financial cycle indicator that was estimated for the purpose of capturing the evolution of cyclical risk in our sample countries. FCI(BIS) is the financial cycle indicator introduced in Drehmann et al. (2012). FCI(ECB) represents the domestic financial cycle indicator described in Lang et al. (2019). Robust standard errors in parenthesis. The constant was estimated but is not reported. Macro controls include real GDP growth and the rate of inflation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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