Working Paper Series

Jan Hannes Lang, Marco Forletta Cyclical systemic risk and downside risks to bank profitability

Abstract

This paper studies the impact of cyclical systemic risk on future bank profitability for a large representative panel of EU banks between 2005 and 2017. Using linear local projections we show that high current levels of cyclical systemic risk predict large drops in the average bank-level return on assets (ROA) with a lead time of 3-5 years. Based on quantile local projections we further show that the negative impact of cyclical systemic risk on the left tail of the future bank-level ROA distribution is an order of magnitude larger than on the median. Given the tight link between negative profits and reductions in bank capital, our method can be used to quantify the level of "Bank capital-at-risk" for a given banking system, akin to the concept of "Growth-at-risk". We illustrate how the method can inform the calibration of countercyclical macroprudential policy instruments.

Keywords: Local projections, quantile regressions, systemic risk, Growth-at-risk, bank profitability.

JEL classification: G01, G17, C22, C54, G21.

Non-Technical Summary

Financial crises are rare events, but when they occur they tend to be associated with large declines in output and oftentimes heavy losses for banks. For example, various studies (Laeven and Valencia, 2012; Lo Duca et al., 2017) have shown that cumulative GDP losses during past financial crises amounted on average to 8 - 20 percent of annual GDP. In addition, the banking sector return on assets in EU countries tended to be considerably lower during past systemic financial crises than during normal or pre-crisis times. In particular, losses of at least 0.6 percent of total assets materialised in more than one quarter of all financial crisis years. Cumulative losses were even larger and amounted to at least 1.5 percent of total assets during half of the systemic financial crises in EU countries.

With this background in mind, this paper studies the impact of cyclical systemic risk on future bank profitability for a large representative panel of EU banks between 2005 and 2017. Our paper builds on recent advances in the literature on measuring cyclical systemic risk and its impact on the real economy. First, we use the domestic cyclical systemic risk indicator (d-SRI) proposed by Lang et al. (2019) as our time-varying cyclical systemic risk measure. The d-SRI is a tractable and transparent country-level measure of the financial cycle that increases on average around five years before the onset of financial crises and that contains information about the likelihood and the severity of financial crises in terms of GDP losses. Second, we employ linear local projections and quantile local projections to quantify the average impact of the d-SRI on the bank-level return on assets (ROA) and on tails of the bank-level ROA distribution over horizons of 1-6 years into the future.

Based on the linear local projections we show that high current levels of cyclical systemic risk predict large drops in the average bank-level ROA many years in advance. A one unit d-SRI value today leads on average to an economically and statistically significant decline in the pre-tax ROA in the range of 0.3-0.6 percentage points between 3 and 5 years ahead. As the median d-SRI value before the onset of past financial crises is close to 1, this estimated response can be interpreted as the negative impact of cyclical systemic risk on bank profits for the average crisis. The shape, magnitude, and statistical significance of the estimated local projection impulse responses are robust to using different econometric estimation techniques, bank samples and country samples. Moreover, similar dynamic patterns are estimated when using longer aggregate banking sector data at the country-level that starts in 1980.

We further show with quantile local projections that the impact of cyclical systemic risk on the left tail of the future bank-level ROA distribution is an order of magnitude larger than on the median. The estimated impact of a one unit d-SRI on the lower fifth percentile of the conditional pre-tax ROA distribution is in the range of -1.1 to -1.8 percentage points for a horizon of 3 to 5 years ahead. The corresponding numbers for the 10th, and 25th lower percentiles are -0.7 to -1.1 and -0.3 to -0.5 percentage points respectively, while for the median the impact of a unit d-SRI is in the range of -0.2 to -0.25 percentage points at the 3 to 5 year horizon. These estimates illustrate that high cyclical systemic risk shifts the entire future bank-level ROA distribution downward, but its impact is by far the highest on the left tail of the future ROA distribution.

Given that negative profits directly reduce bank capital ratios, our method can be used to quantify the level of future "Bank capital-at-risk" for a given banking system, akin to the concept of "Growth-at-risk" developed by Adrian et al. (2016). "Bank capital-at-risk" for a given country is defined as a weighted average of the 5th percentiles of the conditional bank-level ROA distributions, after dividing by the bank-level average risk-weights to rescale results into units of bank capital (weights are given by the relative size of each bank). In addition, the method allows to calculate the "Share of vulnerable banks" (SVB), which is defined as the total asset share of banks with a conditional 5th ROA quantile of less than a certain threshold level. Finally, we show in the paper how the estimated average impact of the d-SRI on future bank capital can be used to inform the calibration of a linear rule for setting countercyclical macroprudential capital buffers.

Compared to the existing "Growth-at-risk" literature, our approach provides three distinct innovations that make it useful for macroprudential policy. First, we employ bank-level micro data instead of aggregate country-level data. The availability of a large cross-section of banks for each country-level financial crisis episode should considerably increase the power to identify the impact of rare aggregate shocks. Second, we focus our analysis on bank profitability as the outcome variable instead of on real GDP as for example in Adrian et al. (2016), Adrian et al. (2018), Aikman et al. (2018), and Lang et al. (2019). As negative bank profits (losses) can be directly translated into bank capital reductions, our method can inform the calibration of macroprudential capital buffers for the banking system. Third, we focus on the impact of cyclical systemic risk (the d-SRI) instead of financial conditions. As shown in the paper, the much longer lead time of the d-SRI of 3-5 years should allow sufficient time to enact mitigating macroprudential policy measures.

1 Introduction

Financial crises are rare events, but when they occur they tend to be associated with large declines in output and oftentimes heavy losses for banks. For example, various studies (Laeven and Valencia, 2012; Lo Duca et al., 2017) have shown that cumulative GDP losses during past financial crises amounted on average to 8 - 20 percent of annual GDP. In addition, as illustrated in panel (a) of Figure 1, the banking sector return on assets (ROA) in EU countries tended to be considerably lower during past systemic financial crises than during normal or pre-crisis times. In particular, losses of at least 0.6 percent of total assets materialised in more than one quarter of all financial crisis years. Cumulative losses were even larger and amounted to at least 1.5 percent of total assets during half of the systemic financial crises in EU countries, as shown in panel (b) of Figure 1. One response to the global financial crisis has therefore been to introduce countercyclical macroprudential capital requirements into the regulatory framework for banks, with the main aim of enhancing banking sector resilience to variations in systemic risk over time (See Basel Committee on Banking Supervision, 2010a).

Figure 1: ROA and maximum cumulative losses during systemic financial crises

(a) Conditional ROA distributions   (b) Maximum cumulative losses during crises
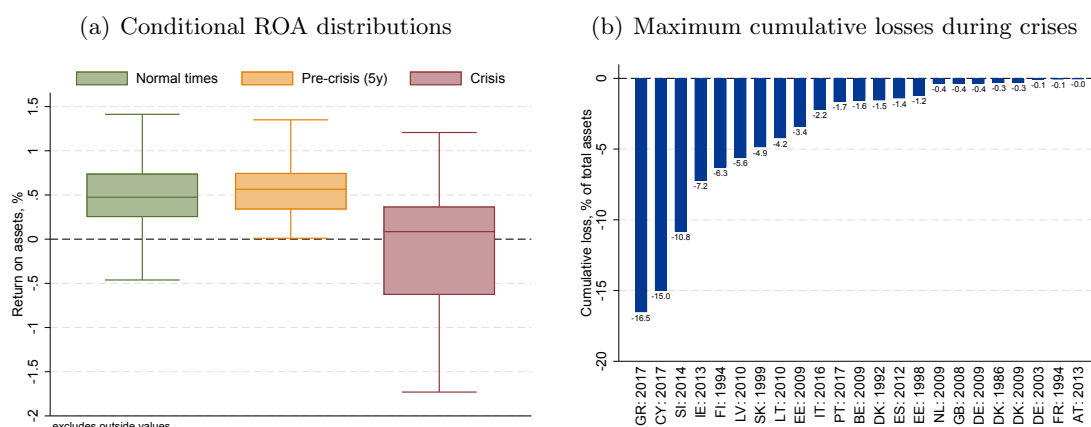
Sources: OECD; CBD2; Authors' calculations.

Notes: (a) The underlying data covers a panel of 22 countries (Euro area countries, Denmark, Sweden, and the UK) since 1980. The number of countries with data varies over time: 1980 (7 countries), 1985 (10 countries), 1990 (14 countries), 1996 (17 countries), 2008 (22 countries). The dating of systemic financial crises in the chart is based on the ECB/ESRB EU crises database described in Lo Duca et al. (2017). Purely foreign induced crises are excluded. In total there are 21 systemic crises underlying the construction of the chart. 7 of these crises occurred before the onset of the global financial crisis. The three lines that divide the coloured box areas into two ranges represent the 25th, 50th and 75th percentiles, while the other two lines represent the lower and upper adjacent values. (b) The maximum cumulative loss in % of total assets is calculated as the sum of a sequence of negative ROAs for a given country. The year on the x-axis indicates the year when the maximum cumulative loss materialised for a given country. In total there are 23 episodes where the banking sector in one of the countries experienced losses in aggregate. The systemic crisis episodes for Belgium and Germany in 2009 were purely induced by foreign factors according the ECB/ESRB EU crises database, which is why two additional crises are reported in panel (b) compared to the 21 crises in panel (a).

Given the high cost of crises and the proliferation of new macroprudential policy tools, research on the measurement and impact of cyclical systemic risk has increased considerably in recent years. Measurement has mostly focused on transformations of credit aggregates (See e.g. Aikman et al., 2015; Borio and Lowe, 2002; Schularick and Taylor, 2012) and more recently on composite financial cycle indicators that combine credit, asset price and risk indicators (See e.g. Drehmann et al., 2012; Lang et al., 2019; Rünstler and Vlekke, 2016; Schüler et al., 2015). The central finding from this research is that credit and asset prices are characterised by long cycles with large amplitudes and that imbalances tend to build-up well in advance of financial crises. Empirical studies regarding the impact of cyclical systemic risk have mainly focused on real GDP as the variable of interest and have employed either local projections as proposed by Jordà (2005) or more recently quantile local projections as proposed by Adrian et al. (2016). The latter approach has become known as "Growth-at-risk", and the central finding of this line of research is that composite risk measures help predict changes in the future real GDP growth distribution and especially changes in its left tail (Adrian et al., 2018; Aikman et al., 2018).

Our paper builds on these recent advances in the literature in order to study the impact of cyclical systemic risk on future bank profitability for a large representative panel of EU banks between 2005 and 2017. First, we use the domestic cyclical systemic risk indicator (d-SRI) proposed by Lang et al. (2019) as our time-varying risk measure. The d-SRI is a tractable and transparent country-level measure of the financial cycle that increases on average around five years before the onset of financial crises and that contains information about their likelihood and severity in terms of GDP losses. Second, we employ linear local projections and quantile local projections to quantify the impact of the d-SRI on average bank profitability and tails of the profitability distribution over horizons of 1-6 years into the future. While local projections are more robust to potential model mis-specification than VARs, their flexibility also allows us to control for a rich set of bank-specific and country-specific (banking sector and macroeconomic) factors, as well as fixed effects at the bank-level, country-level and for specific time periods.

Based on the linear local projections we show that high current levels of cyclical systemic risk predict large drops in the average bank-level return on assets (ROA) many years in advance. A one unit d-SRI value today leads on average to an economically and statistically significant decline in the pre-tax ROA in the range of 0.3-0.6 percentage points between 3 and 5 years ahead. As the median d-SRI value before the onset of past financial crises is close to 1, this estimated response can be interpreted as the negative impact of cyclical systemic risk on bank

profits for the average crisis. The shape, magnitude, and statistical significance of the estimated local projection impulse responses is robust to using different econometric estimation techniques, bank samples and country samples. Moreover, similar dynamic patterns are estimated when using longer aggregate banking sector data at the country-level that starts in 1980.

We further show with quantile local projections that the impact of cyclical systemic risk on the left tail of the future bank-level ROA distribution is an order of magnitude larger than on the median. The estimated impact of a one unit d-SRI on the lower fifth percentile of the conditional pre-tax ROA distribution is in the range of -1.1 to -1.8 percentage points for a horizon of 3 to 5 years ahead. The corresponding numbers for the 10th, and 25th lower percentiles are -0.7 to -1.1 and -0.3 to -0.5 percentage points respectively, while for the median the impact of a unit d-SRI is in the range of -0.2 to -0.25 percentage points at the 3 to 5 year horizon. These estimates illustrate that high cyclical systemic risk shifts the entire future bank-level ROA distribution downward, but its impact is by far the highest on the left tail of the future ROA distribution.

Given that negative profits directly reduce bank capital ratios, our method can be used to quantify the level of future "Bank capital-at-risk" for a given banking system, akin to the concept of "Growth-at-risk" developed by Adrian et al. (2016). To translate our estimates based on pre-tax ROA into impacts on bank capital ratios, results need to be divided by the bank-level risk-weight density, which is on average around 50%. Hence, on average the impact of cyclical systemic risk on capital ratios is twice the impact on ROA. "Bank capital-at-risk" for a given country is then defined as a weighted average of the rescaled 5th percentiles of the conditional bank-level ROA distributions, where weights are given by the relative size of each bank. In addition, the model results allow us to calculate the "Share of vulnerable banks" in a given country, which is defined as the the total asset share of banks with a conditional 5th ROA quantile of less than a certain threshold level. Finally, we show in the paper how the estimated average impact of the d-SRI on future bank capital can be used to inform the calibration of a linear rule for setting countercyclical macroprudential capital buffers.

The contributions of our paper are threefold. First, we focus our analysis on bank profitability as the outcome variable instead of on real GDP as for example in Adrian et al. (2016), Adrian et al. (2018), Aikman et al. (2018), and Lang et al. (2019). As negative bank profits can be directly translated into reductions of bank capital, our method can support the calibration of macroprudential capital buffers for the banking system. Second, we employ bank-level micro data to estimate the impact of cyclical systemic risk instead of aggregate country-level

data. The availability of a large cross-section of banks for each country-level financial crisis episode considerably increases the power to identify the impact of rare aggregate shocks. Third, we develop the concept of "Bank capital-at-risk", which is similar in spirit to the concept of "Growth-at-risk", but uses information on the tails of the future profitability distributions at the bank-level, instead of the future GDP growth distribution at the country-level.

The remainder of the paper is structured as follows. In Section 2 we describe the link between cyclical systemic risk and bank profitability at a conceptual level. Section 3 describes our econometric framework which builds on local projections and quantile regressions. Section 4 describes our dataset, while Section 5 presents the baseline empirical results for the impact of cyclical systemic risk on future bank profitability. Section 6 presents the concept of "Bank capital-at-risk" and outlines how the empirical results can be used for macroprudential surveillance. Section 7 shows that the baseline results are robust to various perturbations. Finally, Section 8 concludes the paper.

2 The link between cyclical systemic risk and bank profitability

Systemic risk is commonly defined as the risk that parts of the financial system become impaired to such an extent that the real economy is negatively affected (See e.g. ECB, 2009). According to the classification proposed by Borio (2003) there are two dimensions of systemic risk: the cyclical dimension is concerned with the build-up of macro-financial imbalances over time, while the cross-sectional dimension is concerned with the build-up of systemic risk due to the (micro) structure of the financial system.

An emerging consensus in the academic literature is that cyclical systemic risk builds-up gradually and well in advance of financial crises. Various papers have shown that credit cycle measures or composite financial cycle measures that combine credit and asset prices display cycle lengths of around 15-20 years and are among the most useful indicators to assess the probability of financial crises with a lead time of many years.[1] In addition, credit or composite cycle measures have been shown to contain advance information about the severity of financial crises and recessions measured in terms of real GDP declines.[2]

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[1] See for example Borio and Lowe (2002), Aikman et al. (2015), Borio and Drehmann (2009), Detken et al. (2014), Schularick and Taylor (2012), Drehmann et al. (2012), Schüler et al. (2015), Rünstler and Vlekke (2016), Aikman et al. (2018), and Lang et al. (2019).

[2] See for example Jorda et al. (2013a), Bridges et al. (2017), Aikman et al. (2018), and Lang et al. (2019).

There are various channels through which the build-up of cyclical systemic risk can also affect future bank profitability. First, macro-financial imbalances (e.g. high leverage and asset price overvaluation) can lead to direct credit losses for banks once a negative shock hits and defaults increase due to the fall in asset prices and tighter borrowing constraints. Second, an excessive build-up of leverage in the non-financial private sector can imply large deleveraging needs once borrowing constraints tighten in a crisis situation, which can exert large downward pressure on credit growth and hence business volumes of banks. Third, abrupt adjustments of asset price overvaluations can cause losses in banks' trading portfolios. Fourth, indirect negative feedback loops between tighter borrowing constraints, falling asset prices, and reduced economic activity can cause further credit losses for banks. This list of transmission channels between the build-up of cyclical systemic risk and future bank profitability is by no means exhaustive, but it illustrates that there are many relevant channels.
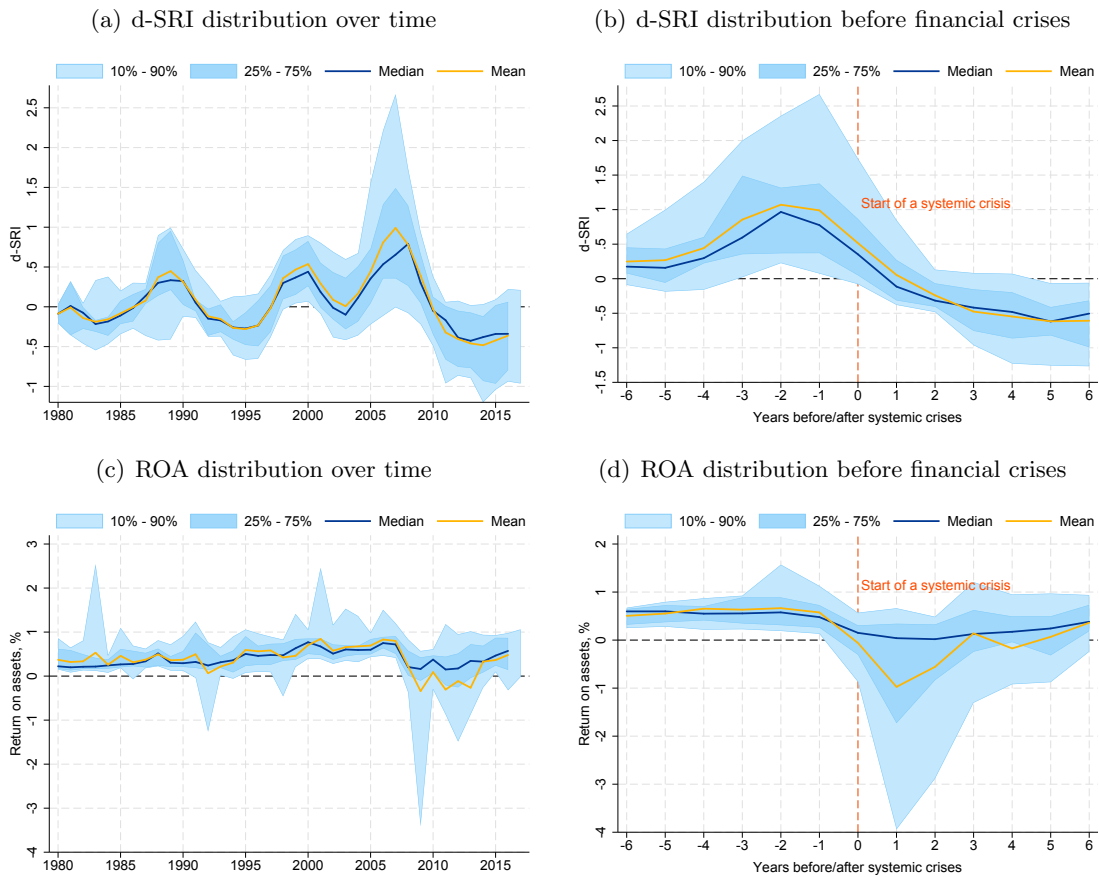
In order to analyse the potential link between cyclical systemic risk and future bank profitability, we make use of the domestic cyclical systemic risk indicator (d-SRI) proposed by Lang et al. (2019), which has been shown to contain useful leading information about the likelihood and severity of financial crises. The d-SRI is a country-level summary measure of the financial cycle and it is constructed as the optimal weighted average of six well-performing normalised early warning indicators in order to capture risks from domestic credit, real estate markets, asset prices, and external imbalances.[3] The d-SRI displays long cycles across euro area countries with three peaks since the early 1980s and tends to increase well before the onset of systemic financial crises as shown in panels (a) and (b) of Figure 2.

Visual comparison of the country-level d-SRI and ROA distributions over time and ahead of financial crises suggest that increases in cyclical systemic risk precede declines in the banking sector ROA. For example, panels (a) and (c) in Figure 2 show that the d-SRI across euro area countries reached peaks in 1989 and in 2007, which were followed by declines in the cross-country ROA distribution with a lag of around three to four years. This lead-lag pattern becomes even more visible if the data is sliced according to the incidence of systemic financial crises. As shown in panels (b) and (d) of Figure 2, the d-SRI tends to peak between one and two years ahead of financial crises, while the banking sector ROA tends to fall significantly following the onset of crises with a trough one to two years into a crisis. These lead-lag patterns motivate our empirical analysis of the impact of cyclical systemic risk on future bank profitability.

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[3]Details regarding the underlying indicators and construction of the d-SRI are provided in section 4.2.

Figure 2: ROA and d-SRI distributions over time and ahead of financial crises

(a) d-SRI distribution over time

(b) d-SRI distribution before financial crises

(c) ROA distribution over time

(d) ROA distribution before financial crises

Sources: OECD; CBD2; Lang et al. (2019); Authors' calculations.

Notes: (a) & (c) The charts show the mean, median, interquartile range and 90-10 percentile range across the 19 euro area countries plus Denmark, Sweden and the UK. The number of countries with data varies over time. For chart (c): 1980 (7 countries), 1985 (10 countries), 1990 (14 countries), 1996 (17 countries), 2008 (22 countries). (b) & (d) The charts show the mean, median, interquartile range and 90-10 percentile range across countries during the 6 years before and after the onset of systemic financial crises. The dating of systemic financial crises in the chart is based on the ECB/ESRB crises database described in Lo Duca et al. (2017). Purely foreign induced crises are excluded. In total there are 21 systemic crises events underlying the construction of the charts. 7 of these crises occurred before the onset of the global financial crisis in 2007.

3   Empirical strategy

To analyse the impact of cyclical systemic risk on future bank profitability we make use of two different econometric tools. First, we employ linear local projections as proposed by Jordà (2005) to study the average impact on bank profitability. Second, we resort to quantile local projections to study the impact of cyclical systemic risk on the tails of the future bank-level profitability distribution. The latter approach is similar in spirit to the emerging "Growth-at-risk" literature (See Adrian et al. (2016), Adrian et al. (2018), IMF (2017), Aikman et al. (2018),

Lang et al. (2019)), but with a focus on bank profitability as the relevant outcome variable instead of real GDP. A focus on bank profitability appears natural in the context of systemic risk, as negative profits directly reduce bank capital. The approach therefore speaks directly to the core of macroprudential policy, which mainly aims at ensuring resilience of the banking system to variations in systemic risk.[4] An additional innovation of our empirical approach is the use of bank-level micro data instead of country-level aggregates, which should considerably increase the power to identify the impact of cyclical systemic risk on bank profitability, due to the availability of a large cross-section of banks for each country-level financial crisis episode.

All results should be interpreted as the reduced-form impact of cyclical systemic risk on bank profitability, which is not necessarily equal to a causal effect. This approach is fully in line with the existing "Growth-at-risk" literature (See Adrian et al. (2016), Adrian et al. (2018), IMF (2017), Aikman et al. (2018), Lang et al. (2019)) and the literature that studies the role of credit and asset bubbles in determining the severity of recessions (Jorda et al. (2013b), Jorda et al. (2015), Bridges et al. (2017)). We leave the study of the causal relationship between cyclical systemic and bank profitability for future research.

3.1 Linear local projections

In order to study the average impact of cyclical systemic risk on future bank profitability we make use of the local projections framework pioneered by Jordà (2005). This methodology allows to estimate impulse response functions in a model-free way, i.e. without the need to specify any underlying dynamic system. Its advantages are flexibility with respect to the model specification and the chosen estimation method, robustness to misspecification of the unknown data generating process (e.g. compared to VARs), and inference facilitation by allowing the use of traditional estimators for standard errors. The basic idea is to project the bank-level return on assets at various future horizons onto the current information set, which includes bank-specific factors, country-specific factors, various fixed effects and our measure of cyclical systemic risk:

$$\pi_{i,j,t+h} = \rho^h \pi_{i,j,t} + \theta^h dSRI_{j,t} + \alpha^{\mathbf{h}} \mathbf{X}'_{\mathbf{i,j,t}} + \beta^{\mathbf{h}} \mathbf{Y}'_{\mathbf{j,t}} + \gamma_i^h + \delta_t^h + \varepsilon_{i,t+h} \qquad (1)$$

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[4]Next to ensuring resilience, the second main objective of macroprudential policy is taming the financial cycle, or in other words reducing macro-financial imbalances.

$\pi_{i,j,t+h}$ is the outcome variable of interest, namely the pre-tax ROA for bank i, located in country j, in year $t + h$, where $h = 1, ..., 6$ indicates the relevant prediction horizon in years. $dSRI_{j,t}$ is the domestic cyclical systemic risk indicator of Lang et al. (2019) for country j at time t and it is our main explanatory variable of interest. $\mathbf{X}_{i,j,t}$ and $\mathbf{Y_{j,t}}$ are vectors of bank- and country-specific control variables respectively, while γ_i are bank fixed effects, δ_t are year fixed effects, and $\varepsilon_{i,t+h}$ is an error term. The coefficients of interest for our analysis are θ^h for different horizons $h = 1, ..., 6$, which trace out the local projection impulse response function (IRF) of the bank-level pre-tax ROA to a one unit increase in the d-SRI. These IRFs reflect the reduced-form information content of the d-SRI for future pre-tax ROA developments and therefore do not necessarily represent a causal effect. As mentioned above, the study of the causal relationship between cyclical systemic and bank profitability is left for future research.

We estimate Equation (1) using three different estimators. First, we use ordinary least squares controlling for country- and time-fixed effects (i.e. without bank-specific fixed effects). Second, we use a standard fixed effects estimator to control for time fixed effects and unobserved fixed bank-level heterogeneity. Third, we implement the Arellano and Bond (1991) GMM estimator for dynamic panel data because of the known feature of persistence in the bank-level ROA ($0 < \rho < 1$). The GMM estimator is useful to address the potential Nickell bias due to the lagged dependent variable and in addition it is the most efficient in the class of estimators for linear models (Hansen (1982), Newey and McFadden (1994)). In any case, given that we are mainly interested in the impact of the d-SRI (a time-varying country-level indicator) on future bank profitability, unobserved bank-level heterogeneity should not be a major concern as long as we control for country fixed effects.[5] For statistical inference, we use robust standard errors that are clustered at the bank-level.

3.2 Quantile local projections

To complement the analysis of the average impact of cyclical systemic risk on future bank profitability, we also estimate quantile local projections as proposed by Adrian et al. (2016) to study the impact on tails of the future profitability distribution. In particular, we estimate quantile regressions for each horizon $h = 1, ..., 6$ where the conditional quantile (τ) of the pre-tax

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[5]We should be mainly concerned about unobserved bank-level fixed effects if they are correlated with the explanatory variable of interest. However, given that the d-SRI is a country-level variable and we have a large bank-level panel dataset at our disposal, it is easy to control for country-level fixed effects. Any remaining bank-level unobserved fixed effect should then be uncorrelated to the country-level d-SRI. Hence, omitted variables bias due to bank-level fixed effects should be of minor importance for our empirical analysis.

ROA distribution is modeled using the same information set (Ω) as in equation (1):

$$Q_{\pi_{i,j,t+h}|\Omega_{i,j,t}}(\tau|\Omega_{i,j,t}) = \rho^{h,\tau}\pi_{i,j,t} + \theta^{h,\tau}dSRI_{j,t} + \alpha^{\mathbf{h},\tau}\mathbf{X}'_{\mathbf{i,j,t}} + \beta^{\mathbf{h},\tau}\mathbf{Y}'_{\mathbf{j,t}} + \gamma_j^{h,\tau} + \delta_t^{h,\tau} \quad (2)$$

Quantile regressions can be estimated by minimizing the weighted sum of absolute errors. We use robust standard errors that are clustered at the bank- level for statistical inference.

3.3 Drivers of bank profits and losses

Our set of bank-specific controls $\mathbf{X}_{i,j,t}$ is useful to account for factors that are idiosyncratic to specific banks and which can have an impact on profitability. Based on findings in the literature on bank profitability we include the following bank-specific control variables: the logarithm of total assets to account for bank size in determining profitability, due for example to economies of scale (Demirgüç-Kunt and Huizinga (1999), Mirzaei et al. (2013)); the share of loans in total assets to capture the portfolio composition of banks following Iannotta et al. (2007) and Mercieca et al. (2007), because lending can on the one hand be a more profitable business than holding securities, but also more costly; the cost-to-income ratio to proxy for cost inefficiency (Valverde and Fernández (2007), Mirzaei et al. (2013)); the net interest margin; the ratio of loan loss provisions over total assets to control for asset quality (Albertazzi et al. (2016)); the average risk weight to proxy for bank risk-taking; and the tangible equity over total assets ratio and the core tier1 capital ratio, to reflect solidity of banks, but also to capture the higher costs of capital (Demirgüç-Kunt and Huizinga (1999)).

The vector $\mathbf{Y}_{j,t}$ contains aggregate country-level factors (including euro area-wide common factors such as the Euribor) that vary over time and can drive bank profitability. First, we control for two banking sector factors that have been identified as relevant in the literature: the Herfindahl-Hirschman Index based on total assets to account for market concentration and the bank credit-to-GDP ratio (Valverde and Fernández (2007), Mirzaei et al. (2013), Rumler and Waschiczek (2012)). Second, we control for various standard macro-financial factors, such as annual real GDP growth, the annual inflation rate, the 3-month Euribor, the slope of the yield curve (difference between the 10-year government bond yield and the Euribor), the annual growth rate of equity prices and the annual growth rate of residential real estate prices (Demirgüç-Kunt and Huizinga (1999), Albertazzi and Gambacorta (2009), Borio et al. (2017)).

4 Data

The dataset for our empirical analysis features three building blocks: a bank-level dataset with a rich set of bank-specific control variables, a country-level dataset with information about the evolution of the d-SRI, our preferred measure of cyclical systemic risk, and a country-level dataset with a large set of macro-financial control variables.

4.1 The bank-level dataset

The bank-level dataset is sourced from SNL Financial and contains information about various balance sheet and income statement variables for around 4,300 banks from the euro area countries, plus Denmark, Sweden, and the UK. The dataset is at an annual frequency and spans the years between 2005 and 2017. As mentioned in section 3.3, the main variables of interest are the bank-level pre-tax ROA, the net interest margin, the cost-to-income ratio, the ratio of impairments to total assets, the share of loans in total assets, the average risk-weight, the leverage ratio, the Tier1 capital ratio, and the log of total assets.

In order to arrive at a bank sample that is representative of aggregate country-level banking systems, we proceed along the following steps. First, starting from an initial sample of 4,298 banks we only select banks that do not have a domestic parent bank. Hence, we exclude subsidiary banks who have a parent in their country of incorporation, while we keep subsidiaries of foreign parents in the sample. This ensures that we always use bank entities at their highest level of consolidation within a country, and avoid double counting of balance sheets. Second, we further restrict this bank sample to entities that have data going back to at least 2008 and 2009 so as to cover the height of the global financial crisis. Third, we also include banks at the highest level of consolidation if they have large balance sheets (larger than the median) compared to the banks that fulfill criteria one and two, even if these banks only start reporting data after 2009.

The final bank-level dataset covers 473 banks from 22 countries. As shown in panel (a) of Figure 3 more than half of these banks are from five countries: Germany (81), Spain (53), Italy (50), the UK (49), and Denmark (47). All other countries are represented with sample sizes of between 5 and 26 banks. Given that not all relevant bank-specific variables are available in every year for the banks of interest, the effective bank sample varies over time between 231 in

Figure 3: Bank sample size over time and across countries

(a) Number of banks by country

(b) Number of banks by year
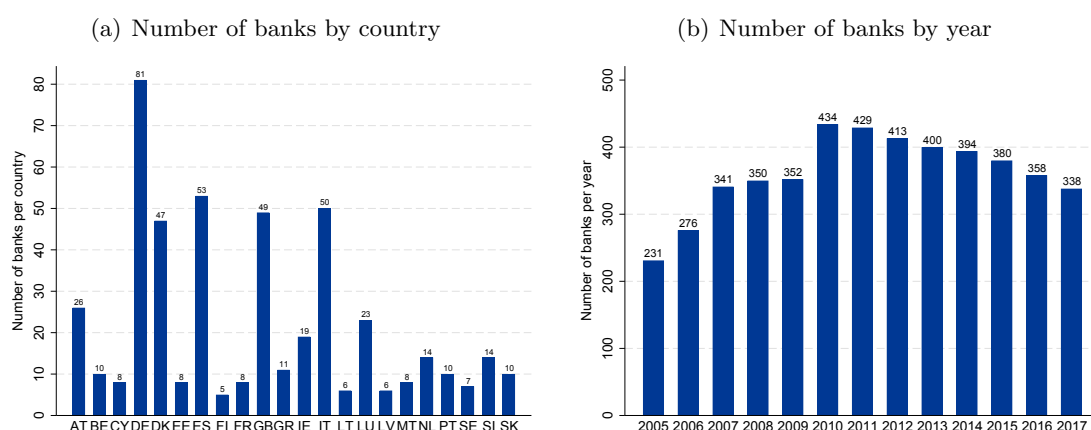
Sources: SNL Financial; Authors' calculations.

Notes: The chart by year indicates the number of banks in a given year with observations for the pre-tax return on assets. The chart by country indicates the number of banks that have at least one year with an obervation for the pre-tax return on assets.

2005, 434 in 2010, and 338 in 2017 at the end of the sample period as shown in panel (b) of Figure 3.

Figure 4 shows that the final micro bank-level dataset is representative of the aggregate banking sectors in most of the 22 European countries that are studied. Panel (a) shows that for the vast majority of countries the micro data covers between 75% and 115% of consolidated banking sector assets taken from aggregate country-level statistics. Coverage can be above 100% because of insurance and other non-banking assets recorded in the balance sheets of some banking groups in the micro dataset. Total asset coverage tends to be a bit lower in smaller countries (Estonia, Luxembourg, Latvia, Lithuania and Malta) but is still between 40% and 70% for virtually all the years.[6] In addition, panel (b) of Figure 4 shows that the level and dynamics of aggregate country-level ROA based on the micro dataset are also representative of the consolidated banking sector data in virtually all countries (Figure A1 in Appendix A shows the representativeness of the bank sample for aggregate Tier 1 ratios and average risk-weights).

[6]Note that aggregate Consolidated Banking Data only starts to be available from 2008 onwards, so that comparisons before that date are not feasible.
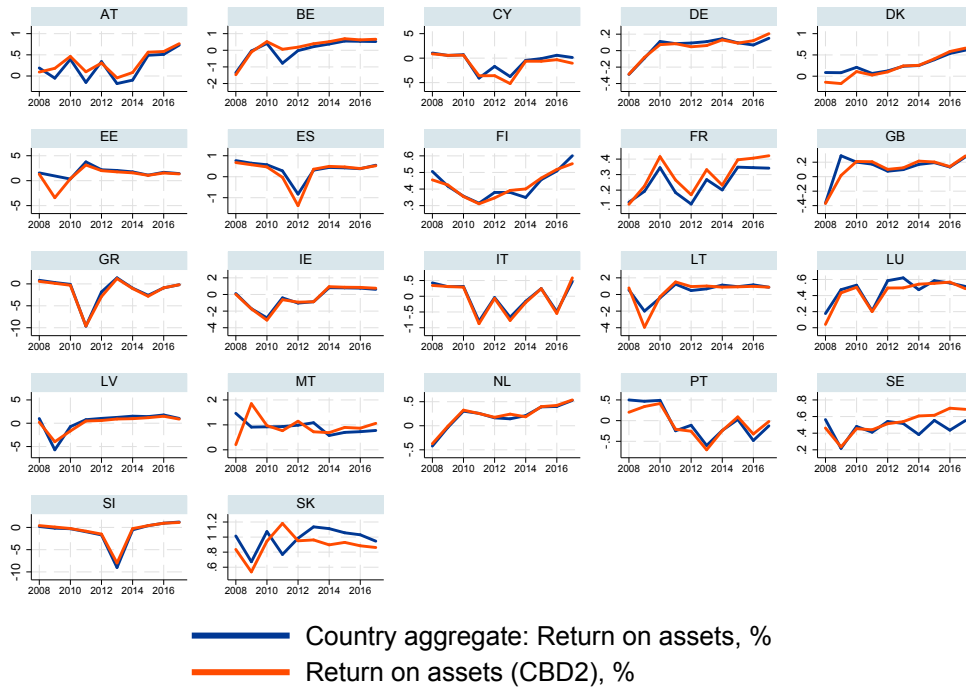
Figure 4: Micro-data coverage in terms of country aggregates

(a) Total Assets
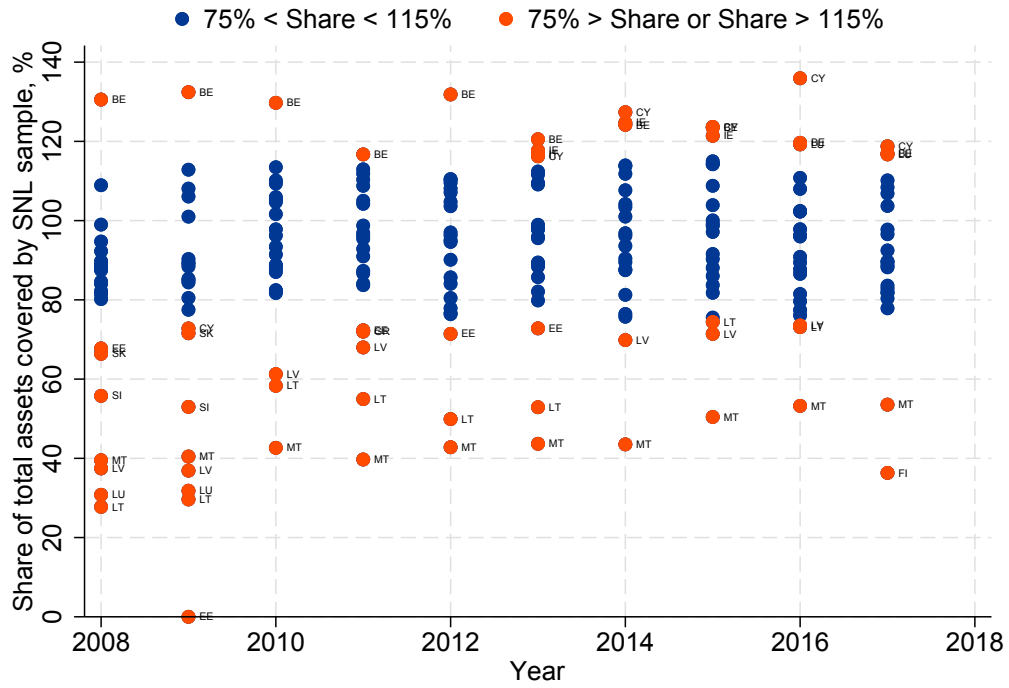
(b) Return on Assets

Country aggregate: Return on assets, %

Return on assets (CBD2), %

Sources: SNL Financial; Consolidated Banking Data (CBD2); Authors' calculations.

Notes: The charts show the representativeness of the micro-level bank sample from SNL for country-level banking sector aggregates. Aggregate banking sector data from CBD2 starts in 2008.

4.2 The cyclical systemic risk indicator

The cyclical systemic risk measure that we use for the empirical analysis is the d-SRI developed by Lang et al. (2019). The d-SRI is a broad-based country-level indicator that captures the build-up of cyclical systemic risk emanating from domestic credit, real estate markets, asset prices, and external imbalances. It is constructed as a weighted average of six well-performing early warning indicators for financial crises, after they are normalised to the same scale. Indicator normalisation is performed by subtracting the median and dividing by the standard deviation of the pooled indicator distribution across countries and time. Formally, the d-SRI is defined as follows:

$$dSRI_{j,t} = \sum_{k=1}^{6} \omega^k \cdot \tilde{x}_{j,t}^k \tag{3}$$

where k, j and t are indices that represent the indicator, country, and time period respectively, $\tilde{x}_{j,t}^k = \frac{x_{j,t}^k - x_M^k}{x_{SD}^k}$ represents the normalised sub-indicator based on the pooled median and standard deviation, and ω^k is the aggregation weight attributed to each sub-indicator.[7]

The d-SRI sub-indicators are selected based on their signalling performance for financial crises in EU countries. Indicator weights are chosen to maximise the early warning performance of the d-SRI for domestically-driven systemic financial crises identified in Lo Duca et al. (2017) with a lead time of 12 to 5 quarters. The optimal weighting procedure for the d-SRI assigns the largest weight to the 2-year bank credit-to-GDP change (36%), followed by the current account balance (20%), the 3-year residential real estate price-to-income ratio change (17%), the 3-year real equity price growth (17%), the 2-year debt service ratio change (5%), and the 2-year real total credit growth (5%).

As shown in Lang et al. (2019) the d-SRI increases on average around five years before the onset of financial crises (see panel (b) of Figure 2), and its early warning properties for euro area countries are superior to those of the total credit-to-GDP gap. In addition, model estimates suggest that the d-SRI has significant predictive power for large declines in real GDP growth three to four years down the line, as it precedes shifts in the entire distribution of future real GDP growth and especially of its left tail ("Growth-at-risk").

The d-SRI is available for all 22 countries of interest (euro area countries, plus Denmark, Sweden, and the UK). Data coverage for some small euro area countries starts slightly after 2005 (2006 for LV, 2007 for LT and SI, 2008 for CY, MT, and SK, 2010 for EE).

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[7]Sub-indicator weights are constrained to be larger or equal to 5% and sum to 100%.

4.3 Country-level control variables

The inclusion of macro-financial variables aims to control for factors that can have an impact on bank profitability, especially in the short-run, and therefore alleviate a potential omitted variables bias in the empirical models. These control variables are mostly expressed as short-term transformations (e.g. 1-year growth rates) of the underlying data and they are standard in the empirical literature on bank profitability (See section 3.3). The control variables include: the Herfindahl-Hirschman Index based on total assets, the bank credit-to-GDP ratio, the annual real GDP growth rate, the annual inflation rate, the 3-month Euribor, the slope of the yield curve, the annual growth rate of equity prices, and the annual growth rate of residential real estate prices. By including these standard macro-financial control variables we are better able to study the marginal impact of the d-SRI, our measure of cyclical systemic risk, on future bank profitability.

While some of the country-level macro-financial control variables appear similar to d-SRI sub-components there are two important differences. First, slightly different concepts of the underlying variables are used. Second, different transformations of the variables are used. For example, the d-SRI includes the 3-year change in the residential real estate price-to-income ratio, while the country-level control variable is the 1-year growth rate in residential real estate prices. In addition, the d-SRI includes the 3-year real equity price growth rate, while the country-level control variable is the 1-year growth rate of nominal equity prices. Finally, the d-SRI includes the 2-year change in the bank credit-to-GDP ratio, while the country-level control variable is the ratio of bank credit-to-GDP. Table B1 in Appendix B indeed shows that the correlation between the d-SRI and these country-level control variables is rather low.

The macro-financial control variables are based on various data sources and were obtained through the European Central Bank's Statistical Data Warehouse. In particular, the following datasets were used: Structural Statistical Indicators (SSI) for the Herfindahl-Hirschman-Index data based on total assets; Balance Sheet Items Statistics (BSI) for bank credit; Eurostat National Accounts Main Aggregates (MNA) for real and nominal GDP; ECB Indices of Consumer Prices (ICP) for inflation; Financial Markets data (FM) for the 3-month EURIBOR and 10-year government bond yields; Residential Property Price Index Statistics (RRP) for RRE prices; and OECD Main Economic Indicators (MEI) for equity prices.

4.4 Key features of the data

Table 1 summarises the key statistical properties of the variables in our dataset. On average the pre-tax ROA stood at 0.32% across all banks and time periods. The median pre-tax ROA was slightly higher than the mean at 0.44%, given some large negative ROA outliers of between -24% and -62%. Half of all pre-tax ROA observations were between 0.14% and 0.84%.

Table 1: Descriptive Statistics for the main variables in the dataset

	mean	sd	p1	p5	p25	p50	p75	p95	p99	N
Bank-specific variables										
Pre-tax return on assets (%)	0.32	1.97	-5.69	-1.75	0.14	0.44	0.84	1.90	3.03	3,771
Net Interest Margin (%)	1.80	1.28	0.00	0.33	1.02	1.62	2.32	3.92	5.07	3,771
Cost-to-Income (%)	64.62	30.10	12.24	31.41	51.77	62.21	72.72	96.63	187.26	3,771
Impairments / Total assets (%)	0.61	1.62	-0.58	-0.09	0.05	0.25	0.68	2.51	5.39	3,771
Net Loans/ Assets (%)	58.06	20.35	0.79	12.86	48.19	62.75	72.20	84.40	89.65	3,771
Risk-weighted Assets/ Assets (%)	52.20	22.55	7.51	17.22	34.52	52.03	68.42	87.45	109.64	3,771
Tangible Equity/ Tangible Assets (%)	7.25	5.77	1.27	2.26	4.40	6.14	8.78	14.82	22.97	3,771
Tier 1 Ratio (%)	14.73	16.51	5.21	6.54	9.40	12.50	16.06	25.82	55.05	3,771
Log of Total Assets	3.02	1.98	-1.67	-0.44	1.92	2.96	4.31	6.38	7.44	3,771
Banking sector variables										
Bank credit to GDP	109.96	40.88	47.98	68.12	83.00	92.50	135.81	187.49	241.49	3,771
Herfindahl Index for total asset	0.08	0.06	0.02	0.02	0.03	0.05	0.11	0.21	0.32	3,771
Macro-financial variables										
Real GDP growth	1.24	2.98	-5.55	-4.89	0.60	1.61	2.57	4.82	8.08	3,771
Inflation	1.67	1.38	-1.12	-0.24	0.62	1.64	2.57	3.69	4.65	3,771
1yr growth in house prices	2.09	6.21	-13.71	-7.37	-1.36	2.98	5.38	10.85	21.82	3,760
1yr growth in equity prices	4.55	18.21	-38.49	-26.91	-5.64	7.21	17.67	31.74	40.12	3,771
Euribor	1.14	1.55	-0.33	-0.33	-0.04	0.49	1.41	4.46	4.46	3,771
Yield Curve slope	1.86	1.95	-0.47	-0.12	0.73	1.39	2.50	4.97	9.68	3,716
d-SRI	-0.13	0.66	-1.60	-0.99	-0.50	-0.27	0.19	1.27	2.10	3,756

Sources: Authors' calculations; SNL Financial; ECB Statistical Data Warehouse.

During the period 2005 - 2017 negative realisations of the pre-tax ROA were not rare, as shown in panel (a) of Figure 5. In 5% of all bank-year observations the pre-tax ROA was at or below -1.75% (Table 1). Losses of this magnitude can represent severe challenges to the solvency position of banks, as associated reductions in Tier1 ratios are usually at least twice as high, given the average risk-weight of 52% in the sample. Panel (b) of Figure 5 further shows that a large downward shift of the entire pre-tax ROA distribution started at the height of the global financial crisis in 2008. Between 2008 and 2016 the lower tail of the ROA distribution, represented by the 10th percentile, was deep in loss territory with a trough of almost -2% in 2012 during the height of the euro area sovereign debt crisis. Moreover, even the 25th percentile of the bank-level pre-tax ROA distribution was close to 0 or even negative during this period. A gradual upward shift of the pre-tax ROA distribution took place between 2012 and 2017 with the biggest improvement visible for the lower left tail.

Figure 5: The distribution of the pre-tax ROA across banks and time

(a) Pooled distribution

(b) Distribution over time
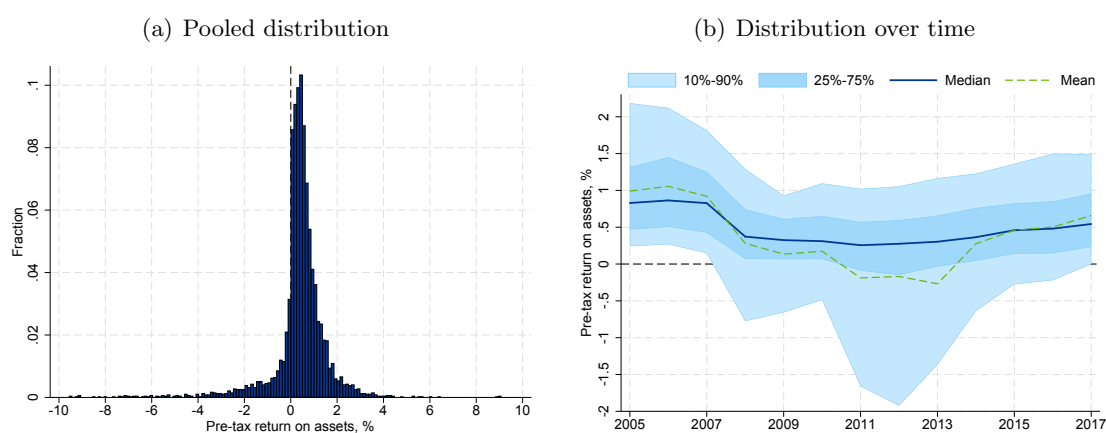
Sources: SNL Financial; Authors' calculations.

Notes: The pre-tax ROA histogram was truncated at - 10 % to ease the exposition. The largest outliers were -62%, -39%, and -24%.

Considerable heterogeneity in the pre-tax ROA distribution is not only visible across time, but also across countries, as shown in figure 6. For example, one quarter of all bank-year observations for Cyprus, Greece, Ireland, and Slovenia between 2005 and 2017 were associated with losses. Apart from differences in the lower left tail, there is also considerable cross-country heterogeneity in terms of the median pre-tax ROA. For example, Denmark, Estonia, Latvia, Malta, and Slovakia have much higher median pre-tax ROA than the other countries. Hence, the characteristics of the data suggest that it is important to control for year fixed effects and country-fixed effects in the empirical investigation.

As a preliminary check of whether the d-SRI can explain shifts in the future ROA distribution, Figure 7 plots the country-level d-SRI values against the bank-level realisations of the pre-tax ROA between 1 and 6 years into the future. As can be seen, for horizons of 1 and 2 years ahead, the scatter plots do not reveal any systematic pattern between the d-SRI and future bank profits / losses. However, for horizons of 3 to 5 years ahead, there is a negative relationship between current d-SRI values and future bank-level profitability. I.e. higher cyclical systemic risk today seems to be associated with lower profitability between 3 and 5 years into the future. The next section presents robust econometric evidence that corroborates this dynamic pattern between cyclical systemic risk and future bank profitability.
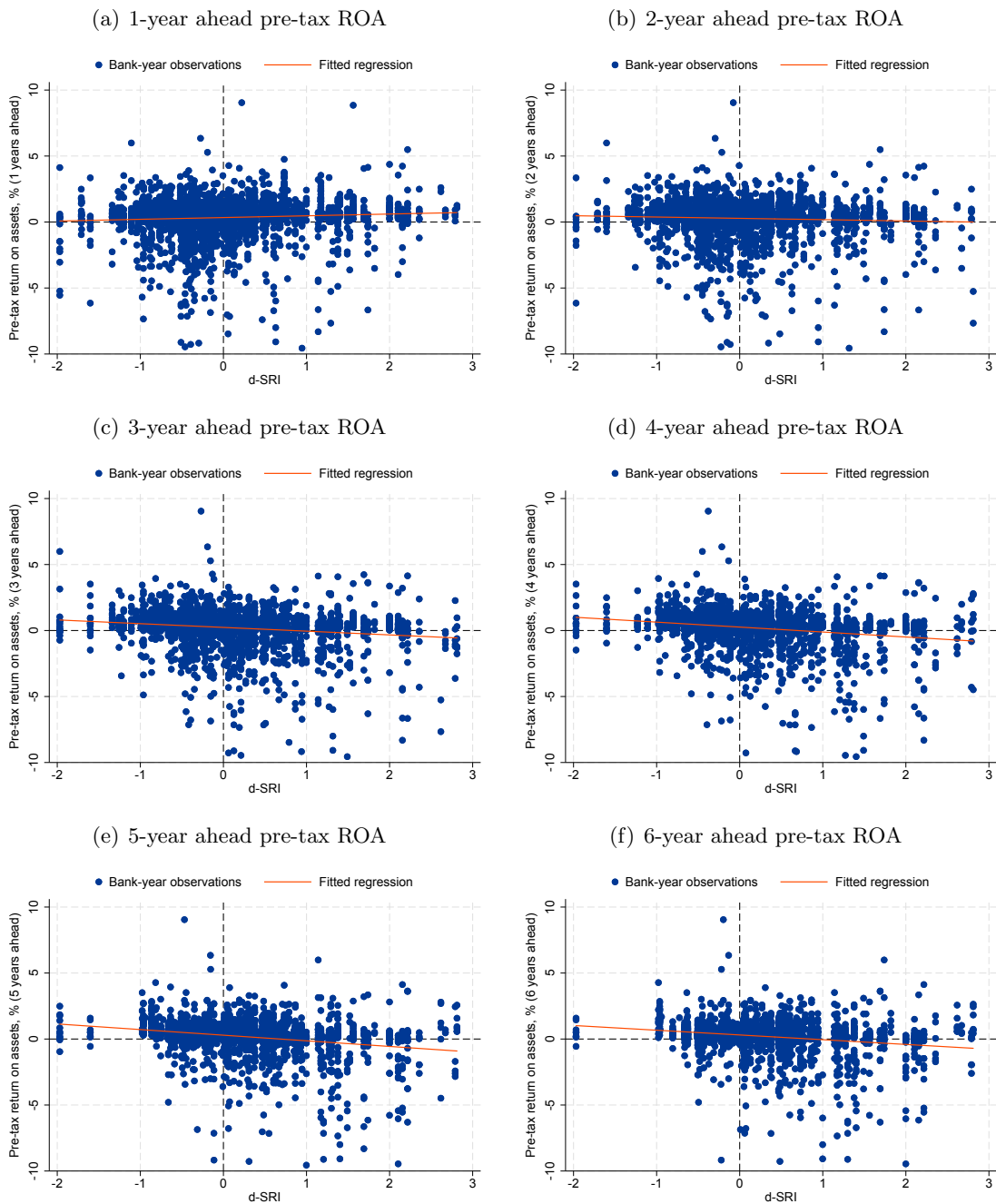
Figure 6: The pre-tax ROA distribution by country
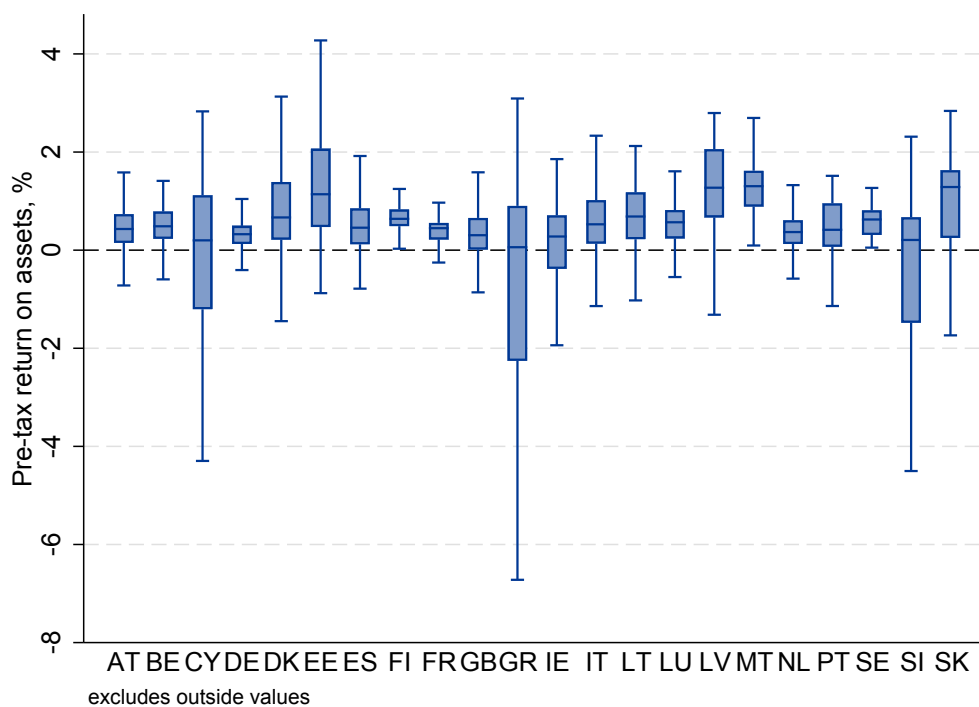
Notes: The chart shows the country-level median, interquartile range, and upper and lower adjacent values for the pre-tax ROA across banks and time (2005-2017).

Figure 7: Relation between the d-SRI and pre-tax ROA at different horizons

(a) 1-year ahead pre-tax ROA

(b) 2-year ahead pre-tax ROA

(c) 3-year ahead pre-tax ROA

(d) 4-year ahead pre-tax ROA

(e) 5-year ahead pre-tax ROA

(f) 6-year ahead pre-tax ROA

Sources: SNL Financial; Lang et al. (2019); Authors' calculations.

Notes: The charts show the relation between the country level d-SRI at time t and the bank level pre-tax ROA at time $t + h$ for $h = 1, 2, ..., 6$. The fitted lines show the estimated relationships based on linear regressions.

5 The impact of cyclical systemic risk on bank profitability

Before going into detailed results regarding the estimated impact of cyclical systemic risk on future bank profitability, it is useful to discuss coefficient estimates for the model specification with a prediction horizon of 1 year, i.e. $h = 1$. For the Arellano and Bond (1991) GMM estimator we use as GMM instruments the first and second lags of the $t + 1$ pre-tax ROA, the loans-to-assets ratio and the tangible equity over total assets ratio. The d-SRI, and macroeconomic control variables are used as IV-type instruments. The Hansen test has a p-value of 0.21, and hence the null hypothesis of non-valid over-identifying restrictions is rejected. The p-values on the AR(1) and AR(2) autocorrelation tests are 0.03 and 0.15, which shows that autocorrelation is not an issue with the GMM specification.

Table 2 shows that the pre-tax ROA is only mildly persistent with an AR(1) coefficient that is mostly insignificant across the different estimators and the highest point estimate being 0.298. Other bank-specific factors have the expected signs and are statistically significant for some of the estimators: the net interest margin and the tangible leverage ratio have a positive impact on pre-tax ROA at a 1-year horizon, while the cost-to-income ratio, the average risk-weight and the Tier 1 ratio all have a negative impact on pre-tax ROA. The log of total assets has a negative coefficient for the estimators that control for bank fixed-effects.

The majority of the country-level control variables are statistically significant and of the expected sign: A higher bank credit-to-GDP ratio as well as higher bank concentration reduce the pre-tax ROA at a prediction horizon of 1 year. Pre-tax ROA pro-cyclicality is shown by the positive and significant coefficient on real GDP growth. Residential real estate and equity price growth along with the 3-month Euribor are also positively correlated with pre-tax ROA at the 1-year horizon. Inflation always has a negative and significant coefficient. The coefficient on the d-SRI is positive across the different estimators, but only significant for for models that control for bank fixed-effects. This suggests that during boom periods, where cyclical systemic risk builds up, pre-tax ROA can be higher than normal at least in the short-term.

5.1 The impact on average future bank profitability

Figure 8 shows the estimated average impact of cyclical systemic risk on future bank profitability for horizons of one to six years ahead. The key result is that elevated cyclical systemic risk leads

Table 2: Overview of different estimators for the baseline model for $h = 1$

VARIABLES	(1) Macro controls	(2) Country-time FE	(3) Bank-time FE	(4) Bank-time DP
d-SRI	0.152	0.129	0.271**	0.371**
	(0.097)	(0.113)	(0.118)	(0.170)
Lag of Pre-tax ROA (%)		0.262**	-0.075	0.298
		(0.115)	(0.113)	(0.200)
Net Interest Margin (%)		0.230***	0.261**	0.044
		(0.075)	(0.125)	(0.343)
Cost-to-Income (%)		-0.004**	-0.003	-0.016**
		(0.002)	(0.002)	(0.007)
Impairments / Total assets (%)		0.113	0.114	0.221
		(0.157)	(0.198)	(0.273)
Net Loans/ Assets (%)		-0.003**	0.001	-0.010
		(0.001)	(0.010)	(0.017)
Risk-weighted Assets/ Assets (%)		-0.022***	-0.013**	-0.051
		(0.007)	(0.006)	(0.031)
Tangible Equity/ Tangible Assets (%)		0.088***	0.029	0.116
		(0.030)	(0.037)	(0.080)
Tier 1 Ratio (%)		-0.019***	-0.014***	-0.050
		(0.007)	(0.005)	(0.031)
Log of Total Assets		0.009	-0.335**	-0.482*
		(0.019)	(0.164)	(0.281)
Bank credit to GDP	-0.014***	-0.012***	-0.010**	-0.008
	(0.004)	(0.004)	(0.005)	(0.007)
Herfindahl Index for total assets	-2.868	-5.239**	-5.586**	-7.272*
	(2.314)	(2.396)	(2.685)	(4.077)
Real GDP growth	0.068***	0.068***	0.072***	0.046**
	(0.023)	(0.024)	(0.027)	(0.021)
Inflation	-0.262***	-0.288***	-0.333***	-0.405***
	(0.068)	(0.076)	(0.092)	(0.107)
1yr growth in house price	0.021***	0.031***	0.043***	0.037**
	(0.007)	(0.011)	(0.013)	(0.015)
1yr growth in equity price	0.011**	0.015***	0.013***	0.017***
	(0.004)	(0.005)	(0.005)	(0.006)
Euribor	0.146**	0.128*	0.152	0.408***
	(0.059)	(0.071)	(0.100)	(0.128)
Yield Curve slope	-0.061	0.071	-0.023	0.108
	(0.043)	(0.050)	(0.057)	(0.068)
Constant	1.892***	2.350***	3.342***	7.142***
	(0.337)	(0.418)	(0.881)	(2.710)
Observations	4,321	3,286	3,286	3,286
Number of banks			438	438
Adjusted R^2	0.128	0.231	0.120	
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	No	No
Bank FE	No	No	Yes	Yes

Sources: Authors' calculations; SNL Financial; Lang et al. (2019); ECB Statistical Data Warehouse.

Notes: Robust standard errors clustered at bank-level are indicated in parentheses. Stars indicate statistical significance: *** p<0.01, ** p<0.05, * p<0.1. The model "Macro controls" is estimated by OLS with country and time fixed effects. The model "Country-time FE" adds bank-specific control variables. The model "Bank-time FE" replaces country fixed effects with bank fixed effects. The corresponding within, between and overall R^2 values are 12.8%, 0.47% and 2.11%. The model "Bank-time DP" is estimated by system GMM to overcome the potential Nickell bias due to a lagged dependent variable (dynamic panel structure). The p-values of the AR(1), AR(2) and Hansen tests are 0.03, 0.15 and 0.21.

Figure 8: Estimated average impact of cyclical systemic risk on future bank profitability
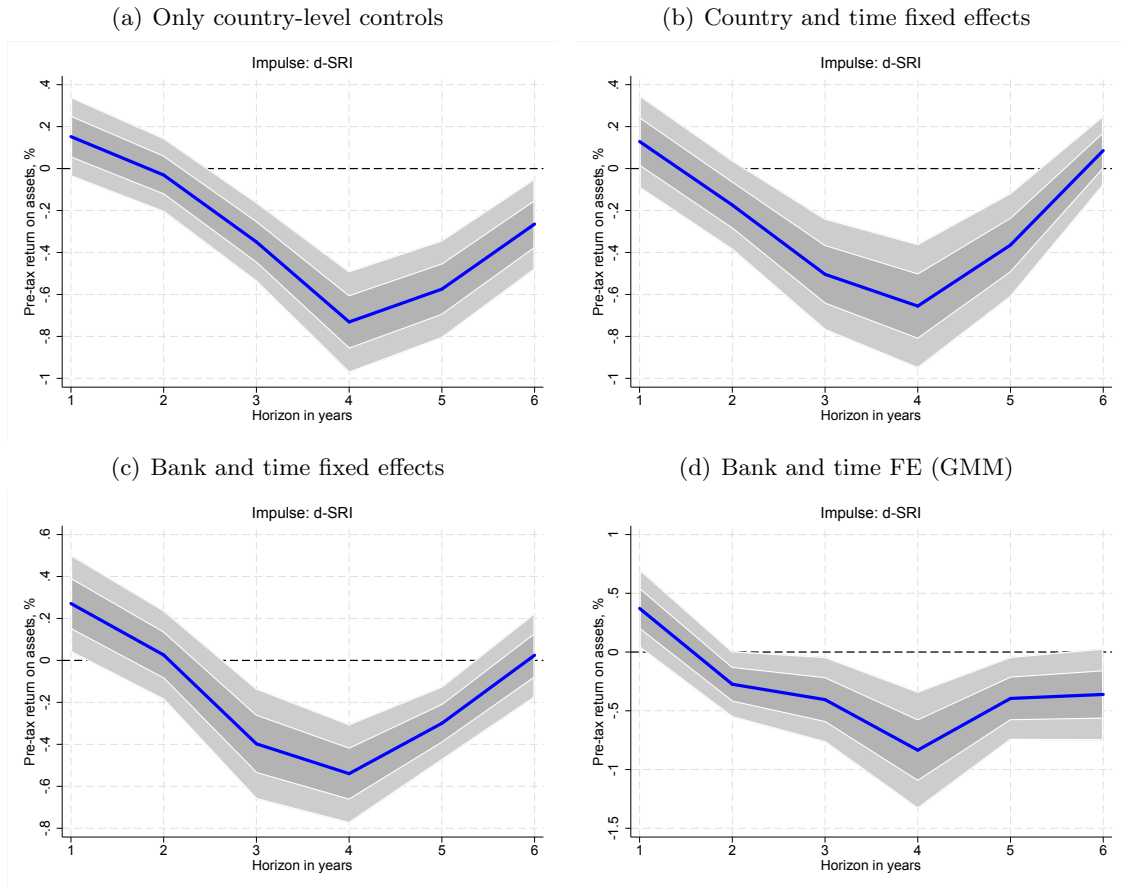
(a) Only country-level controls

(b) Country and time fixed effects

(c) Bank and time fixed effects

(d) Bank and time FE (GMM)

Notes: The charts show linear local projection results for the bank-level pre-tax ROA at horizon $t + h$ on the d-SRI controlling for various other bank- and country-specific variables at time t. The model "Only country-level controls" is estimated by OLS, controlling for country and time fixed effects as well as aggregate country-level variables. The model "Country and time fixed effects" adds bank-specific control variables on top. The model "Bank and time fixed effects" replaces country fixed effects with bank fixed effects and is estimated by standard panel fixed effects techniques. The model "Bank and time FE (GMM)" is equivalent to the previous model but estimated by system GMM to overcome the potential Nickell bias due to a lagged dependent variable. Grey shaded areas represent the one and two standard error bounds based on robust standard errors clustered at the bank-level.

Figure 9: Marginal explanatory power of the d-SRI for bank profitability at different horizons
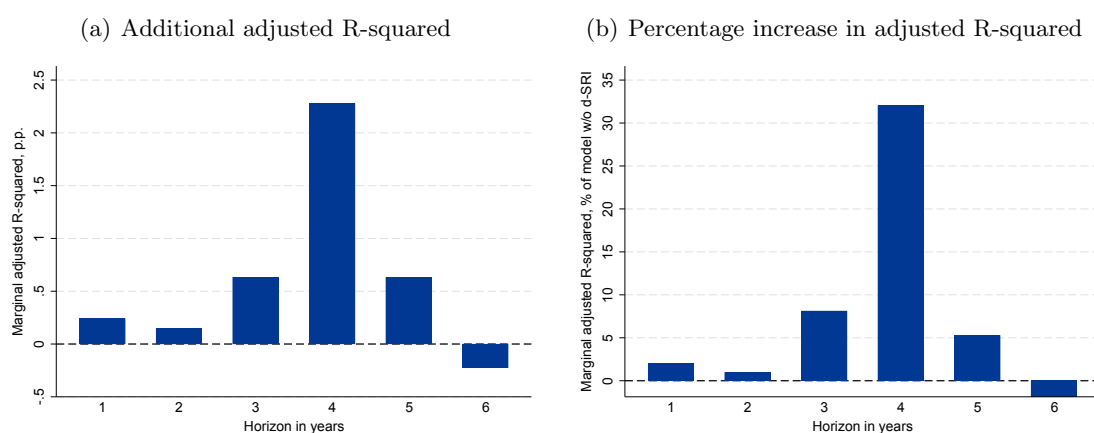
(a) Additional adjusted R-squared

(b) Percentage increase in adjusted R-squared

Sources: SNL Financial; Lang et al. (2019); various other data sources; Authors' calculations.

Notes: Panel (a) displays the difference in the adjusted R^2 of the model including the d-SRI compared to the model excluding the d-SRI (both models include bank and time fixed-effects). Panel (b) displays the percent increase in adjusted R^2 of the model including the d-SRI compared to the model excluding the d-SRI (both models include bank and time fixed-effects).

on average to large and persistent drops in the pre-tax ROA between three to five years ahead. For horizons of one to two years ahead and horizons beyond 5 years, the estimated impact is mostly not statistically significant. In terms of the magnitude, the impact of cyclical systemic risk on future bank profitability is economically highly significant. A one unit d-SRI value leads on average to a drop in the pre-tax ROA of around -0.4, -0.6, and -0.3 percentage points three, four, and five years ahead, which are large numbers compared to the average pre-tax ROA of 0.32 in the sample. As the mean d-SRI before past financial crises is close to 1 (see Figure 2), these estimated coefficients can be interpreted as the impact on bank profitability during the average crisis.

It is important to note that the estimated impact of cyclical systemic risk on bank profitability is quantitatively similar across the different estimation methods. For example, the thee to five year ahead estimates based on OLS with macro controls only are -0.35, -0.73, and -0.57, while the estimates based on the full models with country-level fixed effects and bank-level fixed effects are -0.5, -0.66, -0.36 and -0.40, -0.54, -0.31 respectively. For all estimation methods, the estimated impact for horizons of three to five years ahead is statistically significant at the 1% level. Moreover, similar dynamic patterns are estimated when using longer aggregate banking sector data at the country-level that starts in 1980 as shown in Figure A2 of Appendix A.

Figure 9 further shows that the d-SRI adds significant explanatory power to the model. At the four year horizon, the d-SRI adds 2.25 percentage points in adjusted R-squared compared

to a model without the d-SRI, which is equivalent to an increase of 30% in the explanatory power of the model at this horizon. The rather low absolute marginal adjusted R^2 but high relative marginal adjusted R^2 imply that it is very hard to explain the cross-section of pre-tax ROA four years ahead, but that adding the d-SRI to a model increases the explanatory power considerably. For the three- and five-year horizons, the marginal adjusted R-squared is around 0.6 percentage points and the relative increases in the explanatory power of the model are 8% and 5% respectively.

5.2   The impact on tails of the future profitability distribution

Figure 10 shows that high current cyclical systemic risk shifts the entire distribution of future bank profitability downward, but the impact on the lower left tail is an order of magnitude larger than the impact on the median. For example, the impact of a one unit d-SRI on the median pre-tax ROA at the three to five year horizon is -0.16 to -0.23 percentage points, while the impact on the lower 5th percentile is -1.1 to -1.8 percentage points. The impact on the 25th and 75th percentiles of the pre-tax ROA distribution are between -0.33 to -0.48 and -0.1 to -0.16 percentage points respectively. These numbers illustrate considerable heterogeneity in the impact of cyclical systemic risk on future bank profitability quantiles, which is concealed by the linear local projections presented in Figure 8.

Figure 11 shows that for the three to five year horizon, the impact of the d-SRI increases steadily as we move from higher to lower quantiles of the profitability distribution, leading to considerable left skewness in the future bank profitability distribution. The estimated co-efficients for all quantiles are negative at the three to five year horizon. However, while the difference between the estimated impact on the 95th and 50th percentile is not that large, the difference between the impact on the 50th and the 5th percentile is economically highly signifi-cant (an order of magnitude difference). Panels (c) to (e) in Figure 11 show that the estimated impact on lower quantiles (5th and 10th) and upper quantiles (95th and 90th) both lie outside the one and two standard error bounds of the estimated average impact from the linear local projections, which suggests that there is value added from running quantile local projections. For shorter horizons of one to two years ahead, there is no clearly distinct pattern between different bank profitability quantiles, as shown in panels (a) and (b) of Figure 11.

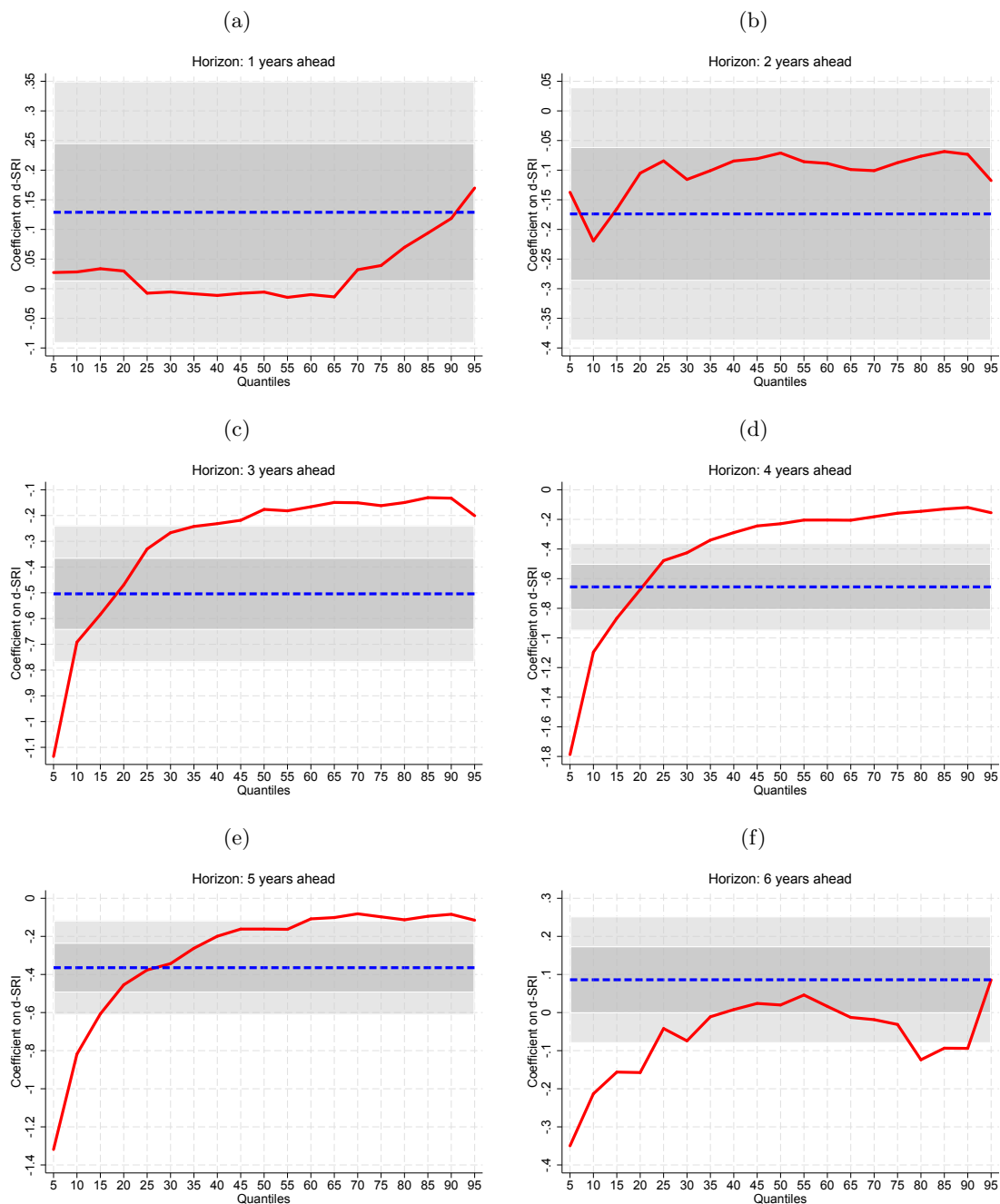The estimated impact of cyclical systemic risk on different bank profitability quantiles at

Figure 10: Estimated impact of cyclical systemic risk on future bank profitability quantiles
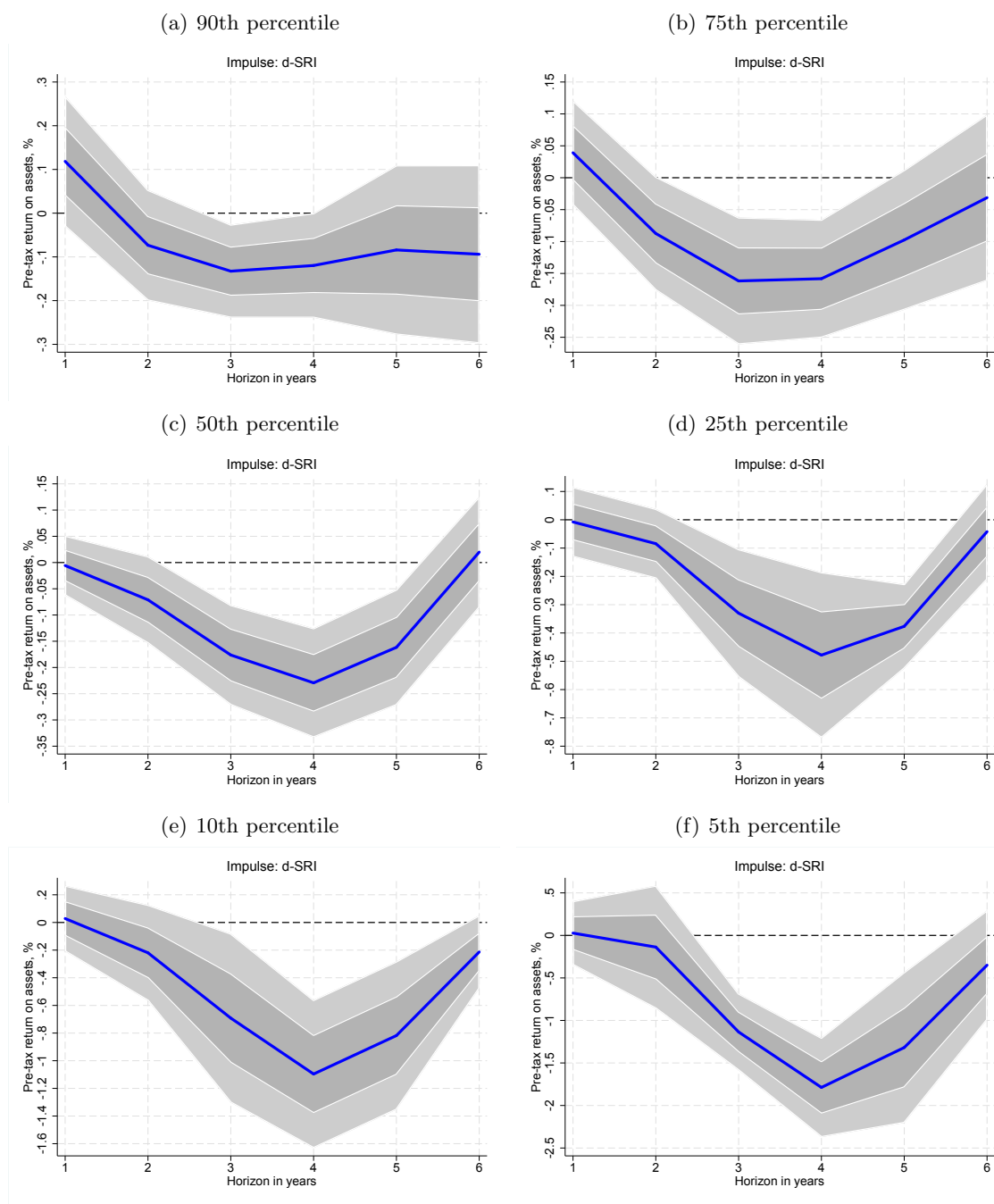
(a) 90th percentile

(b) 75th percentile

(c) 50th percentile

(d) 25th percentile

(e) 10th percentile

(f) 5th percentile

Sources: SNL Financial; Lang et al. (2019); various other data sources; Authors' calculations.

Notes: The charts show quantile local projection results for the bank-level pre-tax ROA at horizon $t + h$ on the d-SRI controlling for various other bank- and country-specific variables at time t, as well as country and time fixed effects. Grey shaded areas represent the one and two standard error bounds based on robust standard errors clustered at the bank-level.

Figure 11: Comparison of quantile local projection estimates with linear local projections

(a)

Horizon: 1 years ahead

(b)

Horizon: 2 years ahead

(c)

Horizon: 3 years ahead

(d)

Horizon: 4 years ahead

(e)

Horizon: 5 years ahead

(f)

Horizon: 6 years ahead

Sources: SNL Financial; Lang et al. (2019); various other data sources; Authors' calculations.

Notes: The red lines in the charts represent the quantile local projection results for the bank-level pre-tax ROA at horizon $t + h$ on the d-SRI controlling for various other bank- and country-specific variables at time t, as well as country and time fixed effects. As comparison, the blue dashed line shows the coefficient estimate from the linear local projections for the same model specification ("Country and time fixed effects" OLS model in Figure 8). Grey shaded areas represent the one and two standard error bounds for the OLS coefficients, based on robust standard errors clustered at the bank-level.

the three to five year horizon is economically and statistically significant. Figure 10 shows that the two standard error confidence bands for the lower half of the bank profitability quantiles are all well below zero at the three to five year horizon. At three and four year horizons, the estimated coefficients for all bank profitability quantiles are significant at either the 1% or 5% level. At the five year horizon, the coefficients for only a few upper quantiles (95th, 90th, 70th, 60th) are not statistically significant at the 10% level. Especially the estimated impact on the 10th and 5th percentile are economically highly significant at the three to five year horizon, with an estimated reduction of -0.7 to -1.8 percentage points in the pre-tax ROA per unit of the d-SRI (See Figure 11). The next section shows how the empirical results presented so far can be used for macroprudential surveillance.

6 Application of results for macroprudential surveillance

6.1 Calibration of countercyclical capital buffers

This section shows how the results of our empirical analysis can be used to inform the calibration of the countercyclical capital buffer (CCyB), which is the key macroprudential policy instrument in the Basel III regulatory framework to ensure resilience of banks over the financial cycle. According to the Basel III framework, calibration of the CCyB should follow the principle of guided discretion, which combines a rules-based approach with discretionary elements. The guidance part of the existing framework is based on a buffer guide which maps values of the credit-to-GDP gap[8] into CCyB rates in a piecewise linear fashion.[9] As shown in Lang et al. (2019), the d-SRI has better financial crisis early warning properties for euro area countries than the credit-to-GDP gap. Hence, a similar piecewise linear CCyB rule based on the d-SRI could be used to complement the calibration guidance based on the credit-to-GDP gap.

The linear local projection results presented in section 5.1 of this paper can help to pin down the conversion rate of d-SRI values into capital buffer requirements within such a simple linear rule. In particular, under the assumption that banks want to continue paying "normal" dividends during a crisis, the estimated cumulative negative impact of the d-SRI on future

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[8]The total credit-to-GDP gap is defined as the cyclical component from a recursive HP-filter with a smoothing parameter of 400,000 applied to the ratio of total credit to the non-financial private sector to GDP.

[9]For values of the credit-to-GDP gap below 2 percentage points the buffer guide is 0%. For values of the credit-to-GDP gap above 10 percentage points the buffer guide is 2.5%. For values of the credit-to-GDP gap between 2 and 10 percentage points, the buffer guide increases linearly according to the following rule: $CCyB_{j,t} = -0.625 + 0.3125 * Gap_{j,t}$. See Basel Committee on Banking Supervision (2010b) for details.

bank profitability could be used as the conversion rate, after scaling it by the inverse of the average risk-weight. The scaling by the average risk-weight is needed to translate the impact measured in units of ROA into the impact measured in units of the regulatory capital ratio. Such an approach would ensure that on average bank capital ratios remain above regulatory requirements when systemic risk materialises, even if banks continue to pay out dividends at a rate commensurate with profitability during non-crisis times.

As shown in the previous subsections, the main negative impact of the d-SRI on future bank profitability materialises between three to five years ahead. Hence, the cumulative negative impact of the d-SRI on bank profitability over this horizon could be used as the basis for the following piecewise linear CCyB calibration rule:

$$CCyB_{j,t} = \max\left\{0, \frac{\sum_{h=3}^{5} -\theta^h}{\bar{rw}_j} * dSRI_{j,t}\right\} \tag{4}$$

where the average risk-weight $\bar{rw}_j$ for country j is used to rescale the impact on profits into the impact on capital ratios, θ^h represents the average estimated impact on future bank-level ROA at horizon h from equation (1), and $dSRI_{j,t}$ represents the level of cyclical systemic risk as measured by the d-SRI in country j at time t. As the sum of the linear local projection coefficients over a three to five year horizon is between -1.25 and -1.65 depending on the estimator used, and the average risk-weight across all banks is around 50%, the rule implies that the CCyB should increase by around 2.5 to 3.3 percentage points per unit of the d-SRI. The long lead time of the d-SRI ahead of systemic financial crises should leave sufficient time for banks to smoothly adjust to changing capital requirements based on this rule.

A number of caveats need to be kept in mind when applying this reduced-form calibration rule. First, to the extent that a positive CCyB reduces the build-up of cyclical systemic risk, the implied CCyB rates could be higher than needed. Second, to the extent that past profitability figures also reflect second-round effects due to financial instability, the implied CCyB rates could be higher than needed if one assumes that the CCyB would reduce such second-round effects. Third, to the extent that the future build-up of cyclical systemic risk is driven by factors not captured by the d-SRI[10], the implied CCyB rates from the reduced-form rule could be lower than needed. However, the same caveats apply to any reduced-form CCyB rule, such as the existing Basel III buffer guide based on the credit-to-GDP gap.

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[10]This could for example occur due to on-going structural changes in the financial system.

Figure 12: Examples of countercyclical capital buffers based on a linear d-SRI rule
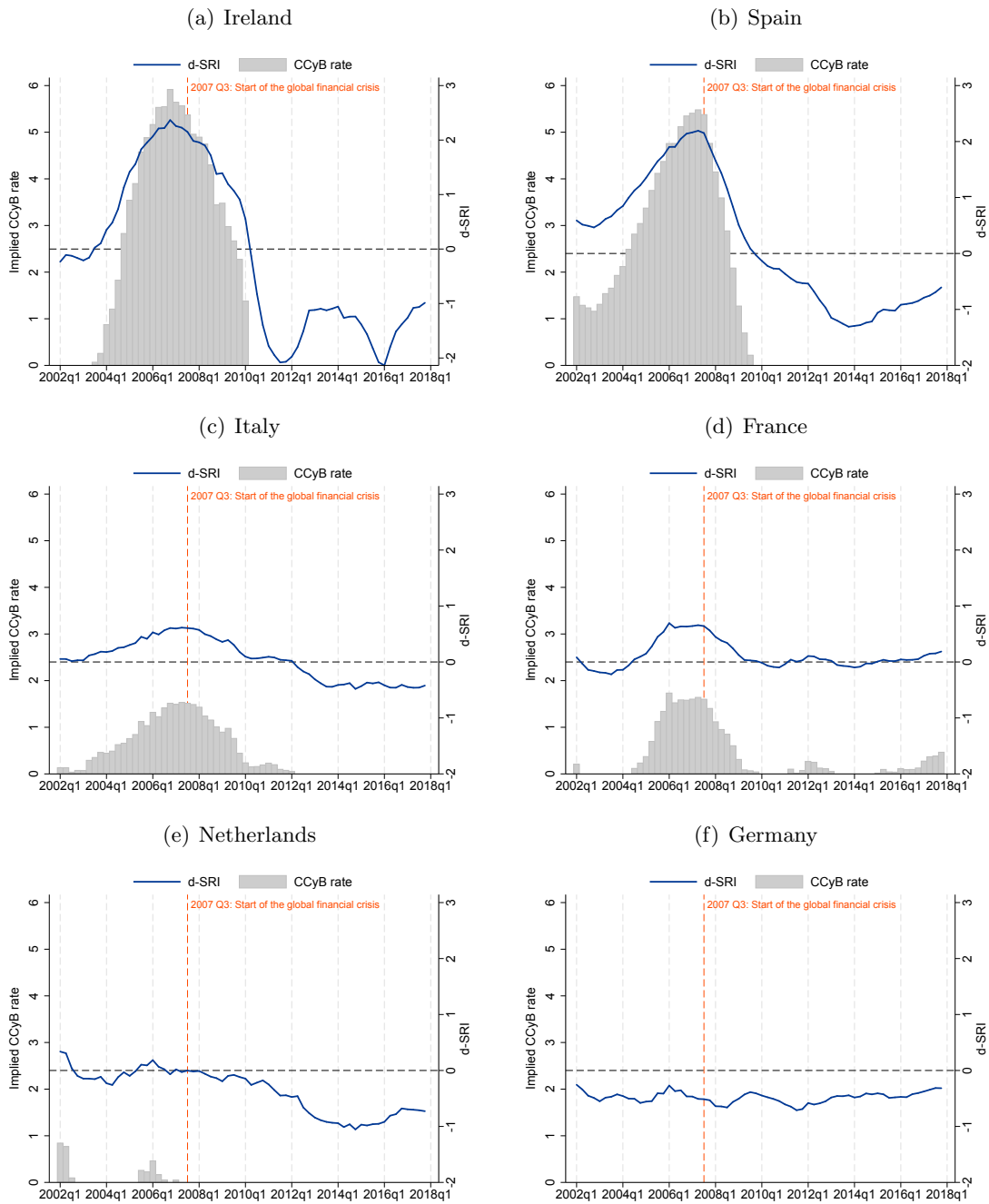
Sources: Lang et al. (2019); Authors' calculations.

Notes: The implied CCyB rates displayed in the charts are derived with a conversion factor of 2.5 per unit of the d-SRI.

Figure 12 illustrates the evolution of the d-SRI and the implied CCyB rates based on the linear calibration rule between 2002 and 2017 for the five largest euro area countries and Ireland. There are three main conclusions. First, the d-SRI implied very different levels of cyclical systemic risk and CCyB rates across the six countries ahead of the global financial crisis, which appears in line with prior expectations. For example, the d-SRI would have implied CCyB rates of more than 5% in Ireland and Spain, of around 1.5% in Italy and France, and 0% in Germany and the Netherlands. Second, cyclical systemic risks already started to increase several years ahead of the global financial crisis in the countries that were most affected by it, leaving sufficient time to raise countercyclical capital requirements. Third, cyclical systemic risk levels and hence the implied CCyB rates reached their peaks a few quarters before the start of the global financial crisis so that capital buffers should have been available at the time the crisis struck.

6.2 Bank capital-at-risk

For macroprudential purposes it is important to go beyond the analysis of average outcomes and focus also on tail risks. Based on the quantile local projection estimates, it is possible to define the level of "Bank capital-at-risk" (BCaR) for country j at time t and prediction horizon h by aggregating the predicted lower 5th percentiles of the bank-level ROA distribution as follows:

$$BCaR_{j,t+h} = \sum_{i=1}^{N_j} Q_{\pi_{i,j,t+h}|\Omega_{i,j,t}}(5\%|\Omega_{i,j,t}) \frac{1}{r\bar{w}_{i,j,t}} \frac{a_{i,j,t}}{\sum_{k=1}^{N_j} a_{k,j,t}} \tag{5}$$

where N_j represents the number of banks in country j, $r\bar{w}_{i,j,t}$ is the average risk-weight of bank i located in country j at time t, and $a_{i,j,t}$ represents total assets of a given bank. Hence, to arrive at the country-level BCaR the bank-level ROA quantiles are first divided by the average risk weight to translate them into impacts on capital ratios and then weighted by the bank-level asset share.

The concept of BCaR is similar to the concept of Growth-at-risk (GaR) developed by Adrian et al. (2016) with the difference that BCaR focuses on the impact on bank capital instead of real GDP growth and it is derived with micro data instead of country-level aggregates. Moreover, BCaR uses the d-SRI - our preferred measure of cyclical systemic risk - as the driver of variations in tail risk, whereas GaR uses financial conditions indices. The lead time of the d-SRI for changes

Figure 13: Aggregate country-level 4-year ahead "Bank capital-at-risk"
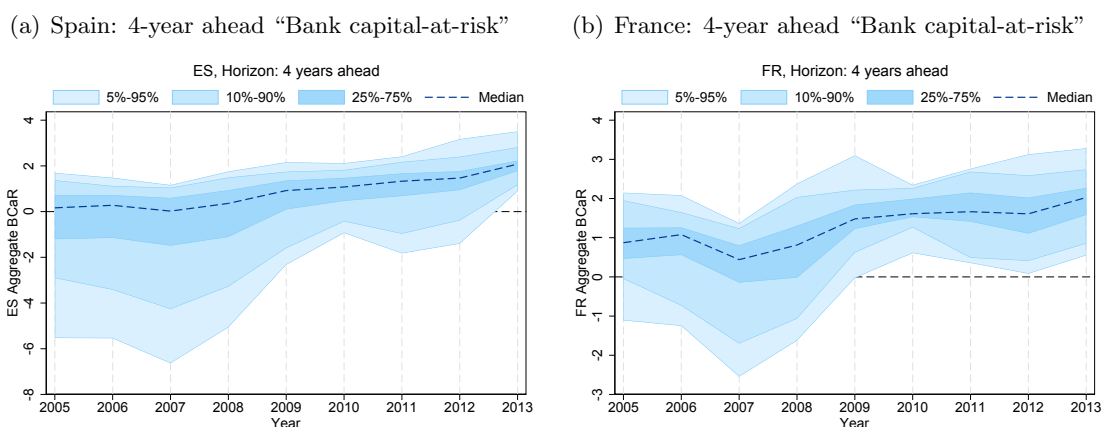
(a) Spain: 4-year ahead "Bank capital-at-risk"   (b) France: 4-year ahead "Bank capital-at-risk"

Sources: SNL Financial; Lang et al. (2019); various other data sources; Authors' calculations.

Notes: The charts show the 4-year ahead "Bank capital-at-risk". I.e. the density plotted in 2005 is the predicted BCaR density for 2009.

in BCaR is mainly between three to five years ahead, while the lead time of financial conditions indices for GaR is mainly between one and four quarters ahead. The long lead time of the d-SRI is an important feature to allow for potential mitigating macroprudential policy action.

To illustrate the method, Figure 13 shows the evolution of the 4-year ahead aggregate country-level BCaR for Spain and France between 2005 and 2013. The BCaR for Spain in 2005 of more than -5% already indicated significant future downside risks to bank capital ratios. The BCaR for Spain increased further to -6% in 2007 and then started to decrease gradually in subsequent years. Panel (a) of Figure 13 further shows that even the 25th percentile of the conditional density of risk to bank capital for Spain was negative between 2005 and 2008. As a comparison, panel (b) of Figure 13 shows that the BCaR for France was also negative in 2005, albeit at a lower level of around -1%, and it peaked in 2007 at around -2.5%. However, the 25th percentile of the conditional density of risk to bank capital for France stayed above or close to zero throughout the period. Hence, BCaR would have clearly distinguished the levels of risk to bank capital in Spain and France ahead of the global financial crisis.

6.3   Aggregate asset share of vulnerable banks

Our framework based on micro data also allows us to derive aggregate country-level risk measures that take into account bank-level heterogeneity. For example, from a policy perspective one could be interested in banks that are expected to have a pre-tax ROA lower than a certain

Figure 14: Asset share of vulnerable banks for the Euro Area
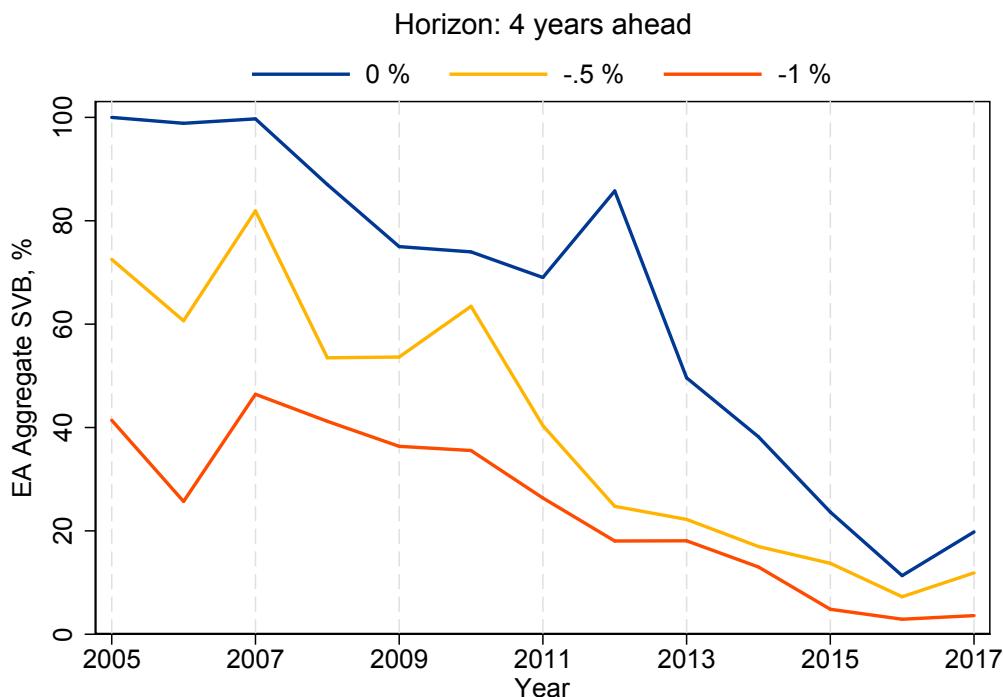
Notes: The chart shows the asset share of banks whose predicted 4-year ahead conditional 5th ROA quantile is below a certain threshold (SVB). For example, the values plotted for 2005 are the predicted SVBs for 2009, conditional on information in 2005. Euro area SVB is plotted for three different ROA thresholds: 0, -0.5, and -1.0.

threshold value $\bar{l}$ with at least a 5% probability. Hence, computing the asset share held by such banks can shed additional light on vulnerabilities in the banking sector. With this objective in mind, we can define the asset "Share of vulnerable banks" (SVB) as follows:

$$SVB^{\bar{l}}_{j,t+h} = \sum_{i=1}^{N_j} \frac{a_{i,j,t}}{\sum_{k=1}^{N_j} a_{k,j,t}} \mathbb{1}_{Q_{\pi_{i,j,t+h}|\Omega_{i,j,t}}(5\%|\Omega_{i,j,t})<\bar{l}} \tag{6}$$

where $\mathbb{1}_{Q_{\pi_{i,j,t+h}|\Omega_{i,j,t}}(5\%|\Omega_{i,j,t})<\bar{l}}$ is an indicator function that takes a value of one when the conditional 5th percentile of the h-year ahead conditional ROA distribution is below the threshold value $\bar{l}$ and zero otherwise.

Figure 14 shows that the asset share of vulnerable banks in the euro area was around 40% between 2005 and 2010, based on a loss threshold of -1% of total assets and it decreased steadily since then to slightly above zero in 2017. For a loss thresholds of -0.5%, the respective euro area SVB values were between 60% and 80% during the period 2005 to 2010, and declined to

around 10% by the end of 2017.

7 Robustness of the empirical results

This section shows that the empirical results regarding the impact of cyclical systemic risk on future bank profitability are robust to changes in the country sample, the underlying bank sample or the exclusion of extreme observations. The robustness results are summarised in Figures 15 to 17.

Figure 15 shows that the impact of cyclical systemic risk on future bank profitability is quantitatively similar to the baseline results if only large or only small countries are used for estimation.[11] Figure 16 shows that the impact is also quantitatively similar to the baseline results if only banks with above median total assets in their country or banks with total assets of more than 30 bn EUR are used for estimation. Figure 17 shows that the estimates are also robust to the exclusion of extreme values in the control variables used in the models.[12]

Hence, the robustness tests confirm that the biggest impact of the d-SRI on bank profitability materialises between three to five years into the future. In addition, the robustness tests confirm that the impact of cyclical systemic risk on the left tail of the future bank profitability distribution is an order of magnitude larger than on the median.

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[11]Large countries encompass DE, ES, FR, IT, NL, GB, while small countries encompass all other countries in the sample.

[12]In particular, we exclude values for bank-specific variables that would under normal conditions be considered as outliers. In the data these observations simply reflect the fact that many of the banking sectors in the sample experienced severe financial crises. For robustness purposes we nevertheless test if results change if these observations are excluded. The following observations were excluded from the sample: net interest margin below 0 or above 5.5, cost-to-income ratio below 0 or above 200, provisions to assets ratio of below -0.5 or above 10, average risk-weight above 100%, a leverage ratio above 30%, a tier 1 ratio of above 60%.
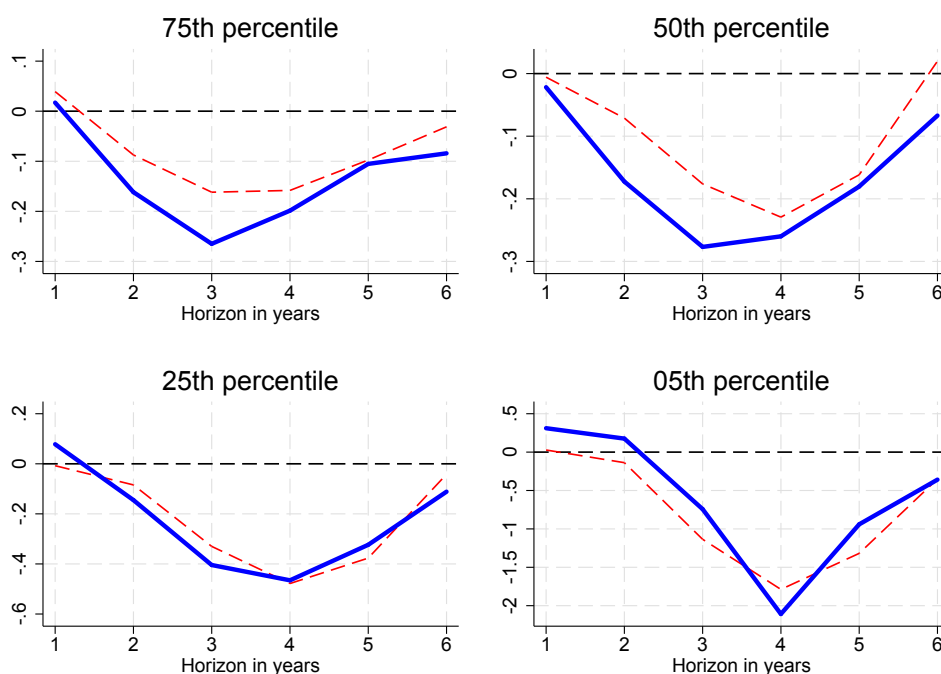
Figure 15: Robustness to changes in the country sample

(a) Only large countries
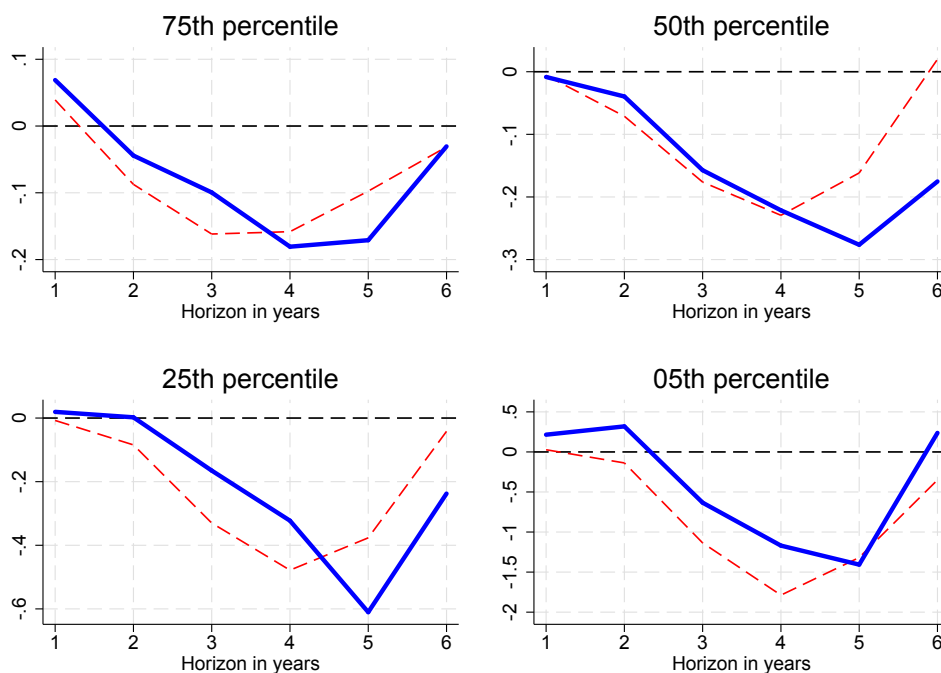
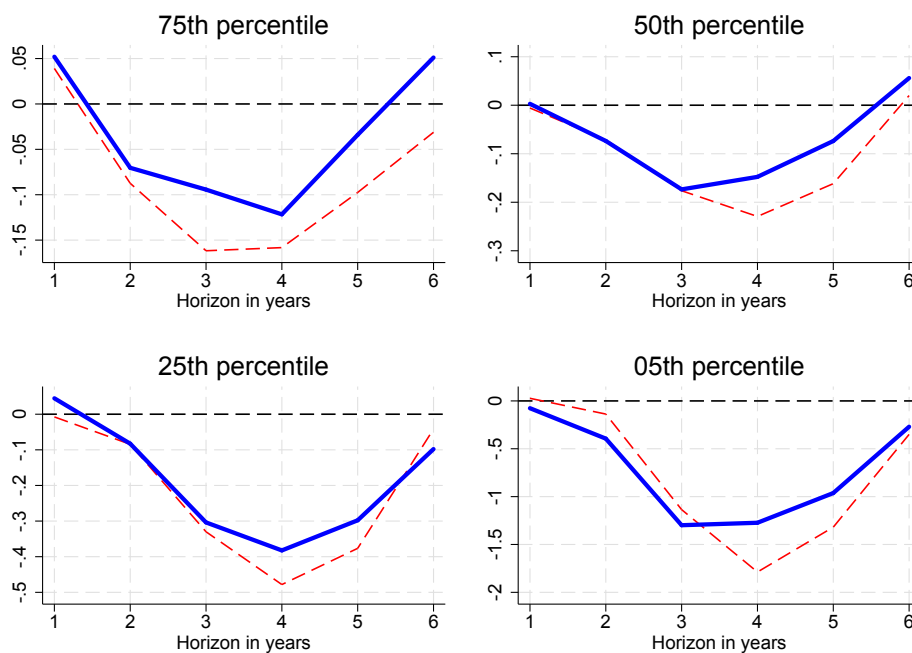(b) Excluding large countries

Sources: SNL Financial; Lang et al. (2019); various other data sources; Authors' calculations.
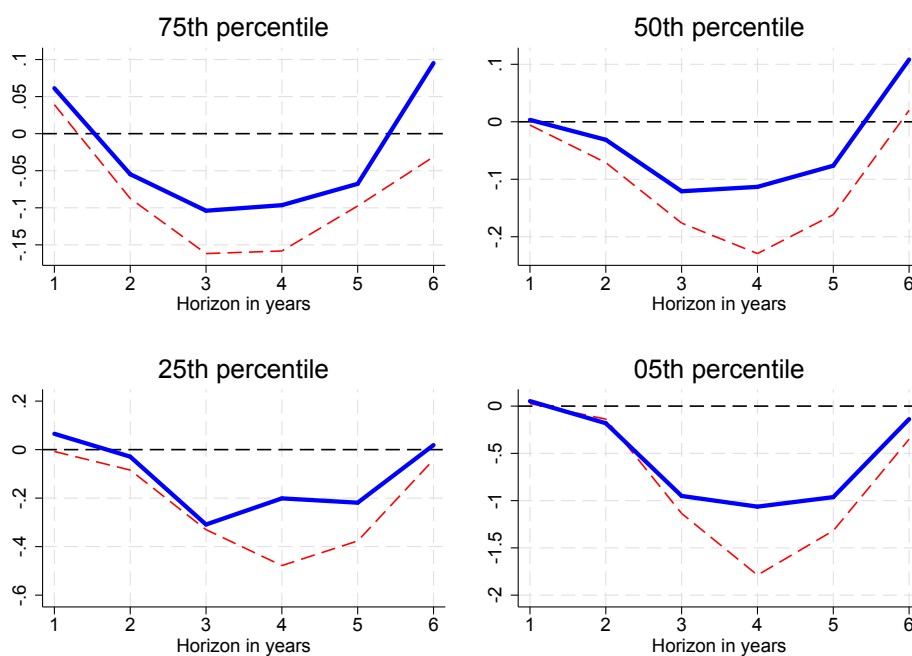
Notes: The dashed red line is the full sample estimate, the blue thick line is the robustness check. Large countries are: DE, FR, ES, IT, NL, GB.

Figure 16: Robustness to changes in the bank sample

(a) Banks above median

(b) Banks larger than 30bn EUR

Sources: SNL Financial; Lang et al. (2019); various other data sources; Authors' calculations.

Notes: The dashed red line is the full sample estimate, the blue thick line is the robustness check. "Banks above median" only considers banks that have total assets larger than the median bank in the given country. "Banks larger than 30bn EUR" only considers banks that had total assets of more than 30bn EUR in at least one year.

Figure 17: Robustness to data cleaned for extreme values
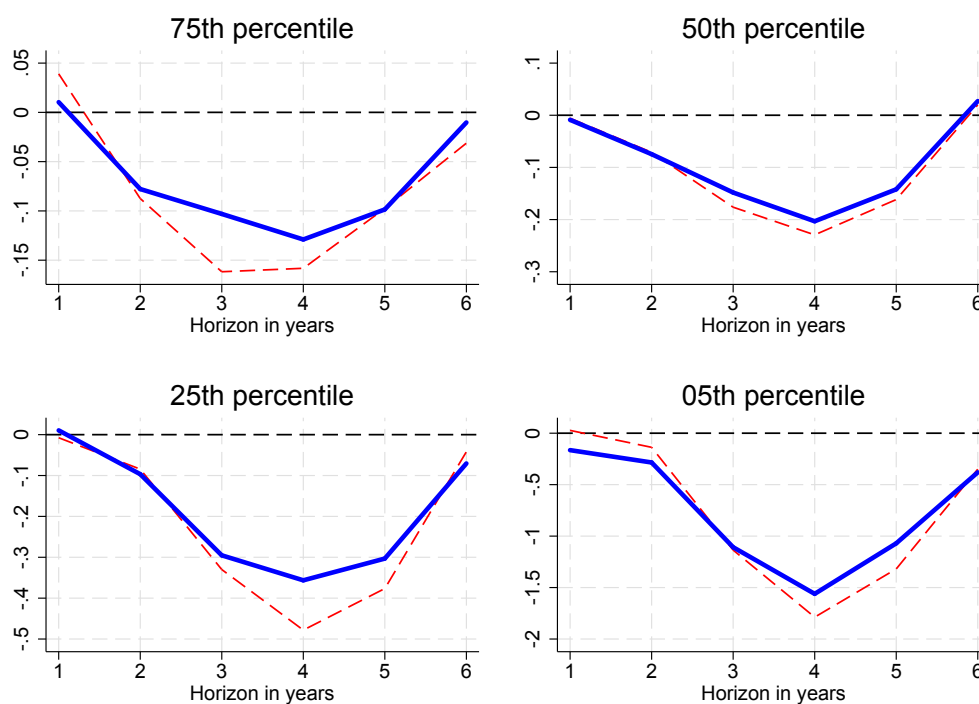
Sources: SNL Financial; Lang et al. (2019); various other data sources; Authors' calculations.

Notes: The dashed red line is the full sample estimate, the blue thick line is the robustness check. The following observations were excluded from the sample: net interest margin below 0 or above 5.5, cost-to-income ratio below 0 or above 200, provisions to assets ratio of below -0.5 or above 10, average risk-weight above 100%, a leverage ratio above 30%, a tier 1 ratio of above 60%.

8   Conclusion

This paper studied the impact of cyclical systemic risk on future bank profitability for a large representative panel of EU banks between 2005 and 2017, building on recent advances in the financial stability literature. First, we used the domestic cyclical systemic risk indicator (d-SRI) proposed by Lang et al. (2019) as our time-varying risk measure. Second, we employed linear local projections as proposed by Jordà (2005) and quantile local projections as proposed by Adrian et al. (2016) to quantify the impact of the d-SRI on average bank profitability and tails of the profitability distribution over horizons of 1-6 years into the future.

The linear local projections showed that high current levels of cyclical systemic risk predict large drops in the average bank-level pre-tax ROA many years in advance. A one unit d-SRI value today leads on average to an economically and statistically significant decline in the pre-tax ROA in the range of 0.3-0.6 percentage points between 3 and 5 years ahead. As the median

d-SRI value before the onset of past financial crises is close to 1, this estimated response can be interpreted as the negative impact of cyclical systemic risk on bank profitability for the average crisis.

We further showed with quantile local projections that the impact of cyclical systemic risk on the left tail of the future bank profitability distribution is an order of magnitude larger than on the median. The estimated impact of a one unit d-SRI on the lower fifth percentile of the conditional pre-tax ROA distribution is in the range of -1.1 to -1.8 percentage points for horizons of 3 to 5 years ahead. The corresponding numbers for the impact on the median of the conditional pre-tax ROA distribution is in the range of -0.2 to -0.25 percentage points. These estimates illustrate that high cyclical systemic risk leads to considerable left skewness in the ROA distribution with a long lead time.

Given that negative profits directly reduce bank capital ratios, our method can be used to quantify the level of "Bank capital-at-risk", akin to the concept of "Growth-at-risk" developed by Adrian et al. (2016). "Bank capital-at-risk" for a given country is defined as a weighted average of the 5th percentiles of the conditional bank-level ROA distributions, where weights are given by the relative size of each bank divided by the bank-level risk-weight density. In addition, the model results allow us to calculate the "Share of vulnerable banks", which is defined as the the total asset share of banks with a conditional 5th ROA quantile of less than a certain threshold. Finally, we showed in the paper how the estimated average impact of the d-SRI on future bank capital can be used to inform the calibration of a linear rule for setting countercyclical capital buffers. Our paper should therefore be of direct value to macroprudential policy makers as well as researchers in the field of financial stability.

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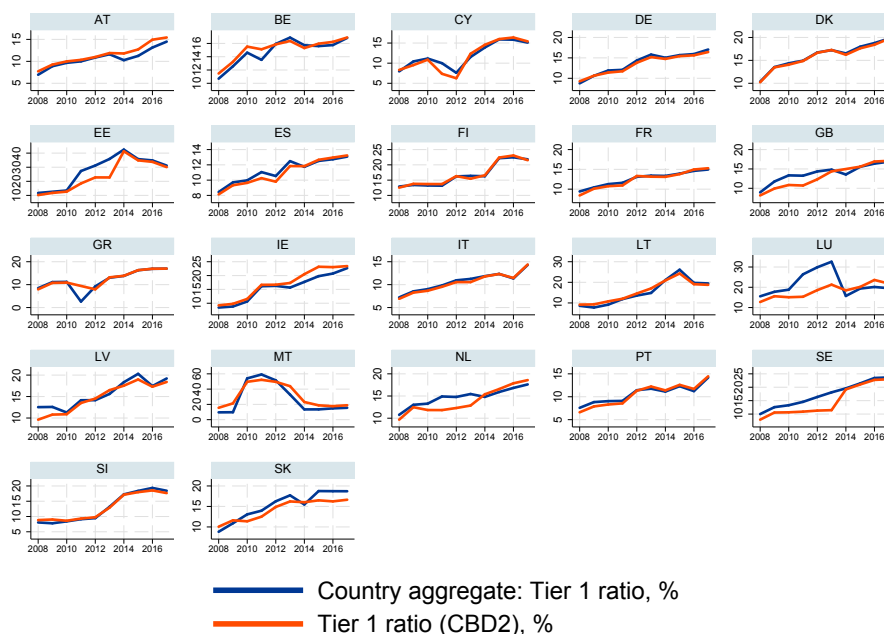
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Appendix A: Additional figures

Figure A1: Micro-data coverage in terms of country aggregates

(a) Tier 1 ratio
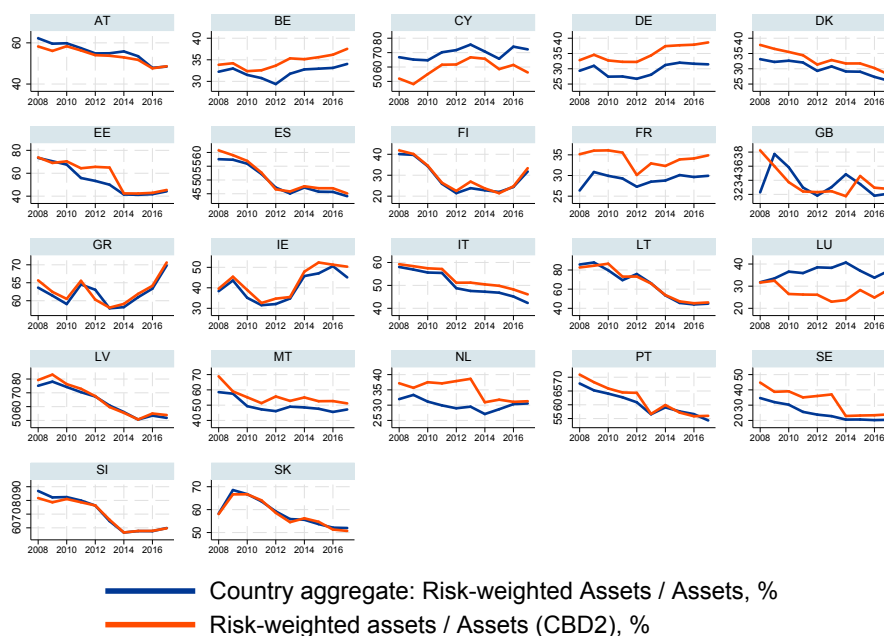
Country aggregate: Tier 1 ratio, %

Tier 1 ratio (CBD2), %

(b) Average risk weights

Country aggregate: Risk-weighted Assets / Assets, %

Risk-weighted assets / Assets (CBD2), %

Sources: SNL Financial; Consolidated Banking Data (CBD2); Authors' calculations.

Notes: The charts show the representativeness of the micro-level bank sample from SNL for country-level banking sector aggregates. Aggregate banking sector data from CBD2 starts in 2008.

Figure A2: Linear local projection results based on aggregate banking sector data

(a) Baseline results

(b) Small countries

(c) Pre-2000

(d) Post-2000
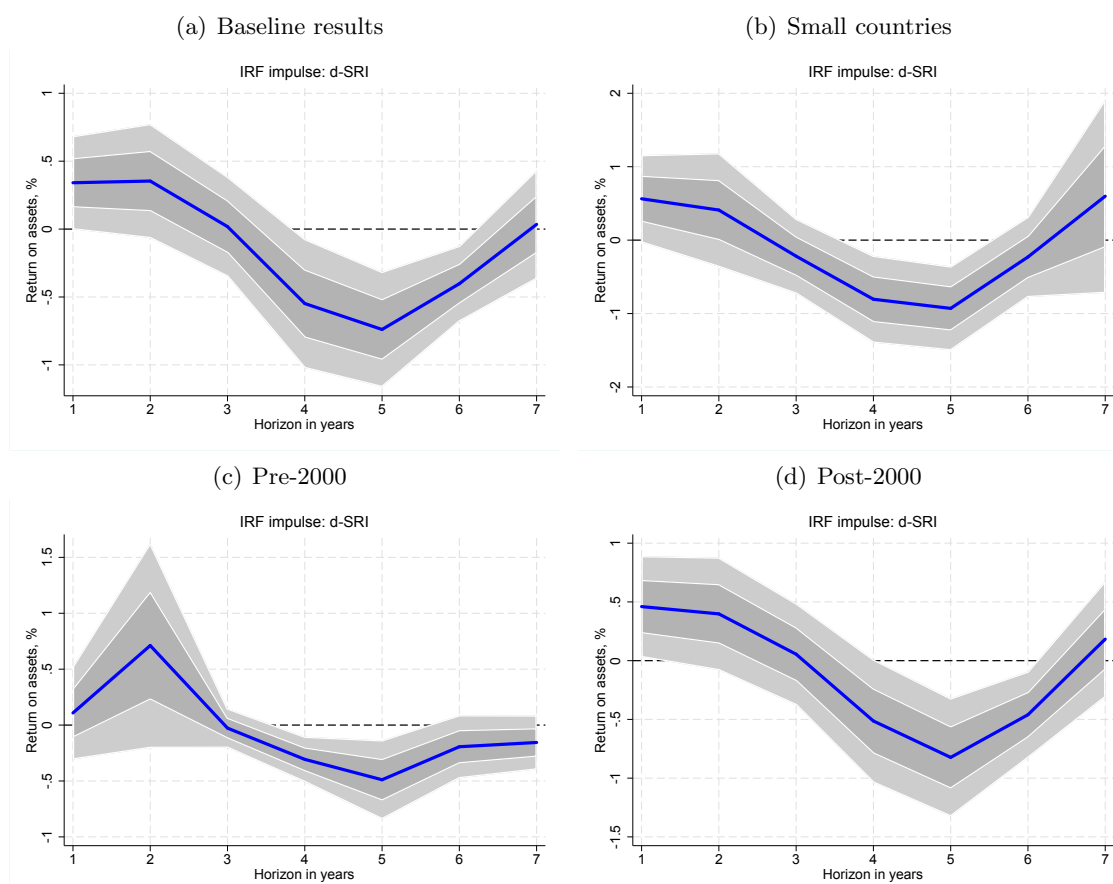
Sources: OECD, CBD2; Lang et al. (2019); Authors' calculations.

Notes: The charts display the impulse response function (IRF) of the aggregate country-level return on assets (ROA) to a one unit d-SRI. The IRF is obtained from local projections as proposed by Jordà (2005), controlling for three lags of the ROA, two lags of the d-SRI, country and time fixed effects, as well as GDP growth, inflation, the real 10-year government bond yield, and the real money market interest rate. Grey areas indicate the one and two standard error bounds. "Baseline" results are for the entire available sample period for euro area countries, Denmark, Sweden, and the UK. "Small countries" excludes DE, FR, IT, ES, NL, DK, SE, UK. "Pre-2000" only uses data up to and including 2000. "Post-2000" only uses data from 2000 onwards.

Appendix B: Additional tables

Table B1: Correlations between the d-SRI and macro-financial variables

VARIABLES	**d-SRI**		**p10**	**p25**	**p50**	**p75**	**p90**	**N**
Real GDP growth	-0.065	*	-0.316	-0.147	0.009	0.146	0.371	22
Inflation	0.400	*	-0.152	-0.040	0.352	0.590	0.719	22
1yr growth in house price	0.255	*	-0.134	0.056	0.330	0.537	0.611	22
1yr growth in equity price	-0.108	*	-0.330	-0.230	-0.028	0.106	0.408	22
Bank credit to GDP	0.229	*	-0.254	0.000	0.000	0.304	0.499	22

Sources: Authors' calculations; Lang et al. (2019); ECB Statistical Data Warehouse.

Notes: The table shows in the first column the linear correlation coefficients between the variables and the d-SRI for the pooled sample across the 22 countries. The stars in the second column indicate statistical significance of the pooled correlation coefficients as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$ The subsequent columns present percentiles of the correlation coefficients when they are computed at the country-level. In total 22 countries are in the sample for which correlations can be computed. The period covered is from 2005Q1 to 2017Q4.

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