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The nonlinear effects of banks' vulnerability to capital depletion in euro area countries

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Abstract

When capital in the banking system becomes depleted, the degree to which financial intermediation and the macroeconomy are adversely affected is likely to depend on the financial and macroeconomic environment. However, existing studies either assume that the effects of bank capital shocks are linear or ignore feedback effects and the impact on the macroeconomy. Using data on the largest euro area countries and Bayesian Panel Threshold VARs, we investigate the importance of different factors in amplifying shocks in banks' vulnerability to capital depletion. Our results demonstrate that nonlinearities matter. When the banking sector is already vulnerable to large capital losses, it is more difficult for banks to accommodate a depletion in capital and lending and economic activity contract more severely. Similarly, low interest rates, which are typically associated with low bank margins and profitability, also lead to a larger decline in lending. De-risking is also more pronounced in these cases. The state of the business cycle, though, does not influence the propagation of shocks to the same extent. We conclude that financial factors play a larger role than the macroeconomic environment in heightening shocks to banks' vulnerability to capital depletion.

Keywords: Bank Capital Vulnerability, Long Run Marginal Expected Shortfall, Bank Balance Sheet, Macroeconomic Adjustment, Panel Threshold VAR, Hierarchical Prior

JEL Codes: C11, C33, E58, G21.

Non-Technical Summary

Banks are vulnerable to losing capital since they transform short-maturity liabilities into long-maturity assets. Deterioration in bank solvency or pressure on bank capital can disrupt bank lending and adversely affect the macroeconomy. Motivated by these concerns, a growing body of literature has estimated the impact of adverse shocks to bank capital. Microeconometric studies have considered the impact of bank-specific shocks on lending by individual institutions. Another strand of literature focuses on the macroeconomic implications of such shocks.

An important assumption in these studies is that the response of the banking sector and the economy is linear. Put differently, the financial and macroeconomic environment do not play a role in the propagation of adverse bank capital shocks. In contrast, we argue that the strength of the response of banking and macroeconomic variables to an aggregate shock in banks' vulnerability to capital depletion depends on the state of the financial and macroeconomic environment. When banks are already vulnerable to losing large amounts of capital, they have less capital headroom to absorb adverse shocks and the impact should be stronger. Similarly, a low interest rate environment, characterised by compressed bank margins and low profitability, or periods of low or negative economic growth constrain capital accumulation. As a result, banks will have more difficulty in accommodating an adverse increase in banks' vulnerability to capital depletion during these exceptional circumstances and will tighten lending supply more strongly than in normal times.

In this paper, we therefore capture the nonlinear propagation of shocks in banks' vulnerability to capital depletion using a macroeconometric model that features changes in regimes. We focus on the four largest euro area economies (Germany, Spain, France and Italy). We employ a macroeconometric model that includes economic activity, inflation and the monetary policy rate and also banking sector variables. We estimate three models to capture three types of nonlinearity. In particular, following a shock to banks' vulnerability we assess whether the subsequent contraction in bank lending and economic activity is more severe when: i) banks are already vulnerable to capital losses; ii) there is a low interest rate environment; or iii) economic growth is low or there is a recession.

Our paper builds on three strands of literature. First, a small number of microeconometric studies provide useful initial evidence of non-linearities. These studies employ bank-level data to estimate the non-linear impact on bank lending supply of changes in bank capital buffers or requirements, where the impact depends on the level of the existing capital buffer or capital ratio, the phase of the business cycle, the monetary policy stance or the profitability of the banking sector. While these single-equation, microeconometric studies have helped shed light on the non-linear impact of shocks to bank capital on lending supply at the bank level

they remain silent regarding feedback effects to the macroeconomy. Additionally, dynamic interaction and feedback effects between different variables are not accounted for. However, when several banks simultaneously face changes in bank capital, economic activity is likely to suffer and lending spreads will widen, feeding back to bank lending. A second strand of literature which takes a macroeconometric approach considers the non-linear amplification of financial shocks and whether these shocks propagate differently during periods of high financial stress or tight credit market conditions. This literature has made an important contribution to understanding the non-linear propagation of shocks during periods of high financial stress. Our paper complements this literature since financial stress can also manifest within the banking sector. Last, the strand of the macroeconometric literature perhaps most closely related to ours focuses on the time-varying impact of aggregate bank lending supply shocks. These studies tend to find a strong impact on output and lending after the recession in 2008-2009 and during the Sovereign Debt Crisis. We build on this literature by being explicit regarding the drivers of the state-dependency.

Our modeling approach has several advantages. First, we can jointly model macroeconomic and banking variables, accounting for dynamic interaction and feedback effects and the impact on the macroeconomy. A second advantage of our approach is that we overcome the estimation challenges associated with exploring nonlinearities using a short sample. We do so by using Bayesian estimation techniques. Third, with each country's banking and macroeconomic environment evolving differently over the last 15 years, capturing cross-country heterogeneity is important. Fourth, the model that we estimate delivers country-specific coefficients and the thresholds for regime change are not subjectively chosen by the researcher. Last, rather than assuming that the economy always remains within the respective regime at the time of the shock, we allow that the estimated response changes regime over the response period.

Across all three models, banks' financial intermediation capacity is impaired when they become more vulnerable to losing capital. As a result, banks tighten lending supply by shrinking their balance sheets (deleveraging) and widening lending spreads. The resulting adjustment helps them to re-build capital positions, increasing loss-absorption. Crucially, though, we also uncover substantial nonlinearities. When the banking sector is already vulnerable to large capital losses or there is a low interest rate environment, it is more difficult for banks to accommodate a depletion in capital. As a result, the impact on bank lending is stronger. In these settings, capital intensive corporate loans also contract more than mortgage loans as banks de-risk their balance sheets. Our results also underscore the importance of considering the macroeconomic effects of shocks to banks' vulnerability. When banks are already vulnerable to losing capital, there is a stronger contraction in economic

activity. However, if we consider the role played by the business cycle, the economy being in a low growth regime does not heighten the impact of vulnerability shocks to the same extent. From these findings we conclude that while the financial environment influences the propagation of shocks in banks' vulnerability, the business cycle does not amplify the effect of such shocks to the same degree.

Finally, we also show that a shock in banks' vulnerability to capital depletion explains a non-negligible share of the variance of variables included in the model, particularly lending volumes and spreads. The share explained by vulnerability shocks is larger in the high vulnerability, low interest rate and low economic growth regimes. This again provides clear evidence in favor of nonlinearities.

1 Introduction

Banks are vulnerable to losing capital since they transform short-maturity liabilities into long-maturity assets. When a large share of the banking system loses capital, a systemic banking crisis emerges. Such crises are common and have substantial economic costs (Laeven and Valencia, 2013 and Reinhart and Rogoff, 2013). Recessions resulting from banking crises appear more severe while recoveries tend to be weak and slow, particularly in advanced countries (Papell and Prodan, 2012; Schularick and Taylor, 2012; Jordà, Schularick, and Taylor, 2013; Kose and Claessens, 2013; Reinhart and Rogoff, 2014; and Baron, Verner, and Xiong, 2020). Banking crises also weaken fiscal positions and lower bank lending growth, particularly to sectors more dependent on external finance (Dell'Ariccia, Detragiache, and Rajan, 2008; Reinhart and Rogoff, 2009; Reinhart and Rogoff, 2013; Laeven and Valencia, 2013; and Baron, Verner, and Xiong, 2020).

Importantly, even in instances where a banking crisis is not triggered, a deterioration in bank solvency or pressure on bank capital can disrupt bank lending and adversely affect the macroeconomy. Consequently, there is a large, growing literature analyzing the effects of bank capital shocks. Microeconometric studies have considered the impact of bank-specific shocks on lending by individual institutions. The literature has focused on the response of individual banks to losses stemming from: real estate exposures (Bernanke and Lown, 1991; Watanabe, 2007 and Mora and Logan, 2012), securities holdings (Woo, 2003), and losses in the parent company (Peek and Rosengren, 1997). Regulatory or supervisory changes at the bank level can also affect lending by individual institutions. Changes considered include those associated with: stricter supervision (Peek and Rosengren, 1995 and Woo, 2003), the 2011 EBA Capital Exercise (Mésonnier and Monks, 2015 and Gropp et al., 2019), bank-specific capital requirements (Aiyar, Calomiris, and Wieladek, 2014; and Aiyar, Calomiris, and Wieladek, 2016) and the dynamic provisioning framework introduced in Spain in the 2000s (Jiménez et al., 2017). To assess the response of economic activity and inflation to system-wide bank capital shocks, the macroeconometric literature has looked at the impact of unexpected changes in bank capital buffers (capital ratios in excess of a target capital ratio), changes in bank capital requirements aggregated at the sector level, changes in aggregate bank capital ratios (capturing changes in the capacity to lend or mimicking changes in aggregate regulatory capital requirements), and exogenous changes in the availability of bank lending (Lown and Morgan, 2006; Berrospide and Edge, 2010; Chodorow-Reich, 2014; Noss and Toffano, 2016; Meeks, 2017; Kanngiesser et al., 2020; and Conti, Nobili, and Signoretti, 2023).[1]

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[1] Herreño (2023) develops a theoretical model that translate the relative, cross-sectional impact of id-

An important assumption in these studies is that the response of the banking sector and the economy is linear. Put differently, the financial and macroeconomic environment do not play a role in the propagation of adverse bank capital shocks. In contrast, we argue that the strength of the response of banking and macroeconomic variables to an aggregate shock in banks' vulnerability to capital depletion depends on the state of the financial and macroeconomic environment. When banks are already vulnerable to losing large amounts of capital, they have less capital headroom to absorb adverse shocks and the impact should be stronger. Similarly, a low interest rate environment, characterised by compressed bank margins and low profitability, or periods of low or negative economic growth constrain capital accumulation (Claessens, Coleman, and Donnelly, 2018; Klein, 2020; and Busch et al., 2021). As a result, banks will have more difficulty in accommodating an adverse increase in banks' vulnerability to capital depletion during these exceptional circumstances and will tighten lending supply more strongly than in normal times.

In this paper, we therefore capture the nonlinear propagation of shocks in banks' vulnerability to capital depletion using Panel Threshold Vector Autoregressions (PTVARs). We focus on the four largest euro area economies (Germany, Spain, France and Italy). We employ a standard monetary policy VAR including economic activity, inflation and the monetary policy rate, extended to include banking sector variables. We consider three types of nonlinearity, estimating three PTVARs. In particular, following a shock to banks' vulnerability we assess whether the subsequent contraction in bank lending and economic activity is more severe when: i) banks are already vulnerable to capital losses; ii) there is a low interest rate environment; or iii) economic growth is low or there is a recession. Consequently, our paper reflects the definition of systemic risk: "a risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and that has the potential to cause serious negative consequences for the real economy" (IMF, 2009). However, we go one step beyond this definition and look at the nonlinear propagation of such disruptions.

Our paper builds on three strands of literature. First, a small number of microeconometric studies provide useful initial evidence of non-linearities, typically as a complement to their benchmark, linear analysis. These studies employ bank-level data to estimate the non-linear impact on bank lending supply of changes in bank capital buffers or requirements, where the impact depends on the level of the existing capital buffer or capital ratio, the phase of the business cycle, the monetary policy stance or the profitability of the banking sector (Bridges et al., 2014; Basten, 2020; Imbierowicz, Löffler, and Vogel, 2020; De Jonghe, Dewachter, and Ongena, 2020; Budnik et al., 2020; De Jonghe, Dewachter, and Ongena (2020); and Sivec and Volk, 2021). While these single-equation, microeconometric studies have helped shed

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iosyncratic shocks to lenders into aggregate effects of symmetric shocks to the banking system.

light on the non-linear impact of shocks to bank capital on lending supply at the bank level they remain silent regarding feedback effects to the macroeconomy. Additionally, dynamic interaction and feedback effects between different variables are not accounted for. However, when several banks simultaneously face changes in bank capital, economic activity is likely to suffer and lending spreads will widen, feeding back to bank lending. Notably, in their study of the US, Berrospide and Edge (2010) find that the impact of an increase in the bank capital-to-asset ratio is larger when feedback effects are accounted for. Our modelling framework will allow us to consider nonlinearities, the impact on the macroeconomy, and dynamic interaction and feedback effects. Moreover, while existing studies rely on an ad hoc threshold to split the sample into regimes, we will endogenously estimate these thresholds to avoid model misspecification.

A second strand of literature which takes a macroeconometric approach considers the non-linear amplification of financial shocks and whether these shocks propagate differently during periods of high financial stress or tight credit market conditions (Balke, 2000; Gilchrist and Zakrajsek, 2012; Hubrich and Tetlow, 2015; Forni et al., 2022; and Barnichon, Matthes, and Ziegenbein, 2022). By looking at corporate bond yields and financial stress indices, this literature has made an important contribution to understanding the non-linear propagation of shocks during periods of high financial stress. Our paper complements this literature since financial stress can also manifest within the banking sector. Last, the strand of the macroeconometric literature perhaps most closely related to ours focuses on the time-varying impact of aggregate bank lending supply shocks (Bijsterbosch and Falagiarda, 2015; and Gambetti and Musso, 2017). These studies tend to find a strong impact on output and lending after the recession in 2008-2009 and during the Sovereign Debt Crisis. We build on this literature by being explicit regarding the drivers of the state-dependency.

Our modeling approach has several advantages. First, by using a VAR framework, we can jointly model macroeconomic and banking variables, accounting for dynamic interaction and feedback effects and the impact on the macroeconomy. A second advantage of our approach is that we overcome the estimation challenges associated with exploring nonlinearities using a short sample. We do so by using a monthly indicator of bank vulnerability and Bayesian estimation techniques. Third, with each country's banking and macroeconomic environment evolving differently over the last 15 years, capturing cross-country heterogeneity is important. We therefore produce country-specific responses while still exploiting the cross-sectional dimension of our dataset. The latter is likely to improve estimation precision (Mumtaz and Sunder-Plassmann, 2021). Fourth, the thresholds and thus regimes in our PTVARs are also country-specific and are not subjectively chosen by the researcher. Instead, the regimes are treated as unknown in our model and estimated in a data-driven fashion. Last, rather than

assuming that the economy always remains within the respective regime at the time of the shock, we estimate generalized impulse response functions (GIRFs). In contrast to linear impulse response functions, we can capture the overall impact of the vulnerability shock and account for the possibility that the economy switches from one regime to another over the impact horizon. This is particularly important in our case because our threshold variables are endogenous. Therefore, a shock affecting these variables may trigger a change in regime.

Across all three PTVARs, we find that banks' financial intermediation capacity is impaired when they become more vulnerable to losing capital. To rebuild capital positions and increase loss absorption, banks tighten lending supply by shrinking their balance sheets (deleveraging) and widening lending spreads. Crucially, though, we also uncover substantial nonlinearities and demonstrate that differences detected across regimes are non-zero. When the banking sector is already vulnerable to large capital losses or there is a low interest rate environment, it is more difficult for banks to accommodate a depletion in capital. As a result, the impact on bank lending is stronger. In these settings, capital intensive corporate loans also contract more than mortgage loans as banks de-risk their balance sheets. Our results also underscore the importance of considering the macroeconomic effects of shocks to banks' vulnerability. When banks are already vulnerable to losing capital, there is a stronger contraction in economic activity. However, if we consider the role played by the business cycle, the economy being in a low growth regime does not heighten the impact of vulnerability shocks to the same extent. From these findings we conclude that while the financial environment influences the propagation of shocks in banks' vulnerability, the business cycle does not amplify the effect of such shocks to the same degree. We also show that a shock in banks' vulnerability to capital depletion explains a non-negligible share of the variance of the variables included in the PTVARs, particularly lending volumes and spreads. The share explained by vulnerability shocks is larger in the high vulnerability, low interest rate and low economic growth regimes. This again provides clear evidence in favor of nonlinearities. These results are robust to a different identification scheme and to employing a different measure of the policy interest rate.

The remainder of the paper is organized as follows. Section 2 presents the data used and carefully discusses how we measure banks' vulnerability to capital depletion. Our econometric methods are presented in section 3. Our main results and a practical application are presented in sections 4 and 5, respectively. Robustness checks are discussed in section 6. Section 7 concludes.

2 Data

2.1 Macroeconomic and Banking Sector Variables

We estimate the nonlinear propagation of shocks in banks' vulnerability to capital depletion for Germany (DE), Spain (ES), France (FR) and Italy (IT). A standard monetary policy framework is augmented to include aggregate banking sector variables. We therefore collect data for each country on eight variables: economic activity proxied by industrial production (IP), inflation (INF), the policy interest rate (INT), corporate lending (CL), mortgage lending (ML), corporate spreads (CS), mortgage spreads (MS) and an indicator of banks' vulnerability to capital depletion, which we discuss in more detail in the subsequent subsection. Economic activity (IP) and inflation (INF) are measured by the monthly log change in the respective index. We use the shadow policy rate by Wu and Xia (2016) in our baseline analysis since the euro area operated in the zero lower bound for more than half our sample.[2] This rate captures unconventional policy tools and better summarizes the overall monetary policy stance. However, we also consider the Euribor rate in our robustness analysis.

Aggregate banking sector variables in our model include the monthly log change in bank lending to domestic non-financial corporations and to households for house purchases. We consider the seasonally adjusted index of notional stocks for loans at all maturities and all currencies combined. Employing notional stocks rather than outstanding amounts is important because the latter not only reflect the cumulative effect of financial transactions but also the impact of other, non-transaction related changes. Excluding non-transaction related changes is more meaningful for economic analysis.

Bank lending spreads are also considered in our framework. While the literature estimating the impact of shocks to bank capital tends to omit bank lending spreads (Lown and Morgan, 2006; Bridges et al., 2014; and Noss and Toffano, 2016), this may lead to omitted variables bias and model misspecification. This is because adverse shocks to bank capital will lead to a re-pricing of loans, affecting loan demand. This is on top of the impact from the bank capital shock (De Jonghe, Dewachter, and Ongena, 2020). In our analysis, bank lending spreads to households for house purchases and to non-financial corporations are computed as the difference between bank lending rates and the 3-month Euribor rate. We include spreads instead of lending rates because spreads are a measure of net interest margins, making them a better indicator of banks' capacity to generate income.

While the Global Financial Crisis, European Sovereign Debt crisis and coronavirus pandemic were all major crises, the drop in real activity in 2020 was deeper than any other

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[2]Faia and Karau (2021) and Kanngiesser et al. (2020) employed the shadow interest rate in linear VAR models for the U.S. and the euro area, respectively.

recession since 1960 by several orders of magnitude (Carriero et al., 2022). Importantly, Diebold (2022) noted that the Great Recession of 2007-09 "appears minor by comparison". Consequently, following Lenza and Primiceri (2022) and Schorfheide and Song (2021) we exclude the extreme observations witnessed during the coronavirus pandemic from our sample, so our data spans January 2005 to December 2019.[3]

2.2 Measuring Banks' Vulnerability to Capital Depletion

Our model includes an indicator of vulnerability to capital losses in the banking system. Specifically, we use the long-run marginal expected shortfall (LRMES) regularly computed by the V-Lab of New York University Stern School of Business.[4] This measure was introduced and developed in a series of papers by Brownlees and Engle (2011), Acharya, Engle, and Richardson (2012), Brownlees and Engle (2016) and Acharya et al. (2017). The LRMES ranges from 0 to 100 and is defined as the percentage point decline in a bank's equity valuation conditional on a financial market crash of 40% over a six-month horizon, the approximate decline in stock market prices during the Global Financial Crisis. Put differently, the indicator captures the equity losses that a financial institution would suffer in a financial crash. When the LRMES is above (below) 40, bank capital is depleted by more (less) than the assumed market crash. The LRMES for each financial institution is computed as follows: $(1 - \exp(ln(1-d) * \beta))$, where d is the six-month crisis threshold for the market index decline (assumed to be 40%) and β is the firm's time varying beta coefficient between the daily returns of the institution and the market. The time varying beta is computed based on the Dynamic Conditional Beta (DCB) model proposed by Engle (2016).[5]

A maximum of 47 institutions are included in our sample. These are quoted banks, most of them large. They are reported in Table A.2 in Appendix A. For each bank, we begin by computing monthly LRMES values as the average of the weekly observations available from V-Lab. Importantly, if only one small firm is vulnerable to capital depletion, other firms may step in to fill the void. In contrast, when capital in the whole banking system is vulnerable at a time when financial markets are already financially constrained, aggregate financial intermediation may be impaired and the economy may suffer (Acharya, Engle, and Richardson, 2012). Consequently, to assess the nonlinear impact of an increase in bank's

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[3]These authors suggest that the unprecedented variation in macroeconomic variables due to the Covid-19 pandemic constitutes a challenge for the estimation of time-series models and can substantially influence VAR parameters. Lenza and Primiceri (2022) suggest that dropping the extreme observations is acceptable for the purpose of parameter estimation. Schorfheide and Song (2021) compare forecasts from a VAR model and the Survey of Professional Forecasters (SPF) and conclude that excluding observations is a promising way of handling VAR estimation during the pandemic.

[4]See https://vlab.stern.nyu.edu/welcome/risk/.

[5]See also Engle and Ruan (2018) for more details regarding the calculation of this indicator.

vulnerability to capital depletion on the macroeconomy, we aggregate the bank-level LRMES into a country-level LRMES using banks' total assets as weights.[6] We compute the country-level LRMES for both a balanced and an unbalanced sample of banks. In the latter, we include banks that started or ended operations over the sample period. We employ the balanced sample for the econometric results as the two resulting country-level LRMES series evolve similarly.[7]

The LRMES has a number of appealing features. First, our indicator closely relates to the literature on extreme events. Banks' vulnerability to capital losses are key to the definition of banking crises. For instance, Laeven and Valencia (2013) date banking crises based on significant capital losses eventually leading to liquidation and intervention. When dating banking crises for a larger panel over two centuries, Reinhart and Rogoff (2008) regret the lack of long time series on stock market prices which would allow them to produce quantitative dates. Furthermore, the authors suggest that the price of bank stocks or financial institutions relative to the market would be a logical indicator to consider. In essence, this is the concept underlying the LRMES.

Second, the LRMES not only relates to the literature on extreme events but also accounts for periods of vulnerability to bank capital losses not considered by this literature. This is because the LRMES is agnostic regarding the cause of a financial market crash which can arise, for instance, from a collapse in the housing market, distress in sovereign debt markets, commodity price or exchange rate crises. This feature is particularly appealing because of the changing nature of financial crises over time (Kose and Claessens, 2013). Baron, Verner, and Xiong (2020), for example, compute banking crises based on large bank equity declines (a market-based indicator, like ours) and find a larger number of crisis in Europe than Laeven and Valencia (2013). We will demonstrate the LRMES's ability to identify different periods of vulnerability in greater detail in the next subsection.

Third, the LRMES is similar in spirit to the capital depletion regularly estimated in stress tests by banking supervisors, where bank losses are estimated conditional on a macroeconomic scenario. Instead, the LRMES reflects the depletion conditional on a financial market crash. An advantage of stress tests is that they are comprehensive, in-depth exercises. By contrast, the measure we employ is simple to compute and is based on publicly available information (which makes it relatively inexpensive to implement).[8] Unlike stress tests in the

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[6]LRMES is aggregated at the national level using the following formula: $LRMES_c = \sum_{i=1}^{N_c} a_i^c * LRMES_i^c$, where $LRMES_c$ is the country-level LRMES, c denotes the country, N_c is the number of banks in country c, a_i^c is the share of bank i' total assets in the banking system of country c, and $LRMES_i^c$ is the bank-specific $LRMES$ of bank i in country c.

[7]This is because the new institutions represent only about 10% of the assets of the existing ones.

[8]Using LRMES is subject to the caveat that the maximum loss in a stress scenario is the total value of equity, while the losses in a stress test can exceed the total value of equity existing at the cut-off date of

euro area, which are implemented every second year, the LRMES is available at a monthly frequency, facilitating time series analysis.

Fourth, and related to the previous point, using the LRMES provides us with 180 observations, three times more information than if we were using quarterly bank capital ratios, as in Kanngiesser et al. (2020). Nonetheless, when attempting to estimate a nonlinear time series model, our sample is still considered relatively small. Hence, we will deploy Bayesian estimation techniques which exploit the panel dimension of the dataset to obtain precise estimates. We will discuss this in further detail in section 3.

2.3   Efficacy of the LRMES as an Indicator of Bank Vulnerability

The narrative regarding the evolution of the LRMES over time and empirical evidence from the literature show that it is a good proxy for impairment to the intermediation capacity of the banking sector. The LRMES in the four countries under consideration is reported in Figure 1. The aggregate LRMES remained above 40% (the threshold for the stock market decline) for most of the period under consideration. This suggests that a financial market crash of 40% would have triggered a decline in bank's equity valuations of more than 40% in most cases.

We can see that there was relative tranquility from 2005 to 2008. The macroeconomic environment was benign and characterized by low inflation and high economic growth, with euro area banks accumulating large amounts of capital and reserves. Specifically, bank capital reserves in the euro area increased by 12% annually in 2008, the highest increase since 2003 (Welch, 2011). This was reflected in the aggregate LRMES which ranged between 45% and 55% in Germany, Spain and France, while it increased steadily from a lower value in Italy.[9]

The Global Financial Crisis (GFC) triggered the first large increase in banks' vulnerability. The LRMES rose starting with the bankruptcy of Lehman Brothers in September 2008, peaking in April 2009. Over this period, the LRMES increased by 14 (Germany), 12 (France) and 16 (Italy) percentage points. These were the countries most exposed to the sub-prime crisis in the US.[10] In Spain, the increase was less pronounced (around 5 percentage points).

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the exercise (*i.e.*, prior to the scenario; Salleo, Homar, and Kick, 2016). Nevertheless, none of the banks in our sample exhibited a decline in equity of 100% over the sample under consideration. Put differently, the capital depletions estimated by LRMES are not binding in our sample.

[9]The fact that Italian banks were estimated to be less vulnerable might be due to the different composition of the banking sector.

[10]While banks in Italy had a lower sub-prime exposure than other countries, the largest bank experienced losses through the German bank HypoVereinsbank, heavily exposed to subprimes. In Germany, the second largest bank suffered losses due to the acquisition of another bank, which was also exposed to the crisis in the US.

More relevant for European banks was the Sovereign Debt Crisis. Following an initial improvement after 2009, banks became more vulnerable to a depletion in capital from the middle of 2010. The collapse in sovereign bond prices of some countries led to significant losses in asset valuations. The euro came under pressure and redenomination risk increased (De Santis, 2019). Banks' vulnerability to capital depletion increased in 2012 above the peak observed during the GFC and remained high until the Summer of 2013.[11] This was despite the decline in redenomination risk observed after the European Central Bank (ECB) announced specific support measures for some eurozone countries. There is recognition that bank capital was under pressure and that supply-side factors were leading to a credit crunch during this period.[12]

The period that followed, between the summer of 2013 and the summer of 2015, was relatively tranquil and vulnerability declined in the second half of 2015, as redenomination risk receded. The Brexit referendum in June 2016, however, brought this improvement to a halt. Vulnerability started to increase again in early 2016 due to the potential disruption to financial intermediation arising from a break in the single market for financial services. Moreover, speculation increased at that time that other countries might leave the EU, again leading to redenomination risk and potentially large losses for the banking sector. This was particularly notable after the UK parliament officially approved the formal request to start the Brexit procedure in February 2017 (Cherubini, 2021). For Italian banks, the impact of Brexit was exacerbated by the publication of the EBA Stress Test results in July 2016. These showed that the third largest bank was the most exposed in the euro area in an adverse scenario.

Overall, these narratives underlying the evolution of the LRMES clearly illustrate that it accurately captures periods of heightened constraints on the intermediation capacity of European banks.

Empirical evidence also suggests that similar measures to the LRMES or computed based on the LRMES are a good indicator of banks' vulnerability to capital depletion. Some studies have uncovered that these indicators and the supervisory stress test results are correlated. Acharya et al. (2017) consider US capital shortfalls identified in spring 2009 by the regulator's Supervisory Capital Assessment Program (SCAP). They find that they are positively correlated with the losses of a financial institution in the tail of the system's loss distribution (the Marginal Expected Shortfall -MES-, an indicator similar to the LRMES). In a different study, Acharya, Engle, and Pierret (2014) consider stress tests in the US and Europe between

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[11]Banks in the US exhibited the opposite pattern. Their risk of capital depletion reacted faster and more strongly to the GFC. See Brownlees and Engle (2016).

[12]See the speech delivered in April 2012 by Benoît Cœuré, former member of the ECB Board: `https://www.ecb.europa.eu/press/key/date/2012/html/sp120411.en.html`

Figure 1: Banks' Vulnerability to Capital Depletion Over Time
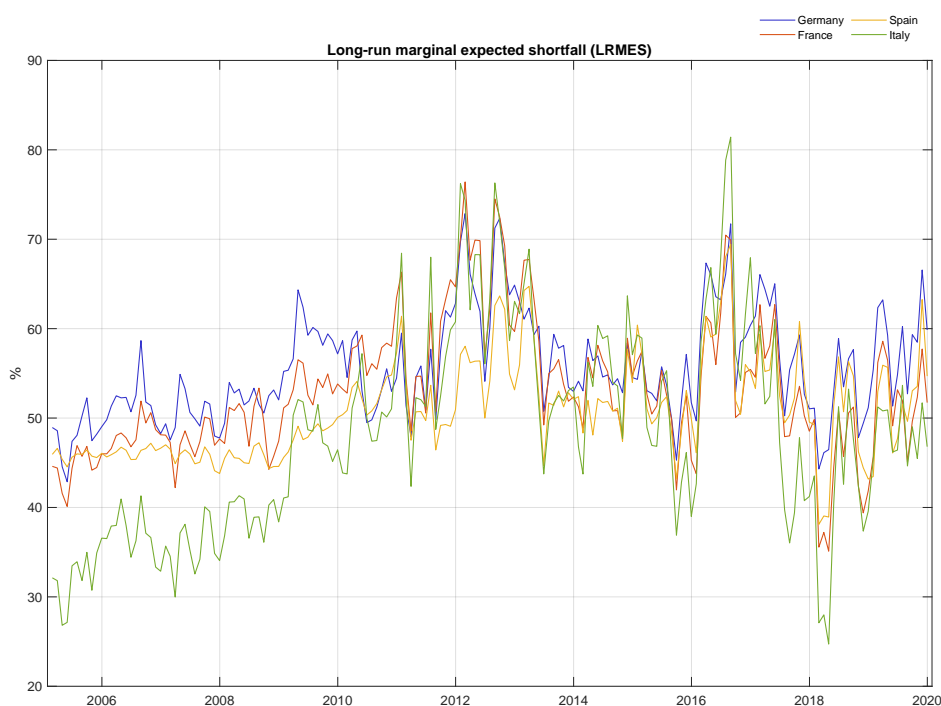
Note: The Figure reports the country-level, long-run marginal expected shortfall (LRMES). The bank-specific LRMES are aggregated at the country level using bank's total assets as weights. Aggregation is based on a balanced sample of banks (see the list of banks in Table A.2 in Appendix A). The indicator ranges from 0 to 100. When the indicator is above (below) 40, bank capital is depleted by more (less) than the assumed market crash.

Source: Computed based on data provided by V-Lab (New York University Stern School of Business) and Bloomberg.

2009 and 2013. They find a positive rank correlation between the capital ratios at the end of the adverse scenarios and the V-Lab's market capital ratio under stress (*i.e.*, the ratio between the market capitalization and the quasi-market value of assets of the institution under a scenario where equity valuations decline according to LRMES).

In addition to predicting the outcome of supervisory stress tests, some indicators also predict bank capital losses when risk materializes. Acharya et al. (2017) show that the MES has significant power in predicting realized losses during the Global Financial Crisis. Similarly, Acharya, Engle, and Richardson (2012) find that the SRISK (the capital shortfall of a financial firm conditional on a systemic event computed by V-Lab) is able to predict nine out of the ten institutions that were rescued or restructured after the bankruptcy of Lehman Brothers.[13] Brownlees and Engle (2016) also show that the SRISK is a significant

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[13]SRISK combines the equity losses expected in a crisis (the LRMES) with the current market value

predictor of Fed capital injections during the 2007-2009 financial crisis.

Last, these indicators have proven effective in identifying Systemically Important Financial Institutions (SIFIs), institutions where there would be significant adverse financial and economic consequences if they fail to meet their obligations to creditors and customers. Engle, Jondeau, and Rockinger (2015) estimate capital shortfalls based on the SRISK for 196 European financial companies. They compare their ranking of systemically risky financial institutions with the first list of global systemically important banks (G-SIFIs) prepared by the Basel Committee on Banking Supervision (BCBS) in November 2011. They find that 16 out of the 17 riskiest banks in their ranking are in the list of G-SIFIs prepared by the BCBS.

To conclude, both the narrative and econometric studies reviewed in this section show that the LRMES effectively captures banks' vulnerability to capital depletion and impairment to the intermediation capacity of the banking system. For brevity, we will deploy the LRMES in our econometric analysis. Results employing SRISK as threshold variable are qualitatively similar and are available from the authors upon request.

3 Econometric Methods

We have emphasized the importance of understanding whether the effects of adverse shocks in banks' vulnerability to capital depletion depend on the financial and macroeconomic environment. Specifically, we wish to consider whether bank lending supply constraints and the impact on the macroeconomy are stronger during periods of: i) high vulnerability to capital depletion; ii) a low policy interest rate environment; and iii) low economic growth or recession. We will estimate three nonlinear panel threshold VAR (PTVAR) models which correspond to these three different environments. In this section, we therefore discuss the PTVAR (subsection 3.1), the regime switching process (subsection 3.2) and the Bayesian methods employed to estimate our PTVARs (subsection 3.3). Finally, we discuss identification and estimation of our generalised impulse-response functions (GIRFs; subsection 3.4).

3.1 The Panel Threshold VAR

The nonlinear PTVAR can be written as follows:

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of equity and debt of the firm. For more details, see Brownlees and Engle (2011) and the V-Lab website: `https://vlab.stern.nyu.edu/docs/srisk`.

$$Y_{i,t} = (c_{1,i} + \sum_{j=1}^{P} \beta_{1i,j} Y_{it-j} + u_{it}) S_{it} \tag{1}$$

$$+ (c_{2,i} + \sum_{j=1}^{P} \beta_{2i,j} Y_{it-j} + u_{it})(1 - S_{it})$$

where Y_{it} is a vector of G dependent variables for euro area country i ($i = 1, ..., N$) at time t ($t = 1, ..., T$) and $p = 1, ..., P$ denotes lags. The vector of endogenous variables includes the eight variables discussed in detail in section 2: industrial production, inflation, corporate and mortgage lending, the LRMES, corporate and mortgage spreads and the shadow interest rate. We focus on the four largest euro area countries, namely Germany, France, Spain and Italy ($N = 4$). We then set $p = 1$ due to the short sample (see Canova, 2005 and Davidson, 2022).[14] The vectors $c_{1,i}$ and $c_{2,i}$ and $\beta_{1i,j}$ and $\beta_{2i,j}$ are country-specific fixed effects and country-specific response coefficients in the two regimes, respectively. The errors u_{it} are distributed as $N(0, \Sigma_{it})$, where the variance covariance matrix is given by:

$$\Sigma_{it} = S_{it} \odot \Sigma_{1i} \tag{2}$$

$$+ (1 - S_{it}) \odot \Sigma_{2i}$$

and $\odot$ denotes element by element multiplication. Our country-specific coefficients and variance-covariance terms allows us to capture cross-country heterogeneity.

The inclusion of the indicator variable $S_{it} \in \{0, 1\}$ allows us to model two distinct regimes for each country and to assess whether the effect of shocks depends on the financial and macroeconomic environment. When $S_{it} = 1$, the second term on the right hand side of Equations (1) and (2) is set to zero, whereas when $S_{it} = 0$, the first term is excluded. Consequently, our PTVAR allows for coefficients and variance-covariance terms which are regime dependent. Regime dependence is also important in our case since heteroskedasticity (which is a common feature of financial data and is captured by our regime-dependent variance-covariance matrix) may also be present in macroeconomic data during crises. These features are important because the vulnerability of the banking systems and the macroeconomic environment has been heterogenous across and within countries over the last 15 years.

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[14]The rapid degree of regime-switching detected in the results section also suggests a short lag length is appropriate.

3.2   Regime Switching Process

Regime switching between our two regimes (*i.e.*, whether $S_{it} = 0$ or 1) depends on whether the level of a specific variable $z_{i,t-d_i}$ is above or below an unknown threshold z_i^*. In particular:

$$S_{it} = 1 \iff z_{i,t-d_i} \leq z_i^*. \tag{3}$$

When the threshold variable at time $t - d_i$ is below or equal to z_i^*, the economy is in regime $S_{it} = 1$ at time t. The delay parameter d_i allows for the possibility that it takes some time to switch regimes after the threshold variable exceeds or falls below the threshold. Importantly, both d_i and z_i^* are country-specific, which allows us to capture cross-country heterogeneity in terms of regime switching. Moreover, these parameters are not specified by the researcher and are instead estimated within the model. This alternative is preferable to imposing the thresholds which may lead to model misspecification.

We estimate three PTVARs corresponding to the three macroeconomic and financial environments shown in Table 1. In each of the three models, the first regime captures the following: *i*) low vulnerability to bank capital depletion (low LRMES); *ii*) the low interest rate environment (low shadow rate); and *iii*) a recession or low-economic growth environment. In the last case, the 12 month moving sum of industrial production growth is used as the threshold variable, a commonly deployed approximation of the annual growth rate. Due to the short nature of our dataset, we consider two regimes for each model. This is in line with the existing literature which considers two or three regimes (see Auerbach and Gorodnichenko, 2012; Hubrich and Tetlow, 2015; Tenreyro and Thwaites, 2016; and Alpanda, Granziera, and Zubairy, 2021, among others). We expect the response of bank lending supply and economic activity to be stronger in periods when the banking sector is already vulnerable, the policy rate is low and the macroeconomy is weak.

Table 1: Summary of PTVAR Models and Regimes

	Model 1	Model 2	Model 3
Threshold Variable $z_{i,t-d_i}$	LRMES	Shadow Interest Rate	Annual IP Growth
Regime 1 ($S_{it} = 1$)	Low vulnerability	Low Shadow Rate	Low Growth
Regime 2 ($S_{it} = 0$)	High vulnerability	High Shadow Rate	High Growth

3.3 Bayesian Estimation of the Panel Threshold VAR

Studying nonlinearities with just 180 observations presents a significant challenge. We overcome this short sample issue by deploying econometric methods which rely on Bayesian estimation techniques and exploit the panel structure of our data to produce precise country-specific estimates. These methods require a prior and a method of posterior computation. The latter is used to approximate the distributions of the estimated model parameters. In this paper, we use a hierarchical model developed by Mumtaz, Pirzada, and Theodoridis (2018) and Mumtaz and Sunder-Plassmann (2021), who in turn build on Jarociński (2010).

To illustrate the intuition behind Bayesian shrinkage, consider the VAR coefficient b. A conventional Normal prior takes the form:

$$b \sim N(\underline{\alpha}, \underline{V}). \tag{4}$$

The choice of prior variance ($\underline{V}$) determines the strength of the prior shrinkage. If the prior mean ($\underline{\alpha}$) is zero, then a small value for $\underline{V}$ implies prior shrinkage of the coefficient to be near zero.

Like Mumtaz, Pirzada, and Theodoridis (2018) and Mumtaz and Sunder-Plassmann (2021), we begin by assuming that the country-specific vector of VAR coefficients in our two regimes have the following prior distribution:

$$\beta_{1,i}|\bar{\beta}_1, \lambda_1 \sim N(\bar{\beta}_1, \lambda_1 \Lambda_i) \tag{5}$$
$$\beta_{2,i}|\bar{\beta}_2, \lambda_2 \sim N(\bar{\beta}_2, \lambda_2 \Lambda_i)$$

where $\bar{\beta}_1$ and $\bar{\beta}_2$ are the cross-country average in regime 1 and 2, respectively. The parameters λ_1 and λ_2 determine the degree of pooling in each regime, estimated within the model. If $\lambda \to 0$, the prior variance is small and we shrink towards the common mean across countries. Put differently, cross-country heterogeneity falls. Conversely, if $\lambda \to \infty$ our coefficients undergo relatively little shrinkage and each country has distinct coefficients.

We can then decompose the error-covariance matrices as:

$$\Sigma_{1,i} = A_{1,i}^{-1} H_{1,i} A_{1,i}^{-1'} \tag{6}$$
$$\Sigma_{2,i} = A_{2,i}^{-1} H_{2,i} A_{2,i}^{-1'}$$

where $A_{1,i}$ and $A_{2,i}$ are lower triangular matrices and $H_{1,i}$ and $H_{2,i}$ are diagonal matrices with shock variances on the diagonal. As before, we use a prior for the nonzero and non-one

elements of $A_{1,i}$ and $A_{2,i}$:

$$a_{1,i}|\bar{a}_1, \delta_1 \sim N(\bar{a}_1, \delta_1 \Xi_i) \tag{7}$$
$$a_{2,i}|\bar{a}_2, \delta_2 \sim N(\bar{a}_2, \delta_2 \Xi_i)$$

where $\bar{a}_1$ and $\bar{a}_2$ are the cross-sectional average in regime 1 and 2, respectively. The degree of pooling is governed by the parameters Ξ_1 and Ξ_2 which are estimated within the model and can be interpreted in the same manner as λ_1 and λ_2.

The prior for our threshold has a similar structure:

$$z_i^*|\bar{z}, \bar{\omega} \sim N(\bar{z}, \bar{\omega}\psi_i) \tag{8}$$

where $\bar{z}$ is the average threshold across countries and $\bar{\omega}$ controls the degree of pooling.

To undertake posterior computation, we use Gibbs sampling.[15] Further details of the algorithm, priors and hyperparameter values selected are provided in Mumtaz, Pirzada, and Theodoridis (2018) and Appendix B. It is helpful to note, however, that in our hierarchical model the algorithm alternates between drawing the country-specific parameters $(c_{1,i}, c_{2,i}, \beta_{1,i}, \beta_{2,i}, \Sigma_{1,i}, \Sigma_{2,i}, z_i^*, d_i)$ and the parameters capturing the common mean and the degree of pooling $(\bar{\beta}_{1,i}, \bar{\beta}_{2,i}, \lambda_1, \lambda_2, \bar{a}_{1,i}, \bar{a}_{2,i}, \delta_1, \delta_2)$. We use a Minnesota type prior for $\bar{\beta}_{1,i}$ and $\bar{\beta}_{2,i}$ and use uninformative priors for $\lambda_1, \lambda_2, \bar{a}_{1,i}, \bar{a}_{2,i}, \delta_1$ and δ_2.

To summarize, our modeling approach has a number of key advantages. First, we allow for regime dependent, country-specific constants $(c_{1,i}, c_{2,i})$, response coefficients $(\beta_{1,i}, \beta_{2,i})$, variance-covariance matrices $(\Sigma_{1,i}, \Sigma_{2,i})$, and country-specific delay and threshold parameters $(d_i$ and $z_i^*)$. Therefore, we capture cross-sectional heterogeneity with a large level of detail. In particular, each country may react differently to the same shock, the variance of the shocks hitting each economy may be different and each economy may switch regimes at a different time. A pooled estimator does not afford us this level of detail.

Second, our hierarchical prior shrinks the country-specific coefficients and error covariances towards a common mean, which contains information from the whole panel and is updated during sampling, increasing estimation precision. As suggested by Mumtaz and Sunder-Plassmann (2021), exploiting the cross-sectional dimension implies that the estimated GIRFs and forecast error variance decompositions (FEVDs) are likely to be more precisely estimated.

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[15]For a more detailed explanation of Gibbs sampling see Koop (2003), pp. 62-64.

3.4 Identification and Impulse Response Functions

We adopt a recursive identification scheme to identify shocks in banks' vulnerability to capital depletion. This approach is widely deployed in the literature studying the impact of banking and financial shocks (see, for example, Lown and Morgan, 2006; Mésonnier and Stevanovic, 2017; Faia and Karau, 2021; and Gilchrist and Zakrajsek, 2012 in a linear setting; and Balke, 2000; Hubrich and Tetlow, 2015 and Forni et al., 2022 in a nonlinear setting).

Our ordering is as follows: industrial production, inflation, corporate and mortgage lending, LRMES, corporate and mortgage spreads and the shadow interest rate. As is widespread in the literature, we order macroeconomic variables first and banking and financial metrics after. This implies that macroeconomic variables do not react contemporaneously to shocks affecting the LRMES, lending volumes and lending spreads, given that it is costly to adjust production and prices are sticky at the aggregate level. Second, as is standard in the monetary policy literature (Bernanke and Gertler, 1995; and Christiano, Eichenbaum, and Evans, 1999), we assume that macroeconomic variables do not immediately react to the policy rate and that inflation is immediately affected by a shock to economic activity. Third, we assume that an adverse shock to the LRMES elicits an immediate response in bank lending and spreads. Finally, according to the two-pillar monetary policy strategy of the ECB, the monetary policy rate is assumed to respond to a large number of indicators (ECB, 2011).[16] Hence, we rank the monetary policy rate last in the VAR as in Bernanke and Boivin (2003), Ciccarelli, Maddaloni, and Peydró (2013), Prieto, Eickmeier, and Marcellino (2016) and Gilchrist and Zakrajsek (2012). In section 6 we present the results of an alternative ordering of the variables as a robustness check. In this new ordering, the policy rate follows the macroeconomic variables (economic activity and inflation), as in Mésonnier and Stevanovic (2017).

Based on the orthogonalized errors, we compute our GIRFs. Rather than assuming that the economy remains within the respective regime at the time of the shock (as is the case when linear impulse response functions are used), we want to capture the overall impact of the shock and allow for the possibility that the economy switches from one regime to another over the impact horizon.[17] This is particularly important in our case because the three threshold variables are also included in the set of endogenous variables in the PTVAR.

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[16]The monetary policy strategy of the ECB was reviewed in 2021 and currently recognizes financial stability considerations in the implementation of monetary policy. For more details regarding the new monetary policy strategy of the ECB see: `https://www.ecb.europa.eu/home/search/review/html/ecb.strategyreview_monpol_strategy_statement.en.html`

[17]Auerbach and Gorodnichenko (2012), Hubrich and Tetlow (2015), Tenreyro and Thwaites (2016) and Alpanda, Granziera, and Zubairy (2021), among others, assume that the economy remains in the same state after the shock.

As a result, a shock that affects such variables may trigger a change in regime.

We estimate country-specific GIRFs using Monte Carlo integration following Koop, Pesaran, and Potter (1996):

$$IRF_{1,i} = E(Y_{i,h}|\varepsilon_1) - E(Y_{i,h}) \tag{9}$$
$$IRF_{2,i} = E(Y_{i,h}|\varepsilon_2) - E(Y_{i,h})$$

where $IRF_{1,i}$ ($IRF_{2,i}$) is the impulse-response function starting in regime 1 (and 2) for country i, $h = 0, 1, ..., 35$ is the horizon and ε_1 and ε_2 are our shocks in banks' vulnerability to capital depletion in both regimes. As shown in Equation (9), for each regime, the GIRFs are the difference between forecasts of the endogenous variables conditional on the relevant structural shocks and a baseline forecast where all shocks are equal to zero. Responses are also conditioned on the initial information set in each regime. For example, in regime 1, $S_{it} = 1$ and our "history" consists of lagged values of Y_{it} which lie in the "low" regime. Conversely, in regime 2, $S_{it} = 0$ and our "history" consists of lagged values of Y_{it} which lie in the "high" regime.

4 The Nonlinear Impact of Shocks in Banks' Vulnerability to Capital Depletion

In this section, we present the results from our three PTVARs for the four euro area countries under consideration. We present three sets of results for each PTVAR discussed in Table 1. First, we report the regimes estimated. Second, we report the GIRFs to an adverse increase in banks' vulnerability to capital depletion in the two different regimes. Finally, we present the FEVDs in each regime, the share of variation in individual variables explained by shocks in banks' vulnerability to capital depletion. We detect important differences across regimes, demonstrating that the response of the banking sector and the macroeconomy is non-linear.

4.1 Financial and Macroeconomic Regimes

The regimes associated with each of our three PTVARs are reported in Figure 2. The shaded area shows the periods belonging to the first regime in each model, namely: i) the low vulnerability to bank capital depletion regime (top panel); ii) the low interest rate regime (middle panel); and iii) the low economic growth regime (bottom panel). For each country, the regimes are computed based on the estimated delay (d_i) and threshold (z_i^*)

parameters (see Equation 3). Across models and countries, the median delay is estimated to be one month in all cases, except for Spain when the transition variable is the LRMES (the median delay is two months in this case). This suggests that regime-switching occurs quickly in all countries and that cross-country differences are driven by different thresholds. In this regard, differentiation among countries is more marked in the first and third model than in the second one (see below). Overall, the heterogeneity observed in the estimation of the country-specific regimes confirms the importance of the endogenous estimation of the threshold parameters.

Our first PTVAR with the LRMES as the threshold variable (top panel in Figure 2) detects periods where it is well established that bank vulnerability was low and high. Vulnerability was low in all countries in the early stages of the sample, until the Global Financial Crisis. Thereafter, there are differences among countries. Germany, Spain and Italy entered a high vulnerability regime already in 2009, while France entered later, in 2010. The model suggests that a high vulnerability regime was entered again during the Sovereign Debt Crisis and also following Brexit in France and Germany. Spain and Italy reacted differently after the Global Financial Crisis and once they entered the high vulnerability regime, they remained there for longer. In all countries, vulnerability receded after Brexit. In this model, the threshold is higher in Germany (0.56) and France (0.54) compared to Spain (0.47) and Italy (0.42) (top panel in Figure 2). This means that the LRMES need only be slightly higher than 40% for the high vulnerability regime to be entered in the latter two countries.

Regarding the second PTVAR where the shadow interest rate is the threshold variable (middle panel in Figure 2), nearly all economies are estimated to enter the low interest rate environment when the shadow interest rate is zero (in Germany it is slightly higher at 0.1). The regimes estimated are similar across countries, reflecting the single monetary policy in the euro area. A low interest rate regime started in 2012, when the shadow interest rate hit zero due to policies implemented to counter the decline in economic activity following the Global Financial Crisis and the Sovereign Debt Crisis. This regime lasted until the end of the sample.

Figure 2: Regimes Estimated for Three PTVAR Models with Different Threshold Variables
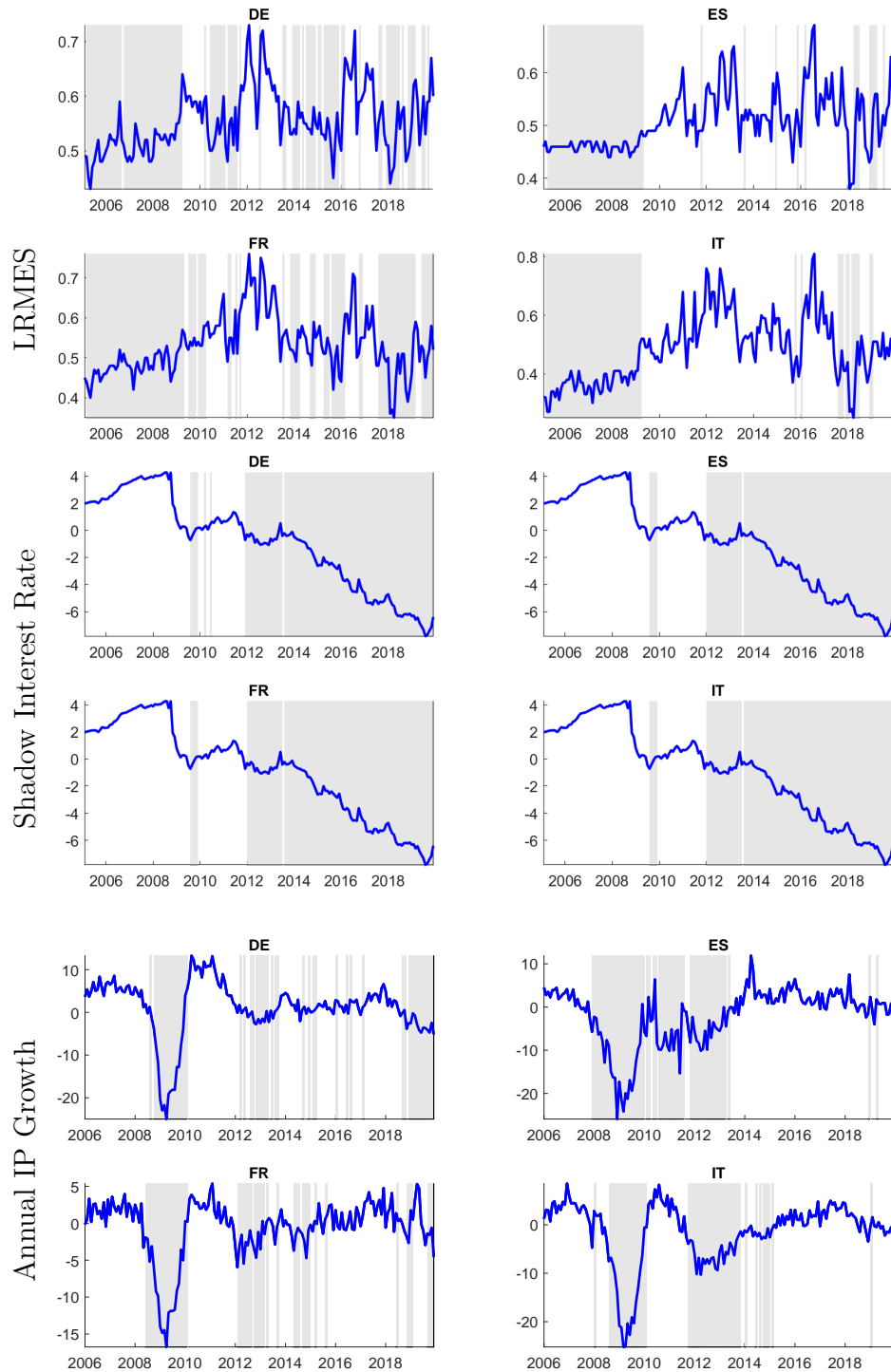
Notes: The Figure reports the country-specific regimes estimated by each model for Germany (DE), France (FR), Spain (ES) and Italy (IT). The shaded areas show the 'low' regime in each model and are computed based on whether the threshold variable is above or below the posterior mean of the threshold.

Finally, the third model also accurately identifies periods of high and low economic growth (bottom panel in Figure 2). The results point to a high economic growth regime in the four economies until the Global Financial Crisis, when economic activity contracted. As with the first threshold variable (LRMES), the business cycles are less synchronized afterwards. Germany, France and Italy recovered until the Sovereign Debt Crisis. By contrast, Spain remained in the low growth regime for longer, until late 2013. France and Italy started a new high growth regime only later, in 2015. Germany exhibited a long period of high economic growth in 2017 and 2018, followed by another long period of low economic growth at the end of the sample. The threshold in this model is higher in Germany and France (0.2 and -1.0, respectively) than in Spain and Italy (-2.0 and -2.2, respectively). This means that economic activity needs to exhibit a larger contraction in order to enter the low growth regime in the last two countries.

4.2   Dynamic Responses to Shocks in Banks' Vulnerability

This subsection presents the GIRFs to an adverse, one standard deviation increase in banks' vulnerability to capital depletion.[18] Figures 3, 4 and 5 (top panels) report the GIRFs over a three year (36 month) horizon for the PTVARs using the LRMES, shadow interest rate and annual growth rate in industrial production as threshold variables, respectively. The economy starts in either the low (red straight line) or high (black dotted line) regime. GIRFs are cumulated for industrial production, inflation and corporate and mortgage lending, while they are reported in levels for the bank lending spreads and the shadow rate. The posterior median together with the 68% credible interval are reported for each regime.

We also demonstrate that there are non-zero differences between the impulse responses in both regimes by following the procedure outlined in Mumtaz and Sunder-Plassmann (2021). Specifically, we calculate the difference between the responses in the high and low regimes for each saved draw. We then consider the median of these differences together with the corresponding 68% credible interval. If the interval excludes zero, we have detected non-zero differences and found evidence in favor of regime dependence. For ease of exposition, we summarize our findings compactly in the bottom panels of Figures 3, 4 and 5. A green cell indicates that there are non-zero differences between responses while a red cell indicates that there are not.[19] If non-zero differences are detected, we also report the longest horizon at which differences are non-zero.

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[18]We did not detect substantial differences when considering shocks of different signs and sizes. These results are available upon request from the authors.

[19]A red cell is also used if the top panel indicates that the responses in both regimes are not different from zero.

As expected, Figure 3 (top panel) shows that an increase in banks' vulnerability to capital depletion (fifth column) leads to a tightening in bank lending supply in both regimes. Accordingly, in most regimes and countries, corporate and mortgage lending decline persistently (third and fourth columns). Spreads widen following the shock to boost net interest income (sixth and seventh columns; see De Jonghe, Dewachter, and Ongena, 2020). Monetary policy relaxes on impact and subsequently tightens (eighth column). Higher policy interest rates help to support bank's efforts to strengthen their balance sheets, consistent with evidence suggesting that overall bank risk declines after a contractionary monetary policy shock (Angeloni, Faia, and Lo Duca, 2015).[20] The rise in bank lending spreads and decline in bank loans depresses economic activity, while the response of inflation is not different from zero (first and second columns). These results are consistent with Engle, Jondeau, and Rockinger (2015), who find that an increase in SRISK Granger causes a decrease in bank lending.

Despite these shared characteristics, there are pronounced differences in the response of the variables across regimes. As hypothesized, banks tighten lending supply more strongly in the high vulnerability regime. Because the banking sector is already vulnerable to large capital losses in this regime, the resulting adjustment forces are stronger. In particular, at the end of the horizon the cumulative decline in corporate lending ranges between 0.2 (Spain) and 0.4 percentage points (France). The corresponding decline in the low vulnerability regime is smaller and ranges between 0 (the response is within the credible bands for Spain and Italy) and 0.2 percentage points (France). For mortgage lending, the difference in the responses between regimes is less marked. Accordingly, Figure 3 (bottom panel) shows that the responses of mortgage lending do not differ across regimes, but for corporate lending there are important non-zero differences.

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[20]Empirical evidence also suggests that banks become more selective regarding their clients to reduce risk (Maddaloni and Peydró, 2011; Jiménez et al., 2014; and Neuenkirch and Nöckel, 2018).

Figure 3: LRMES as Threshold Variable
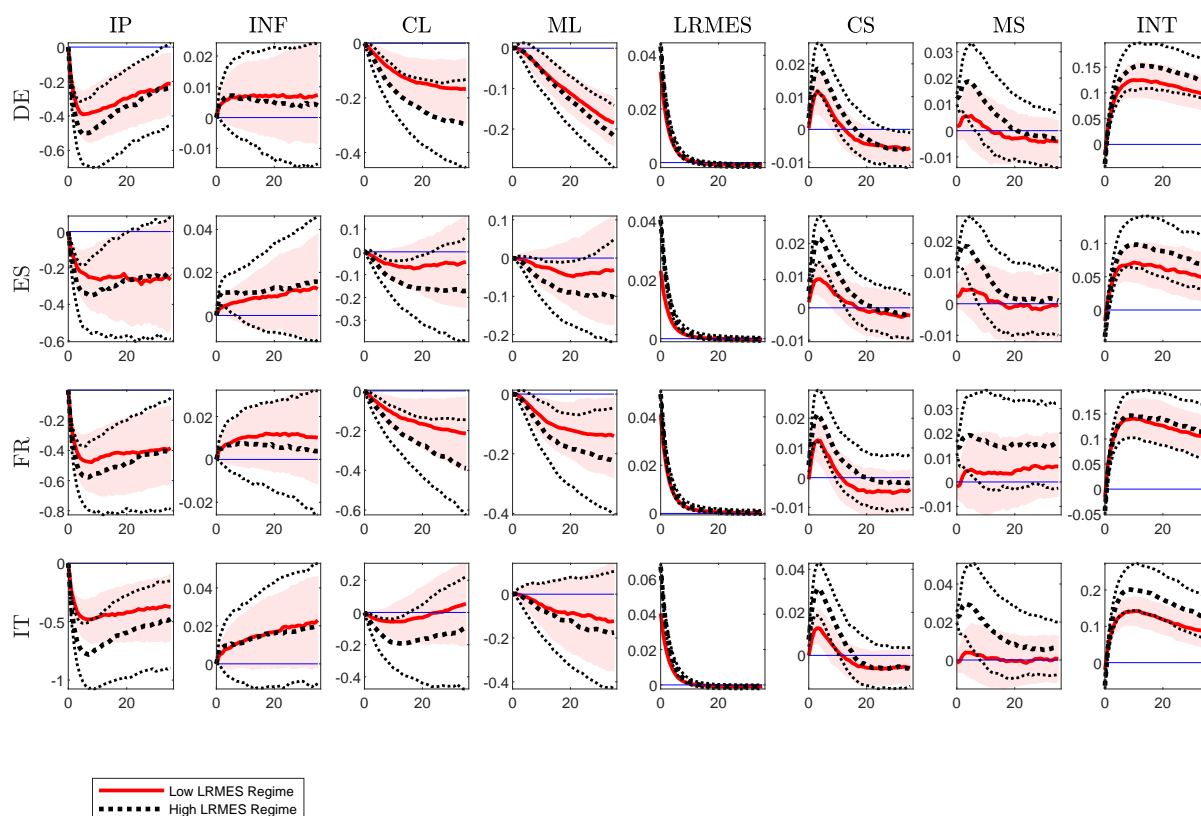
(a) Dynamic Responses to an LRMES Shock

Legend:
— Low LRMES Regime
····· High LRMES Regime

(b) Longest Horizon where there are Non-Zero Differences in Responses across Different Regimes

	IP	INF	CL	ML	CS	MS	INT
DE	10		35		12	12	28
ES		4	35		12	6	14
FR	6		35		14	17	1
IT	20		35		11	12	33

Notes: The top panel reports the country-specific responses to a one standard deviation shock in banks' vulnerability to capital depletion. The economy starts in either the low (red straight line) or high (black dotted line) regime. The posterior median in each regime is reported together with the 68% credible interval. Cumulative impulse responses are computed for industrial production, inflation and corporate and mortgage lending. The bottom panel considers whether the responses across regimes are different from zero. Differences are non-zero if: *i)* the response in at least one regime is non-zero (top panel); and *ii)* the difference between responses does not span zero based on 68% credible bands. A red or green cell shows when the two responses are the same or different. In the latter case, the longest impact horizon is reported. The variables are defined as follows: IP = industrial production, INF = inflation, CL = corporate lending, ML = mortgage lending, $LRMES$ = long-run marginal expected shortfall, CS = corporate lending spread, MS = mortgage lending spread, INT = shadow interest rate.

Looking at the responses of each loan category in each regime, we can see that corporate lending falls more strongly than mortgage lending in the high vulnerability regime. By contrast, there is no discernable pattern in the low vulnerability regime. The de-risking of the balance sheet observed in the high vulnerability regime reflects a strategy to shift the portfolio away from loans which are capital intensive when facing pressure on bank capital. This finding is in line with banks' responses to the ECB Bank Lending Survey (BLS) which suggest that banks respond to mounting pressure on bank capital positions not only by deleveraging but also de-risking their balance sheets.[21] These results are also in line with macroeconometric evidence following an aggregate adverse shock to bank capital (see Bridges et al., 2014; Noss and Toffano, 2016; and Meeks, 2017 for the UK and Kanngiesser et al., 2020 for the euro area). Similar findings are reported by Huljak et al. (2022) for euro area countries following an exogenous increase in non-performing loans (NPLs) and associated losses.

The widening in bank lending spreads and contraction in economic activity are also stronger in the high vulnerability regime. This underscores the importance of allowing for feedback effects to real economic activity. As shown in the bottom panel of Figure 3, the difference across regimes is non-zero for spreads and economic activity.[22]

Turning to Model 2 which uses the shadow interest rate as the threshold variable, we find that an adverse increase in banks' vulnerability has a stronger effect in the low interest rate regime for both corporate and mortgage lending and spreads (Figure 4, top panel). The different responses seen in the two regimes are non-zero (see the bottom panel of Figure 4). We also find evidence of de-risking in the low interest rate regime, while the difference is less marked in the high interest rate regime. When banks are more vulnerable to losing capital in a low interest rate environment, the adjustment of the banking sector is stronger. This is because the compressed bank margins and the low bank profitability associated with the low interest rate environment constrain organic capital accumulation (Claessens, Coleman, and Donnelly, 2018; Busch et al., 2021; and Klein, 2020). The response of economic activity typically lies within the credible interval while the response of inflation is positive (likely reflecting the relaxation in monetary policy on impact). Their response is broadly the same in both regimes.

Our findings for Model 2 lend support to the existing microeconometric evidence. De

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[21]See publication of the various issues of the BLS for more details: `https://www.ecb.europa.eu/stats/money/surveys/lend/html/index.en.html`

[22]Evidence of a nonlinear impact of bank capital shocks on lending rates is presented in Basten (2020), who finds that the activation of the Counter Cyclical Capital Buffer on mortgage lending in Switzerland led to a raise in mortgage interest rates that was stronger for poorly capitalised banks. This is one of the few studies looking at lending rates.

Jonghe, Dewachter, and Ongena (2020) find that lending is curtailed more strongly due to increasing pressure on capital (higher capital requirements) when banks are less profitable. They also find that this effect is stronger during periods of expansionary monetary policy. Brei, Borio, and Gambacorta (2020) also find a stronger shift away from lending when banks become poorly capitalized in a low interest rate environment.

Figure 4: Shadow Interest Rate as Threshold Variable
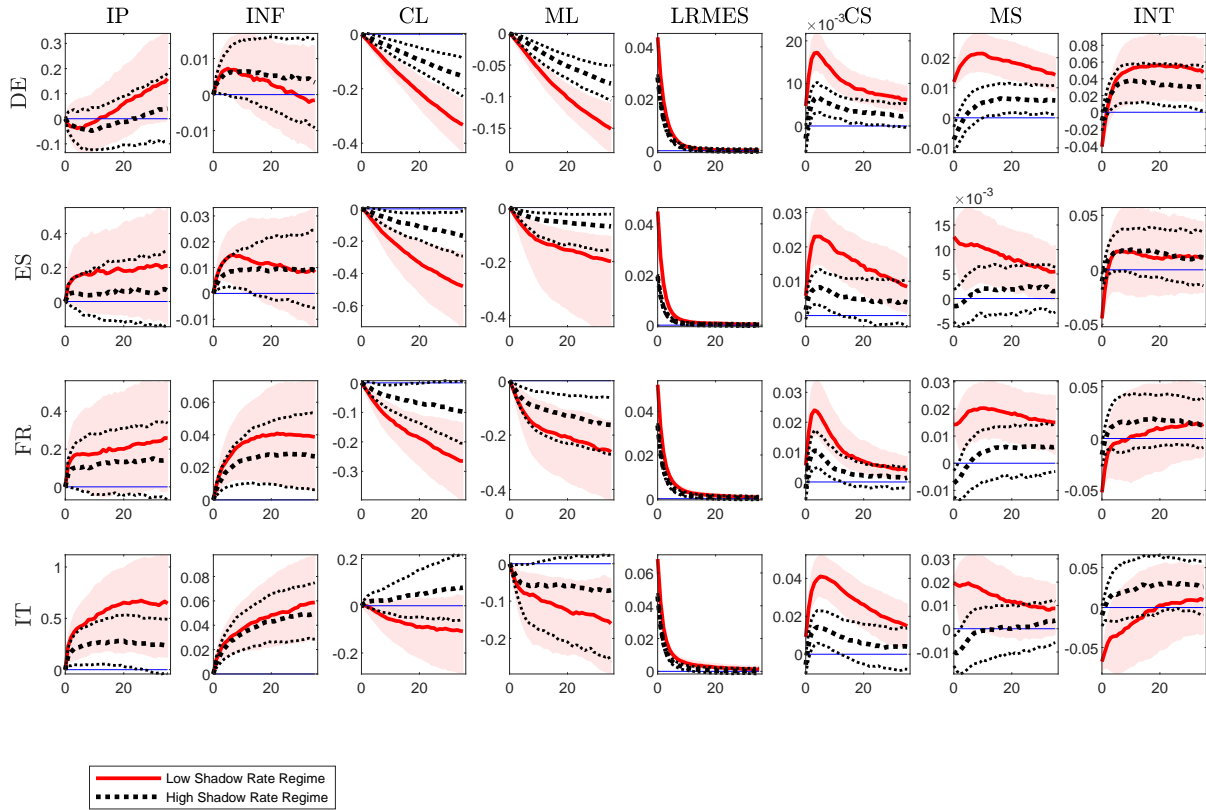
(a) Dynamic Responses to an LRMES Shock

Low Shadow Rate Regime
High Shadow Rate Regime

(b) Longest Horizon where there are Non-Zero Differences in Responses across Different Regimes

	IP	INF	CL	ML	CS	MS	INT
DE			35	35	35	35	1
ES		13	35	35	23	19	1
FR		26	35	35	26	28	3
IT	35	9		8	35	23	15

Notes: The top panel reports the country-specific responses to a one standard deviation shock in banks' vulnerability to capital depletion. The economy starts in either the low (red straight line) or high (black dotted line) regime. The posterior median in each regime is reported together with the 68% credible interval. Cumulative impulse responses are computed for industrial production, inflation and corporate and mortgage lending. The bottom panel considers whether the responses across regimes are different from zero. Differences are non-zero if: *i)* the response in at least one regime is non-zero (top panel); and *ii)* the difference between responses does not span zero based on 68% credible bands. A red or green cell shows when the two responses are the same or different. In the latter case, the longest impact horizon is reported. The variables are defined as follows: IP = industrial production, INF = inflation, CL = corporate lending, ML = mortgage lending, $LRMES$ = long-run marginal expected shortfall, CS = corporate lending spread, MS = mortgage lending spread, INT = shadow interest rate.

Our results from Model 3, which uses the annual growth rate of industrial production as a threshold variable, suggest that the macroeconomic environment alters the transmission of shocks in banks' vulnerability to capital depletion to a lesser extent (see Figure 5 top panel). Our previous results demonstrated that the response of both bank lending and spreads was stronger in the high vulnerability and low shadow rate regimes. However, in the low economic growth regime we only find a stronger response for lending spreads. That said, we also find evidence of deleveraging and de-risking, but this is not stronger in the low economic growth regime. The response of economic activity is generally not different from zero in both regimes while that of inflation is also not different from zero in the high growth regime. Our results suggesting the same response of bank lending in both economic growth regimes align with Gambetti and Musso (2017), who found the same response of bank loans to loan supply shocks during recessions and the subsequent expansions in the euro area.

Figure 5: Annual Industrial Production Growth as Threshold Variable
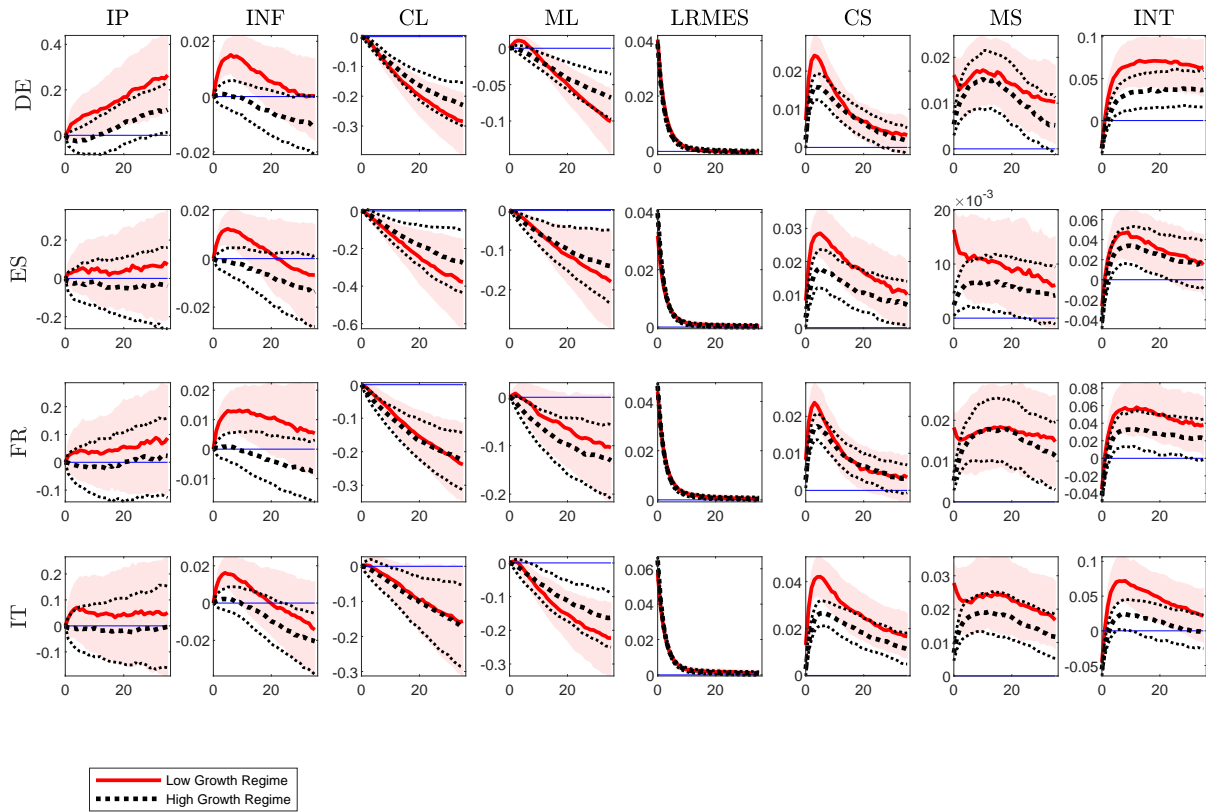
(a) Dynamic Responses to an LRMES Shock

Low Growth Regime
High Growth Regime

(b) Longest Horizon where there are Non-Zero Differences in Responses across Different Regimes

	IP	INF	CL	ML	CS	MS	INT
DE	24	25		7	7	1	24
ES		13			10	3	0
FR		31	5		5	1	9
IT		9			3	2	16

Notes: The top panel reports the country-specific responses to a one standard deviation shock in banks' vulnerability to capital depletion. The economy starts in either the low (red straight line) or high (black dotted line) regime. The posterior median in each regime is reported together with the 68% credible interval. Cumulative impulse responses are computed for industrial production, inflation and corporate and mortgage lending. The bottom panel considers whether the responses across regimes are different from zero. Differences are non-zero if: *i)* the response in at least one regime is non-zero (top panel); and *ii)* the difference between responses does not span zero based on 68% credible bands. A red or green cell shows when the two responses are the same or different. In the latter case, the longest impact horizon is reported. The variables are defined as follows: IP = industrial production, INF = inflation, CL = corporate lending, ML = mortgage lending, $LRMES$ = long-run marginal expected shortfall, CS = corporate lending spread, MS = mortgage lending spread, INT = shadow interest rate.

To summarize, four main findings emerge from the analysis presented in this subsection. First, when banks become more vulnerable to losing capital, we find consistent evidence across models and regimes that their financial intermediation capacity is impaired. As a result, they tighten bank lending supply by shrinking their balance sheets (deleveraging) and widening lending spreads. Second, deleveraging is stronger in the high vulnerability regime (for non-financial corporations) and the low interest rate regime (for both households and non-financial corporations). In contrast, the state of the business cycle does not appear to amplify the impact of bank capital shocks to the same extent. From this finding we conclude that the financial environment (banks' existing vulnerability and the monetary policy stance) is more important than the macroeconomic environment (business cycle) in amplifying adverse shocks in banks' vulnerability to capital depletion. Third, we find that banks de-risk their balance sheet in the high vulnerability regime, the low interest rate regime and both economic growth regimes. All these findings suggest that banks boost capital positions and loss absorption following an adverse shock by deleveraging and de-risking their balance sheets and that the effects are particularly strong in the high vulnerability and low interest rate regimes. Fourth, by accounting for feedback effects to macroeconomic variables, we are able to show that economic activity suffers more following an adverse shock when banks are already vulnerable to capital depletion.

4.3 Forecast Error Variance Decompositions

This section presents the FEVDs, the percentage of variation in individual variables explained by the shock in banks' vulnerability to capital depletion over three years. FEVDs help to uncover further insights regarding the nonlinear relationships among the variables included in the models. If the threshold variables are relevant in propagating the shock nonlinearly, then the shock should explain a higher share of variation in variables in the high vulnerability regime, the low interest rate environment and the low growth regime. The results of this analysis are presented in Figures 6 to 8 for each of the models.

Our empirical results show that shocks in banks' vulnerability explain a larger share of the variation in corporate and mortgage lending and in the respective spreads in the high vulnerability regime, as expected. For corporate (mortgage) loans, the share explained ranges between 3% and 8% (1% and 15%) in the high vulnerability regime (third and fourth columns in Figure 6). The corresponding shares in the low vulnerability regime are 2% to 3% for corporate loans and 2% to 9% for mortgages. For lending spreads, the shares range between 5% and 15% for corporate spreads (8% to 15% for mortgage spreads) in the high vulnerability regime, compared with 2% to 4% (around 3%) in the low vulnerability

regime (sixth and seventh columns in Figure 6). The results are qualitatively similar for the model that employs the shadow rate as threshold, but the difference between the two regimes is more pronounced (Figure 7). Finally, for the model with the annual growth rate of industrial production as threshold variable, similar results are found for corporate and mortgage lending (the share of the variance explained is higher in the low growth regime), while evidence of differences is weaker for spreads (Figure 8).

Regarding economic activity, as expected, the shock explains a smaller share of the variance compared with the banking variables in the three models, while still being larger in most of the cases in the high vulnerability (around 2% to 7%), low interest rate (1.8% to 5%) and low growth regimes (2% to 3.5%).

Our results are well within the estimates found in the literature. Mésonnier and Stevanovic (2017) compute the FEVDs for a shock to their quarterly bank capital buffer and find that it explains 4% in the variation of GDP, 11% of the variation in loans and 9% of the variation in credit spreads at a 12-quarter horizon. Lown and Morgan (2006) also report the FEVDs for shocks to the capital-to-assets ratio and find that it explains 5.4% of the variation in GDP and 6.7% of the variation in loans, also at the 12-quarter horizon.
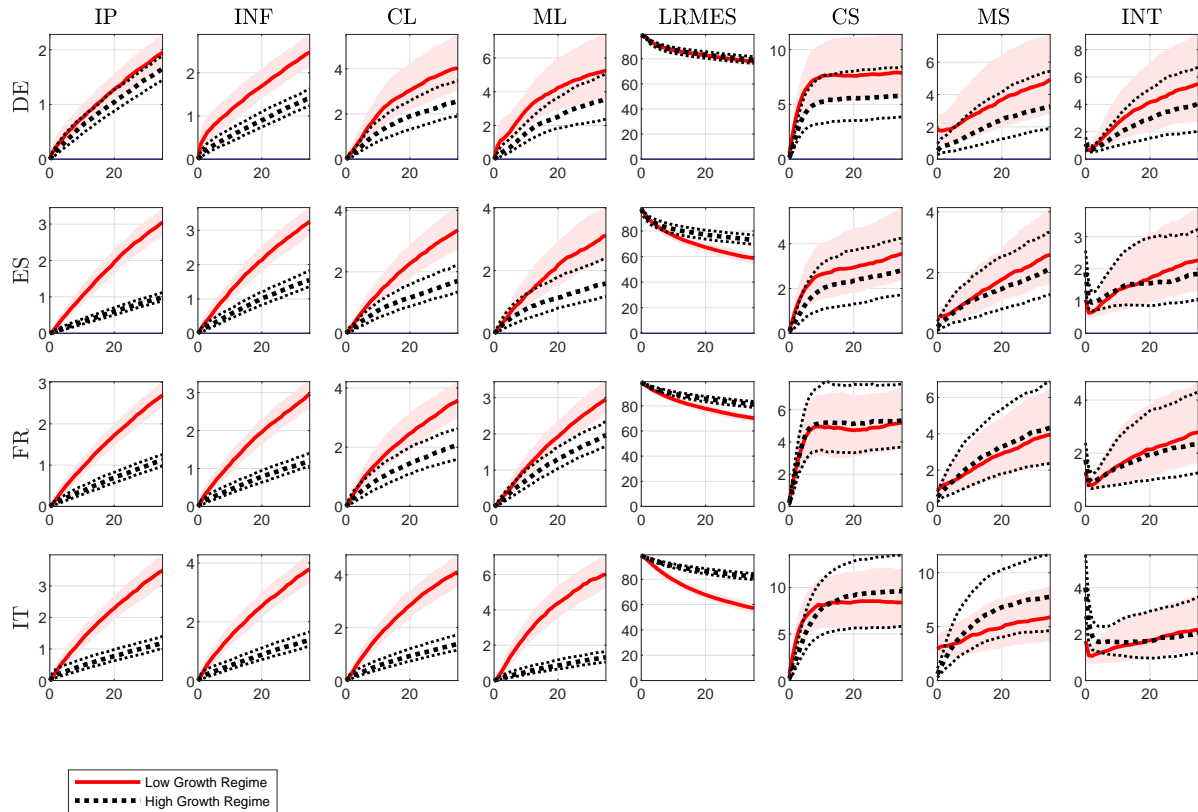
Figure 6: LRMES as Threshold Variable: Fraction of Variance Explained by LRMES Shocks
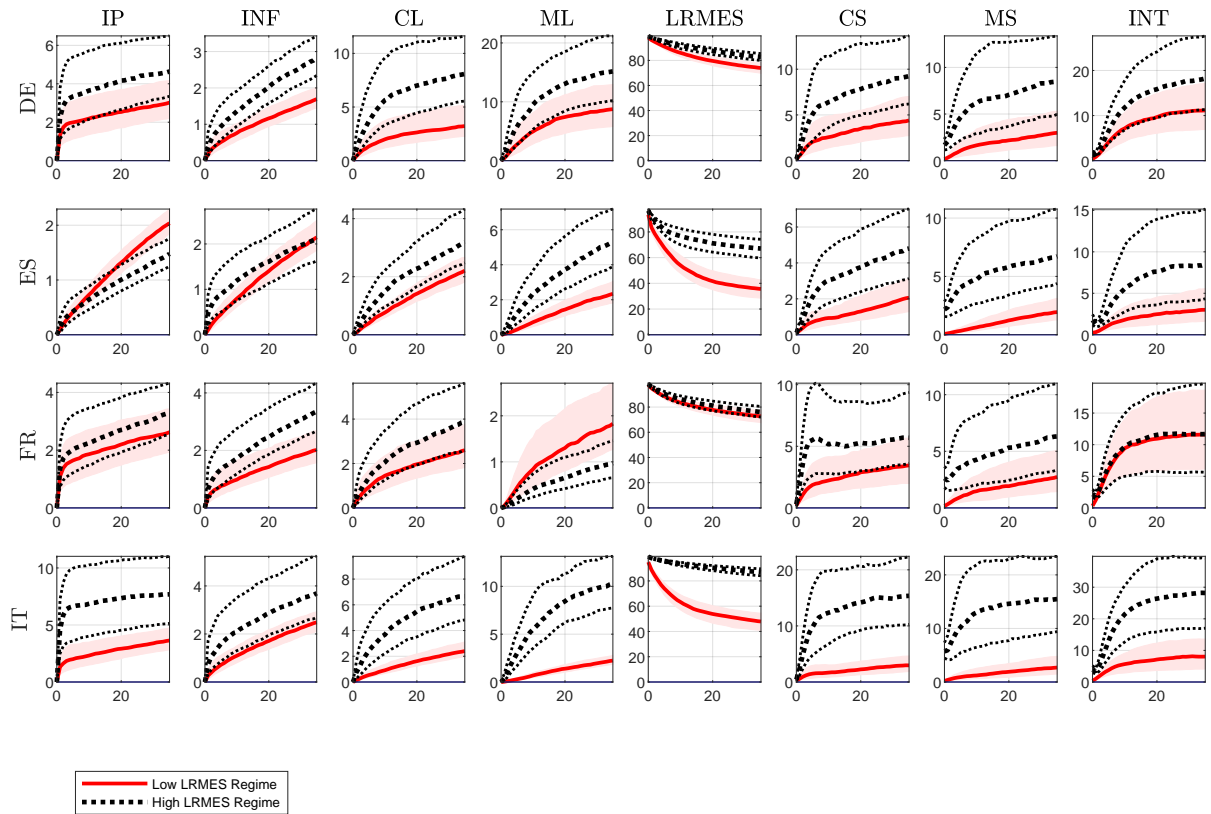
Notes: We report the share of variation in each variable explained by LRMES shocks in the high and low regimes. The variables are defined as follows: IP = industrial production, INF = inflation, CL = corporate lending, ML = mortgage lending, $LRMES$ = long-run marginal expected shortfall, CS = corporate lending spread, MS = mortgage lending spread, INT = shadow interest rate. The posterior median is reported, together with the 68% credible intervals.

Figure 7: Shadow Interest Rate as Threshold Variable: Fraction of Variance Explained by LRMES Shocks

Notes: We report the share of variation in each variable explained by LRMES shocks in the high and low regimes. The variables are defined as follows: IP = industrial production, INF = inflation, CL = corporate lending, ML = mortgage lending, $LRMES$ = long-run marginal expected shortfall, CS = corporate lending spread, MS = mortgage lending spread, INT = shadow interest rate. The posterior median is reported, together with the 68% credible intervals.

Figure 8: Annual IP Growth as Threshold Variable: Fraction of Variance Explained by LRMES Shocks

Notes: We report the share of variation in each variable explained by LRMES shocks in the high and low regimes. The variables are defined as follows: IP = industrial production, INF = inflation, CL = corporate lending, ML = mortgage lending, $LRMES$ = long-run marginal expected shortfall, CS = corporate lending spread, MS = mortgage lending spread, INT = shadow interest rate. The posterior median is reported, together with the 68% credible intervals.

5 Banks' Vulnerability and the Global Financial and Sovereign Debt Crises

This section uses the results from Model 1 to estimate the quantitative impact of banks' increase in vulnerability to capital losses observed during the Global Financial and Sovereign Debt crises. In the first crisis, the downturn in the US housing market triggered a financial crisis that spread to the rest of the world through linkages and cross-exposures in the global financial system. Several banks around the world incurred large losses. In the second crisis,

the collapse in southern euro area sovereign bond prices led to declines in asset valuations and redenomination risk, increasing fragility in the banking sector. As a result, bank lending supply and economic activity suffered.

To quantify the impact of the increase in vulnerability to bank capital losses, we need to first define the periods over which we compute the increase in the LRMES. For the Global Financial Crisis (GFC), the increase in banks' vulnerability to capital depletion is computed between July 2007 (the start of the international crisis) and April 2009, when the peak in the LRMES is observed in the four countries under consideration. For the Sovereign Debt Crisis (SDC), the increase is computed between January 2010 (the start of the run up to the crisis) and the highest peak observed in each country. This peak was reached earlier in Germany and France (February 2012) than in Italy and Spain (August 2012 and March 2013, respectively). Importantly, as observed in Figure 2, the four countries were in a low-vulnerability regime at the start of the GFC, while they were already in a high vulnerability regime at the start of the SDC (shaded and white areas in Figure 2, respectively). Subsequently, we employ the GIRFs for each country and each regime presented in Figure 3 (top panel) to compute the maximum impact over a 3-year horizon on bank lending and lending spreads (to households and corporations) and on economic activity. We report the cumulative impact for loans and industrial production and the level for the spreads. We also report the average impact across countries for each crisis. The results of this exercise are presented in Panels (a) and (b) of Table 2 for the Global Financial and the Sovereign Debt Crises, respectively.

A comparison between the two crises suggests that the impact in Germany is slightly stronger for both spreads and lending to non-financial corporations during the SDC, while being the same for economic activity. The estimated maximum cumulative decline in corporate lending during the SDC is -1% (vs. -0.7% during the GFC) while both spreads widen by 6 basis points (vs. 2-5 basis points during the GFC). Industrial production contracts by 1.7% in both cases.

In the other three countries, the impact of the SDC is much more visible. For lending, the maximum cumulative impact ranges between -0.4% and -1.0% for households (vs. -0.1% and -0.6% during the GFC) and between -0.6% and -1.8% for non-financial corporations (vs. -0.1% and -0.6% in the GFC). Spreads also widen much more during the SDC in these three countries. Finally, for industrial production the impact ranges between -1.2% and -3.8% during the SDC, compared with a decline of -0.5% to -2.3% during the GFC.

These results align with existing evidence, showing that Germany was exposed to the sub-prime crisis in the US almost to the same degree that it was exposed to the SDC, while the other countries were more exposed to the latter.

Table 2: Vulnerability to Bank Capital Losses, Bank Lending Supply and Economic Activity During the GFC and the SDCs

a) Global Financial Crisis (GFC)

| | Loans | | Spreads | | Industrial |
	Households	NFCs	Households	NFCs	production
DE	-0.8	-0.7	2	5	-1.7
ES	-0.1	-0.1	1	2	-0.5
FR	-0.4	-0.6	2	3	-1.3
IT	-0.6	-0.3	2	6	-2.3
Average	*-0.5*	*-0.4*	*2*	*4*	*-1.4*

b) Sovereign Debt Crisis (SDC)

| | Loans | | Spreads | | Industrial |
	Households	NFCs	Households	NFCs	production
DE	-0.7	-1.0	6	6	-1.7
ES	-0.4	-0.6	7	8	-1.2
FR	-1.0	-1.8	9	10	-2.7
IT	-0.9	-0.9	14	15	-3.8
Average	*-0.7*	*-1.1*	*9*	*10*	*-2.4*

Notes: The Table reports the maximum impact over a 3-year horizon on lending and lending spreads (for households and non-financial corporations) and on industrial production of the increase in banks' vulnerability to capital depletion observed during the GFC (Panel a) and the SDC (Panel b). We report the cumulative impact for loans and industrial production and the level for the spreads. For each crisis, the simple average of the impact is also reported. For the GFC, the increase in LRMES is computed between July 2007 and April 2009. For the SDC, the increase is computed between January 2010 and February 2012 (Germany and France), August 2012 (Italy) and March 2013 (Spain). The countries start in the low-vulnerability regime during the GFC and in the high-vulnerability regime during the SDC.

6 Robustness

This section implements two robustness checks to assess the reliability of our results. These results are presented in Appendix C. First, we generate GIRFs relying on a different ordering of the variables in the PTVAR. In this new ordering, the policy rate follows the macroeconomic variables (economic activity and inflation), as in Mésonnier and Stevanovic (2017). The idea is that the monetary authority follows a Taylor rule and responds on impact to changes in inflation and economic activity. Our findings remain largely unchanged. If anything, there is no relaxation of monetary policy on impact when ranking the shadow rate right after the macroeconomic variables.

Second, we replace the shadow interest rate with the Euribor rate as a measure of monetary policy. Before the implementation of unconventional measures in the euro area, several studies used the Euribor or Eonia rate as a measure of monetary policy (Maddaloni and Peydró, 2011; Ciccarelli, Maddaloni, and Peydró, 2013; Bijsterbosch and Falagiarda, 2015). Again, our results are broadly unchanged. In Model 2, both corporate and mortgage lending continue to decline more strongly in the low interest rate regime but sometimes we observe a rebound in lending after a few quarters, particularly in the high interest rate regime. We also observe a stronger increase in both lending spreads in the high interest rate regime, likely reflecting a stronger decline in the Euribor (the Euribor declines very little in the low interest rate environment due to the zero lower bound, while it declines more strongly in the high interest rate environment).

7 Conclusion

The nonlinear propagation of adverse, aggregate shocks to bank capital has been overlooked in the macroeconometric literature, which relies on linear VAR models. Such a framework cannot capture the role of the financial and macroeconomic environment in the amplification of shocks. Only a few single-equation microeconometric studies have focused on nonlinearities, mainly as a complement to otherwise benchmark, linear results. However, modeling dynamic interaction, feedback effects and the impact on the macroeconomy are of paramount importance when aggregate shocks hit the economy.

We bridge this gap in the literature and estimate the nonlinear impact of shocks in banks' vulnerability to capital depletion. Three PTVARs are deployed to consider whether the response of bank lending supply and the macroeconomy to an adverse shock will be stronger during periods of: i) high vulnerability to capital depletion; ii) a low policy interest rate environment; and iii) low economic growth or recession.

We find that banks' financial intermediation capacity is impaired when they become more vulnerable to losing capital. As a result, they tighten bank lending supply by shrinking their balance sheets (deleveraging) and widening lending spreads. The resulting adjustment helps them to re-build capital positions, increasing loss-absorption. Crucially, we find strong evidence of nonlinearities. When the banking sector is already vulnerable to large capital losses, it is more difficult for banks to accommodate a depletion in capital and lending and economic activity contract more severely. Similarly, when interest rates are low, we again find a larger decline in lending. In contrast, the state of the business cycle does not appear to amplify the impact of bank capital shocks to the same extent. Importantly, we find that banks de-risk their balance sheets in the high vulnerability regime, the low interest rate regime and both economic growth regimes. From this analysis, we conclude that the financial environment (existing vulnerability to capital losses and the monetary policy stance) is more important than the macroeconomic environment (business cycle) in amplifying adverse shocks in banks' vulnerability to capital depletion.

Finally, we also find that a shock in banks' vulnerability to capital depletion explains a non-negligible share of the variance of variables included in the PTVARs, particularly lending volumes and spreads. The share explained by vulnerability shocks is larger in the high vulnerability, low interest rate and low economic growth regimes. This again provides clear evidence in favor of nonlinearities.

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Appendix A Data

Table A.1: Data Sources and Transformations

Variables	Description	Source	Trans.
IP	Industrial Production Index	Eurostat	Δ ln*100, SA
INF	Harmonised Index of Consumer Prices Excl. Energy & Unprocessed Food	ECB SDW	Δ ln*100, SA
CL	Bank Lending to Non-Financial Corps.^{a}	ECB MFI Balance Sheet and Interest Rate Statistics	Δ ln*100, SA
ML	Bank Lending to Households for House Purchases^a	ECB MFI Balance Sheet and Interest Rate Statistics	Δ ln*100, SA
$LRMES$	Long Run Marginal Expected Shortfall	V-Lab	Levels
CS	Corporate Spread	ECB MFI Balance Sheet and Interest Rate Statistics	Levels
MS	Mortgage Spread	ECB MFI Balance Sheet and Interest Rate Statistics	Levels
INT	Shadow Policy Rate	Wu and Xia (2016)	Levels

^{a} The index of notional stocks is computed based on outstanding amounts and financial transactions (flows) and it is computed as follows: $I_t = I_{t-1} * (1 + T_t/L_{t-1})$, where I_t is the index of notional stocks, T_t are transactions and L_t are outstanding amounts, all at time t.

Table A.2: Banks Used to Construct Country-level LRMES

France	BNP Paribas SA	(2005m1-2019m12)
	Caisse Regionale de Credit Agricole Mutuel Alpes Provence	(2005m7-2019m12)
	Caisse Regionale de Credit Agricole Mutuel Nord de France	(2005m7-2019m12)
	Caisse Regionale de Credit Agricole Mutuel d'Ille-et-Vilaine	(2005m7-2019m12)
	Caisse Regionale de Credit Agricole Mutuel de Normandie-Seine	(2005m7-2019m12)
	Caisse Regionale de Credit Agricole Mutuel de Paris et d'Ile-de-France	(2005m7-2019m12)
	Caisse Regionale de Credit Agricole Mutuel de la Touraine et du Poitou	(2005m7-2019m12)
	Credit Agricole Atlantique Vendee	(2005m1-2019m12)
	Credit Agricole Loire Haute-Loire	(2005m7-2019m12)
	Credit Agricole SA	(2005m1-2019m12)
	Credit Agricole Sud Rhone Alpes	(2005m7-2019m12)
	Credit Agricole du Morbihan	(2005m7-2019m12)
	Natixis SA	(2005m7-2019m12)
	Rothschild & Co	(2007m10-2019m12)
	SCOR SE	(2005m1-2019m12)
	Societe Generale SA	(2005m1-2019m12)
	Union Financiere de France BQE SA	(2005m7-2019m12)
Germany	Aareal Bank AG	(2005m1-2019m12)
	Comdirect bank AG	(2005m1-2019m12)
	Commerzbank AG	(2005m1-2019m12)
	Deutsche Bank AG	(2005m1-2019m12)
	GRENKE AG	(2005m1-2019m12)
	HSBC Trinkaus & Burkhardt AG	(2005m1-2019m12)
	MLP AG	(2005m1-2019m12)
Italy	BPER Banca	(2005m1-2019m12)
	Banca Carige SpA	(2005m1-2018m12)
	Banca Generali SpA	(2008m4-2020m11)
	Banca Intermobiliare SpA	(2005m1-2019m12)
	Banca Monte dei Paschi di Siena SpA	(2005m1-2019m12)
	Banca Popolare di Sondrio SCARL	(2009m3-2020m11)
	Banca Profilo SpA	(2005m4-2019m11)
	Banco BPM SpA	(2008m4-2019m11)
	Banco di Desio e della Brianza SpA	(2005m1-2019m12)
	Banco di Sardegna SpA	(2005m4-2019m11)
	Credito Emiliano SpA	(2005m1-2019m12)
	Credito Valtellinese SpA	(2005m7-2019m12)
	FinecoBank Banca Fineco SpA	(2005m7-2019m12)
	Intesa Sanpaolo SpA	(2005m1-2019m12)
	Mediobanca SpA	(2005m1-2019m12)
	UniCredit SpA	(2005m1-2019m12)
	Unione di Banche Italiane SpA	(2005m1-2019m12)
Spain	Banco Bilbao Vizcaya Argentaria SA	(2005m1-2019m12)
	Banco Santander SA	(2005m1-2019m12)
	Banco de Sabadell SA	(2005m1-2019m12)
	Bankia SA	(2012m7-2019m12)
	Bankinter SA	(2005m1-2019m12)
	CaixaBank SA	(2011m6-2019m12)

Note: The Table reports the banks employed in the country-level aggregations. The months in parentheses are the periods when data for the LRMES are available.

Appendix B   Technical Appendix

Full details of the algorithm are provided in Mumtaz, Pirzada, and Theodoridis (2018). Here, we briefly outline the priors and hyperparameters used as well as modifications made to the algorithm. For the coefficients $\beta_{1,i}$ and $\beta_{2,i}$, the prior variance Λ_i is set using a Minnesota procedure implemented using dummy observations (Banbura, Giannone, and Reichlin, 2010) where the overall prior tightness is set to 0.1. For the non-zero, non-one elements of the variance covariance matrices $\alpha_{1,i}$ and $\alpha_{2,i}$, the prior variances Ξ_i is set to $10 \times abs(a_{i,ols})$. For the threshold z_i^*, the prior variance ψ_i is set to 0.001.

The priors for the degree of pooling on the coefficients (λ_1 and λ_2), variance covariance terms (δ_1 and δ_2) and threshold (ω) are assumed to be inverse Gamma with shape parameter $\frac{s_0}{2}$ and scale $\frac{v_0}{2}$. Gelman (2006) and Jarociński (2010) recommend using a weakly informative prior with low values of s_0 and v_0 when fewer than six countries are included in the analysis. We pursue this strategy but find that our results are not sensitive to instead using a uniform prior as in Mumtaz, Pirzada, and Theodoridis (2018).

We assume a normal uninformative prior for the incercepts $c_{1,i}$ and $c_{2,i}$. Following Mumtaz and Sunder-Plassmann (2021), the prior for $h_{1,i}$ and $h_{2,i}$ is inverse Gamma with mean h_0, an estimate of the average variance of the error terms obtained using OLS estimation of the VAR for each country. The variance is set equal to 1 for all shocks.

The threshold is drawn using a Metropolis Hastings step. However, we exclude draws which are above the 70th percentile or below the 30th percentile of the threshold variable z_i. This ensures we have sufficient observations in each regime.

Appendix C   Robustness

C.1   GIRFs with an Alternative Identification Scheme

This subsection of the Appendix estimates the panel threshold VAR (PTVAR) employing the Cholesky scheme in Mésonnier and Stevanovic (2017).

Figure C1: LRMES as Threshold Variable: Dynamic Responses to a LRMES Shock with Alternative Ordering
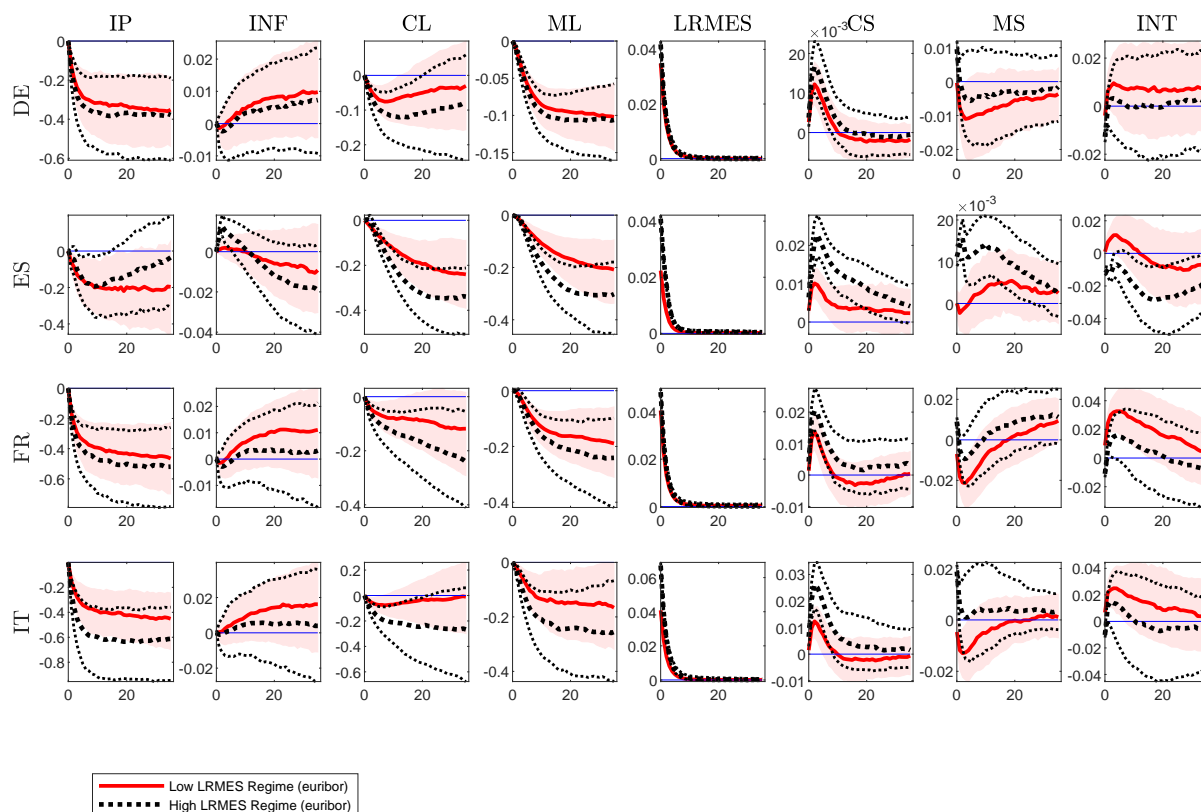

Notes: We report the country-specific dynamic response of the endogenous variables to a one standard deviation shock in banks' vulnerability to capital depletion in each regime using the LRMES as the threshold variable. The economy starts in either the low (red straight line) or high (black dotted line) regime. The countries are Germany (DE), France (FR), Spain (ES) and Italy (IT). The ordering of the variables in the VAR follows Mésonnier and Stevanovic (2017): economic activity, inflation, the policy interest rate, corporate and mortgage lending, the LRMES and corporate and mortgage spread. The posterior median in each regime is reported together with the 68% credible interval. Cumulative impulse responses are computed for industrial production, inflation and corporate and mortgage lending.

Figure C2: Shadow Interest Rate as Threshold Variable: Dynamic Responses to a LRMES
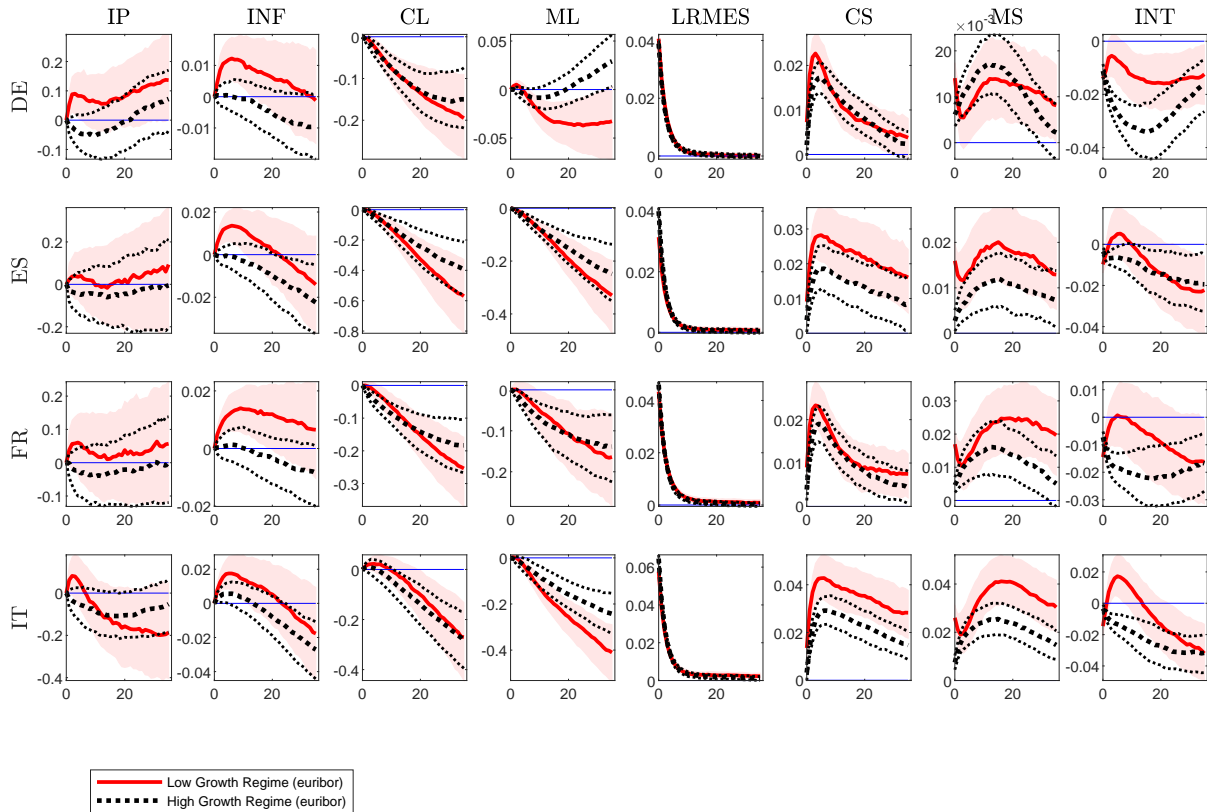Shock with Alternative Ordering

Notes: We report the country-specific dynamic response of the endogenous variables to a one standard
deviation shock in banks' vulnerability to capital depletion in each regime using the shadow interest rate
as the threshold variable. The economy starts in either the low (red straight line) or high (black dotted
line) regime. The countries are Germany (DE), France (FR), Spain (ES) and Italy (IT). The ordering of
the variables in the VAR follows Mésonnier and Stevanovic (2017): economic activity, inflation, the policy
interest rate, corporate and mortgage lending, the LRMES and corporate and mortgage spread. The
posterior median in each regime is reported together with the 68% credible interval. Cumulative impulse
responses are computed for industrial production, inflation and corporate and mortgage lending.

Figure C3: Annual IP Growth as Threshold Variable: Dynamic Responses to a LRMES Shock with Alternative Ordering

Notes: We report the country-specific dynamic response of the endogenous variables to a one standard deviation shock in banks' vulnerability to capital depletion in each regime using the annual growth rate in industrial production as the threshold variable. The economy starts in either the low (red straight line) or high (black dotted line) regime. The countries are Germany (DE), France (FR), Spain (ES) and Italy (IT). The ordering of the variables in the VAR follows Mésonnier and Stevanovic (2017): economic activity, inflation, the policy interest rate, corporate and mortgage lending, the LRMES and corporate and mortgage spread. The posterior median in each regime is reported together with the 68% credible interval. Cumulative impulse responses are computed for industrial production, inflation and corporate and mortgage lending.

C.2 GIRFs with the Euribor Instead of the Shadow Interest Rate

This subsection of the Appendix estimates the PTVAR including the Euribor rather than the shadow rate and the identification scheme described in subsection 3.4.

Figure C1: LRMES as Threshold Variable: Dynamic Responses to a LRMES Shock with Euribor

Notes: We report the country-specific dynamic response of the endogenous variables to a one standard deviation shock in banks' vulnerability to capital depletion in each regime using the LRMES as the threshold variable. The economy starts in either the low (red straight line) or high (black dotted line) regime. The countries are Germany (DE), France (FR), Spain (ES) and Italy (IT). The model includes Euribor instead of the shadow rate as policy rate. The posterior median in each regime is reported together with the 68% credible interval. Cumulative impulse responses are computed for industrial production, inflation and corporate and mortgage lending.

Figure C2: Shadow Interest Rate as Threshold Variable: Dynamic Responses to a LRMES Shock with Euribor
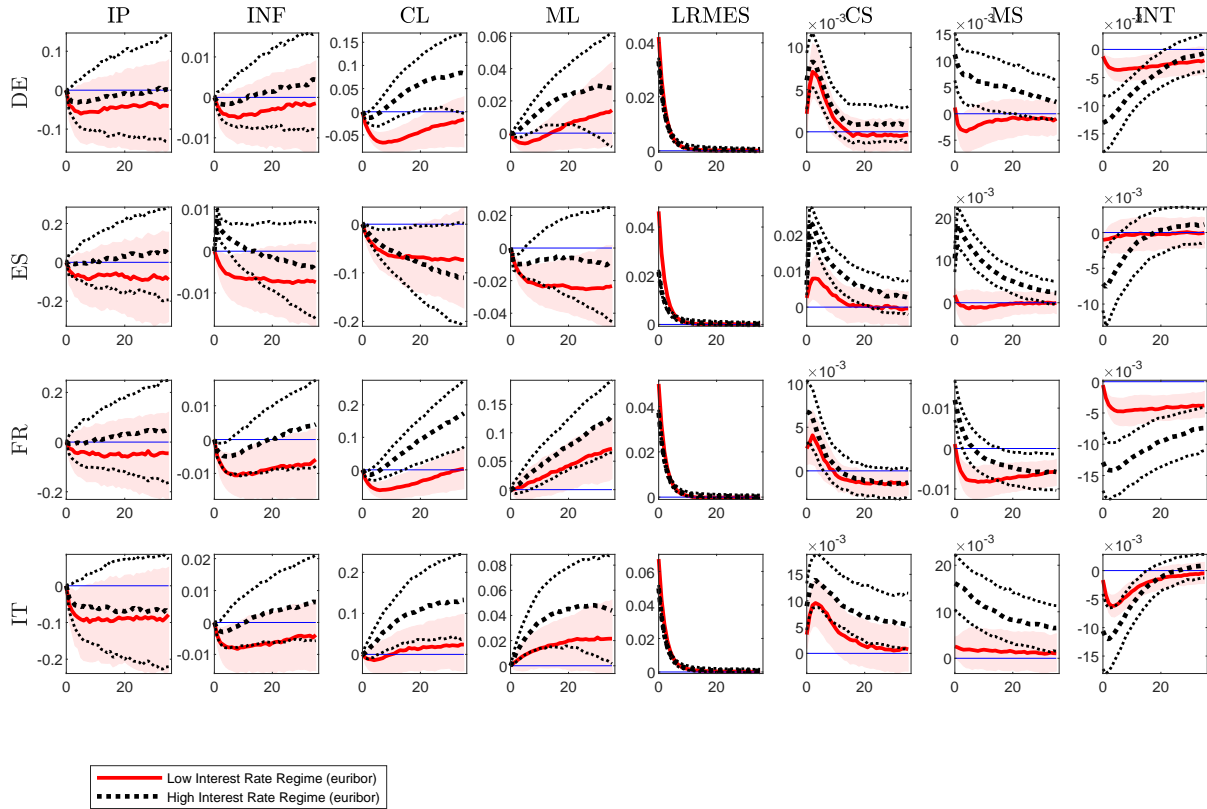
Notes: We report the country-specific dynamic response of the endogenous variables to a one standard deviation shock in banks' vulnerability to capital depletion in each regime using the Euribor as the policy rate and threshold variable. The economy starts in either the low (red straight line) or high (black dotted line) regime. The countries are Germany (DE), France (FR), Spain (ES) and Italy (IT). The posterior median in each regime is reported together with the 16% and 84% credible bands. Cumulative impulse responses are computed for industrial production, inflation and corporate and mortgage lending.

Figure C3: Annual IP Growth as Threshold Variable: Dynamic Responses to a LRMES Shock with Euribor

Notes: We report the country-specific dynamic response of the endogenous variables to a one standard deviation shock in banks' vulnerability to capital depletion in each regime using annual industrial production growth as the threshold variable. The economy starts in either the low (red straight line) or high (black dotted line) regime. The countries are Germany (DE), France (FR), Spain (ES) and Italy (IT). The posterior median in each regime is reported together with the 16% and 84% credible bands. Cumulative impulse responses are computed for industrial production, inflation and corporate and mortgage lending.

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