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Doctoral Thesis

Essays on Financial Stability, Credit Dynamics and Policy Challenges

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Declaration of Authorship

I declare that this thesis titled, Essays on Financial Stability, Credit Dynamics and Policy Challenges and the work presented in it are my own. I confirm that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements.

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Introduction

" There are many more economic expansions than there are manias. But every mania has been associated with the expansion of credit. In the last hundred or so years the expansion of credit has been almost exclusively through the banks and the financial system; earlier, nonbank lenders expanded the supply of credit." Charles P. Kindleberger

"Unless we understand what it is that leads to economic and financial instability, we cannot prescribe – make policy – to modify or eliminate it. Identifying a phenomenon is not enough; we need a theory that makes instability a normal result in our economy and gives us handles to control it."
Hyman Minsky

The Global Financial Crisis (GFC) led to a deep and long-lasting economic depression worldwide. The financial meltdown that followed the subprime crisis in the United States spread rapidly, with dramatic consequences for the well-functioning of the global financial system. As a consequence, several countries experienced huge costs in terms of output deterioration and unemployment rates. Between 2007 and 2010, the total unemployment rate almost doubled in the United States (from 5 to 10 percent) and it rose dramatically in the European GIIPS countries (from 7 to 17 percent). In the last economies, the unemployment rate continued to rise sharply also as a consequence of the sovereign debt crisis that started in the fall 2011.

Governments and taxpayers were hit by high social costs that threatened the economic recovery of the following years. Rescue plans for the banking system involved massive interventions to bailout credit institutions. In 2015, the Special Inspector General for the Troubled Asset Relief Program accounted that the US government's total commitment amounted to 16.8 trillion dollars while, according to the European Commission State Aid Scorecard, in 2011, European governments allocated more than 3 trillion euros for banks' bailout.

This evidence motivates the main research question addressed by this Dissertation: How should the financial system oversight be organized in order to minimize social costs?

The GFC took the immune defense system of advanced economies by surprise, as policy makers had just "mopped up" when the GFC erupted. Before this event, a large part of central banks – by endorsing the so-called "Greenspan doctrine"– believed that the costs of any ex-ante intervention would have been larger than its benefits and that financial crises were almost unpredictable. This ex-post approach was reflected in the economic theory, as the mainstream framework at that time was almost absent of any modelling structure allowing for financial market failures.

Things changed drastically at the dawn of 2008. Economists and scholars started to investigate more in deep the main de-stabilizing mechanisms behind the financial system, the link between the latter and the real economy, and whether it would be possible to predict financial crises, or at least to attenuate their detrimental power before eruption. This research agenda is nowadays the rule rather than the exception.

The Chicago Booth Review has recently conducted a survey among economists, asking what were in their opinion the main causes of the GFC. Each of the twelve items in Figure 1 reflects, not just personal beliefs, but also different topics currently addressed by economic research. However, the larger part of both U.S. and European economists believe that the main factor that exacerbated the effects of the GFC was the lack of regulation and supervision of financial markets.

In the aftermath of the GFC, a new set of rules and policy tools – embedding also an ex-ante perspective– was activated in order to make the system more resilient to financial meltdowns. Improving the understanding of how risk-taking spreads across financial actors, in general, and how to monitor the exposure to risk of credit institutions, in particular, have become a primary concern that falls into the scope of the so-called macroprudential policy. The larger part of central banks, governments, national and international financial supervisory authorities conceive now the macro-approach to financial regulation as an independent pillar of their policy mandate. However, after a decade of research, many doubts about the functioning, the implementation, the effectiveness and the impact of macroprudential measures continue to feed the policy debate.

The identification of a single system-wide risk measure that can support policy makers to steer macroprudential tools remains one of the unsolved challenges. Powerful indicators may help to provide policy makers with timely (ex-ante) warning signals, but these signals, in their turn, depend on how sensitive the definition of financial stability is, and ultimately on the empirical identification of the financial cycle. Figure 2 shows the business (GDP) cycle in the United States and its financial cycle, according to the estimation of the Bank of International Settlements (BIS). The financial cycle is obtained as co-movements in the medium-term dynamics of credit and property prices. The graph shows that all financial crises origin at the peak of the financial cycle and, most importantly, that when recessions coincide with a contractionary phase of the financial cycle GDP drops more than in other recessions. This is why, over the last decade, the benchmark measures monitored by the authorities to gauge the buildup of risks overtime relate, one way or another, to credit dynamics. Moreover, the availability of both brand-new datasets and more sophisticated econometric tools has given the opportunity to build a solid empirical evidence suggesting that excessive credit growth actually played a central role in determining the severity of the GFC and that credit boom-bust cycles dramatically affect the real economy through amplification mechanisms.

The three chapters of this dissertation add to the debate on the subject matter by providing a theoretical model highlighting the relevance of credit dynamics for policy makers, as well as new empirical insights about the control of credit dynamics and the conduct of macroprudential policy.

The idea of considering credit as a key driver of financial crises and/or as an amplifying engine of exogenous shocks is not new in the literature. This view, –particularly in the pioneering contributions by Fisher (1933), Minsky (1977) and Kindleberger (1978)– looks at the credit dynamics as an endogenous force that is prone to generate instability. Once speculative opportunities are present in the system, prolonged increases in the demand for goods and financial assets transmit themselves to prices. Higher prices means new profit's opportunities that attract further investors. This positive feedback is characterized by the "euphoria" of economic actors and the boom starts to develop. The so-called "mania" phase comes as people's judgment on speculation for profits does not reflect the economic fundamentals of the underlying goods or assets. As booms are generally fed by expansions of banks' credit, the latter is taken as an indicator of the temperature of systemic risk.

In line with this theoretical perspective, Chapter 1 investigates the anatomy of credit booms –which are defined as statistical events obtained from the filtering of credit's

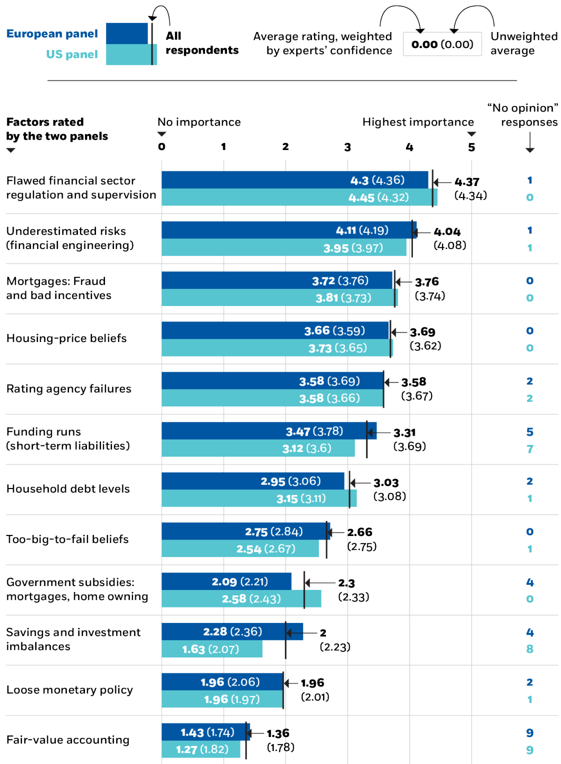


Figure 1: Source: *"What contributed most to the financial crisis?", The Chicago Booth Review*

time-series– and their connections with financial crises. Furthermore, the chapter explores the relative power of macro-financial measures to provide policy makers with anticipatory warning signals relative on the occurrence of credit events. A correct and timely identification of these events motivates the setup of ex-ante measures addressing the control of credit dynamics. The latter can be carried out directly or indirectly, in the sense that policies can also influence the attitude towards risk, which leads credit to grow faster, rather than limit the volume of credit itself. Direct measures are, for instance, reductions in the loan-to-value ratios (LTV) or in the debt-to-income ratios (DTI) that banks set to borrowers, or limits on concentration and exposures. As for indirect measures, authorities can set capital ratios, or counter-cyclical capital buffers to banking institutions. However, these measures are not a free-lunch. Though reducing systemic risk is a benefit for financial stability, a policy that damps credit growth may trigger side-effects, like credit crunch and fire-sales that, if the economy is in a bad

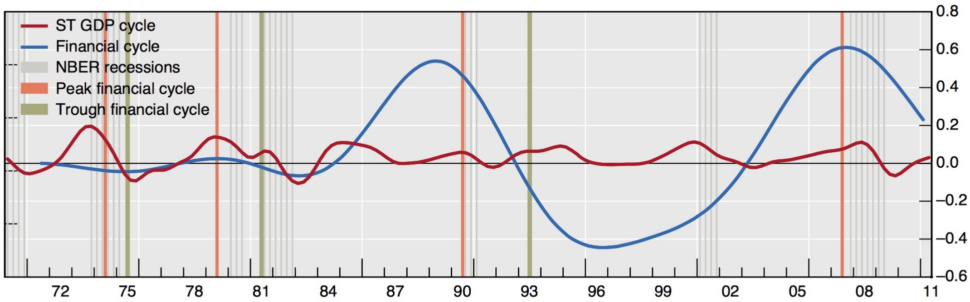


Figure 2: Financial and business cycles in US. Source: *"Characterising the financial cycle: don't lose sight of the medium term!"*, BIS Working Papers 380.

shape, may threaten the recovery.

The theoretical above-mentioned underpinning and the empirical evidence presented in Chapter 1 suggest that economic break-downs accompanied by financial unbalances are deeper and readjustment processes are long-lasting than normal recessions, so that the standard policy approach might be insufficient to put the economy back on a stability path. As in the case of the GFC, central banks might be forced to implement unconventional tools to stimulate economic recovery. Yet, the fact that the mechanisms behind financial instability underlie a nonlinear behavior of the economy is also an hardship to face in the ex-ante policy approach.

Chapter 2 addresses this issue, both theoretically and empirically. On the theoretical side, nonlinearities represent a severe challenge to central banks' monetary policy. Here the (nonlinear) credit dynamics becomes a policy target to monitor financial stability, inasmuch as the central bank is allowed to lean against the buildup of financial unbalances by increasing the policy rate when credit overheats. Against this background, this chapter presents a small scale nonlinear quadratic model, where credit flows and credit spreads enter the reaction function of the central bank and where implied feedback effects impact the overall adjustment path of the economy. The feedback effects are thought as representing credit standards that the banking sector set to private borrowers. Policy decisions in two business-cycle regimes are then studied from the perspective of relaxing or tightening credit standards.

The chapter also presents a non-linear estimation of the macro impact of policy changes to credit standards, conceived as arising from a structural innovation to banking supervision. On the overall, the results confirm that the impact of supervisory measures is stronger when real activity is contracting. This leads to the conclusion that, in that economic regimes, policy targeting risk-taking can be relatively costly. Intuitively this result is not surprising, as banks' risk-sensitivity tends to be lower in good times and higher in bad phases.

This result raises new questions about the effectiveness of indirect ex-ante measures. For instance, prudential capital regulation implies that banks are asked to improve some capital ratio of their balance sheets. Banks can meet higher requirements by lowering their (risky) exposure, or by issuing new equity (retaining earnings). However, if banks' risk-perception is high and financial markets are stuck, so that it becomes burdensome to rise new equity, banks will be forced to shrink the supply of new loans. This result can be very unpleasant for policy makers if the economy is recovering from a recession.

Chapter 3 deepens this issue by studying empirically the macro impact of capital measures in Euro-Area countries under different economic regimes. Though capital regulation in Europe mostly comes from the implementation of Basel's international agreements, the narrative of country-specific capital rules advocates to analyze about the effects of unexpected changes in that regulation. Capital requirements are hence studied in the form of policy innovations. By following the economic theory and the empirical evidence, the analysis assumes that a capital requirement shock increases the capital ratio of the banking system and it makes the equity a relatively costly source of funding for banks, while increasing lending rates. In the final part of this chapter, state-dependent responses to capital requirement shocks are shown to confirm that bank credit falls more during contractions, with amplifying negative effects on the macroeconomy.

The results I obtain in this Dissertation suggest that financial supervision, in general, and capital measures, in particular, can actually exacerbate credit procyclicality. The policy message of the last two chapters is that macroprudential policies might be detrimental if hurriedly implemented in regimes of financial or economic turmoils. The first chapter shows however that the predictive power of real-time information in detecting systemic risks' buildups is a good guideline for policy makers. This information provides anticipatory signals that can help to distinguish credit growth reflecting adjustment to economic fundamentals from the one which reflects increasing appetite for risks. From this perspective, an ex-ante intervention limiting the tendency of the banking system to embrace new risks by extending lending activities becomes desirable.

Chapter 1

Real-time signals anticipating credit booms in Euro Area countries

This paper identifies credit booms in 11 Euro Area countries by tracking private loans from the banking sector. The events are associated with both financial crises and specific macro fluctuations, but the standard identification through threshold methods does not allow to catch credit booms in real time data. Thus, an early warning model is employed to predict the explosive dynamics of credit through several macro-financial indicators. The model catches a large part of the in-sample events and signals correctly both the global financial crisis and the sovereign debt crisis in an out-of-sample setting by issuing signals in real-time data. Moreover, while tranquil booms are driven by global dynamics, crisis-booms are related to the resilience of domestic banking systems to adverse financial shocks. The results suggest an ex-ante policy intervention can avoid dangerous credit booms by focusing on the solvency of the domestic banking system and financial market's overheating.

1.1 Introduction

The legacy of the Global Financial Crises prompted a widespread debate about ex-ante policy, that is an early intervention of policymakers during economic expansions, in order to make the economic system more resilient to adverse financial shocks and to avoid expensive ex-post measures, like bank bailouts or unconventional policies during downturns. This paper provides empirical evidence about credit booms and a strategy to provide early signals to introduce an ex-ante intervention with focus on the dynamics of credit of several Euro Area countries. A preliminary analysis confirms the well-established findings that credit booms are frequent events and that they are strictly related with states of macroeconomic and financial instability. These facts motivate to build an early warning model which signals coming credit booms and shows whether those signals are useful indicators of future crises.

A widespread empirical literature highlights the importance of the financial cycle in triggering long-lasting real crises and the potential amplification mechanisms that it can engender, in particular through banking crises (Borio [2014]). Yet, many authors stressed the pre-emptive power of credit and asset prices in signaling systemic financial risks (Borio and Lowe [2002]). Important works like Jordà et al. [2015, 2013]; Schularick and Taylor [2012] build long-run analyses to study the historical determinants of financial crises. They find that credit growth is a key predictor of financial crises and suggest that credit aggregates are superior policy indicator to pursue financial stability. Mendoza and Terrones [2012, 2008] (henceforth MT) find credit booms are source of economic turbulence and identify these as unusual expansions in the cyclical component of private credit.

This paper identifies credit booms through a threshold method like in MT, then it employs an early warning model (EW henceforth) in the same spirit of Schularick and Taylor [2012]. However, three main differences characterize the analysis here. First, credit booms are identified exploiting real-time information exclusively. Second, the EW predicts states that anticipate the starting date of the event, that is *credit-boom buildups*. Third, in line with further works, the EW evaluation criteria are based on the signaling approach — developed by Kaminsky and Reinhart [1999] and extended in Alessi and Detken [2009, 2011]— to provide signals subject to policy preferences. This strategy accounts for the relative aversion of policymakers against Type I errors (not issuing a signal when an event is imminent) and Type II errors (issuing a signal when no event is imminent). The final goal is to compute an optimal threshold to qualify the predicted probability estimated through the EW and to test its predictive power.

Furthermore, the EW developed in this paper takes into account the different adjustment processes of macro variables during crisis states, i.e. the so called crisis and post-crisis bias (Bussiere and Fratzscher [2006]). In the same spirit, a multinomial logit model is implemented also to distinguish credit booms that are followed by crisis from tranquil credit booms. The latter provides useful insight to policymakers to distinguish those booms that reflect adjustment of credit to economic fundamentals.

This work relates to recent EW advancements such as the work of Sarlin [2013], which emphasizes the role of policymakers' preferences in the optimal threshold determination. Also it relates to Duca and Peltonen [2013] and Behn et al. [2016a] who identify systemic events through a financial stress index and find that global variables have a greater impact with respect to the domestic dimension. Similar analyses can be found in Behn et al. [2013] and Behn et al. [2016b], showing that this model can help policymakers to set counter-cyclical capital buffers and to gauge the benefits of capital ratio macroprudential measures through the estimated probability of having a financial crisis. Yet, the results in this paper are presented so to allow a comparison with the latter.

A recent contribution by Richter et al. [2017] shares many similarities with this paper. However, here credit-boom thresholds are set to identify large displacements from the long-run trend, consistently with the theoretical intuition that credit booms are out-of steady-state phenomena (Brunnermeier and Sannikov [2014]). Moreover, the boom-threshold factor here is based on a real-time standard-deviation of the credit cyclical component, so that the EW might be used for actual predictions or out-of-sample analyses. However, one drawback with respect to Richter et al. [2017] is that, due to a shorter sample, the logistic EW cannot be used to distinguish bad from good credit booms directly. Alternatively, the paper provides estimates of tranquil and bad credit booms through an multinomial logit. The latter allows to highlight new insights about the nature of credit booms which are at odds with Richter et al. [2017].

Though the research have extensively deepened the relevance of credit cycle and its relationship with the real economy, the role of credit booms for policy purposes is much more controversial. This paper encourages EA's policymakers to use real-time EW models to set ex-ante interventions targeting the credit cycle. Besides to confirm well-known results of the literature and that real-time EWs provide accurate signals anticipating credit booms, the paper adds also another important result. Dangerous credit-boom buildups can be distinguished from tranquil ones, inasmuch the former are significantly characterized by a low capitalization of the domestic banking system and a high stock prices growth.

The paper is structured as follows: Section 1.2 defines credit booms and filtering techniques to identify them in a sample of EA countries. Also, an event analysis shows the relationship between credit booms and macro-financial patterns, while a frequency analysis shows whether these booms are related with financial crises. Section

1.3 presents the logistic EW and its evaluation criteria. Section 1.4 reports baseline results and further analysis. Section 1.5 collects some concluding remark.

1.2 Credit filters, booms and financial instability. Stylized facts and macro implications

There are several arguments about financial instability drivers, but a consistent part of the literature relies on the private credit dynamics as a broad measure of the financial cycle. From an ex-ante perspective, the salient part of its dynamics is linked with buildup phases, when a consistent deviation of private credit from its long-run trend is observed. In this paper credit booms are identified through several strategies, but it follows as a benchmark the one proposed in MT. The latter relies on a threshold method: more specifically, it takes significant and positive deviation of private credit from its long-run trend. Thus, the credit boom is a time period where the following condition holds:

$$l_{i,t} \geq \phi\sigma(l_{i,t}) \tag{1.1}$$

where $l_{i,t}$ is the cyclical component of the private credit for country i at time t, $\sigma(l_{i,t})$ is its standard deviation and ϕ is the boom threshold factor. The latter is set equal to 1.65 because the 5% tail of the standardized normal distribution satisfies $P(l_{i,t}/\sigma(l_i) \geq: Q1.65) = 0.05$. However, this specific ϕ's calibration is subject to hypothesis testing of normality of the cyclical components that are discussed next.

Three points in time are defined to identify the event: the peak ($\hat{t}$), the starting date (t^s) and the ending date (t^e). The peak is the date of the contiguous dates set satisfying the (1) that shows the maximum difference between $l_{i,t}$ and $\phi\sigma(l_i)$. The starting date of the credit boom is defined as a date $t^s < \hat{t}$ yielding the smallest difference $|l_{i,t} - \phi^s\sigma(l_i)|$. The ending date is a date $t^e > \hat{t}$ yielding the smallest difference $|l_{i,t} - \phi^e\sigma(l_i)|$. The start and the end thresholds, ϕ^s and ϕ^e respectively, for simplicity are set both equal to one, although robustness checks have been implemented without changing the results. The thresholds setting is so that $\phi^s = \phi^e < \phi$, and the duration of the credit boom is obtained from the difference $t^e - t^s$. Notice that, following this definition, the whole event is described by both the upswing and the downswing of credit deviation. Therefore, in real-time data such an event can be identified only once the credit cycle collapses, i.e. ex-post. Although the credit boom's identification of this section relies on this definition, the EW in next section focuses only on the buildup phases of the event, so as to generate timely signals to implement an ex-ante policy intervention.

In MT the credit-cycle component of the credit is obtained through a two-sided Hodrick and Prescott [1997] (HP) filter with smoothing parameter set equal to $\lambda = 1600$ for quarterly data. However, the use of the HP filter has been recently criticized in Hamilton [2018]. The Hamilton filter regresses an actual observation on its past observations for a given time horizon, so that the cyclical component is just the error term coming from this regression. In other words, the long-run trend is conceived as all of what can be explained using historical data. With two-sided HP, instead, cycle-waves are shaped on the whole information available in the sample and forecasts would be then flawed by this extra-information.

In Richter et al. [2017] the use of the Hamilton filter is central for the identification of credit booms. However, Drehmann and Yetman [2018] find that de-trended credit-to-GDP ratio obtained through one-sided HP filter, with an higher smoothing parameter $\lambda = 400000$, outperforms many other measure of credit gap in predicting financial crisis.

Figures 1.1-1.3 show the series of the cyclical component of the (log) CPI-deflated credit of the banking system obtained through the three filtering techniques.[1]These are obtained in a sample of 11 Euro-Area countries (EA)[2] for the largest time span available at quarterly frequency (1974:Q1–2018:Q1) in order to minimize the loss of information and reported from 1990:Q1. The Hamilton filtered cycles (red lines) are the one presenting more amplified swings.

Table 1.2 reports peak-dates of credit cycle for the Hamilton, one-sided and two-sided HP filters. Peaks are identified by employing the Harding and Pagan [2002] algorithm with a minimum length of each phase of four quarters. The number of cycle-peaks are 31, 9 and 22 respectively. Notice that the latter do not identify always a credit-boom event. All the filters indicate credit-cycle peaks in the around of the dot-com bubble (1998–2002) for the largest part of EA countries. The Hamilton and the two-sided HP filters peak in period 1990–1992 in Finland, France and Italy. The latter indicate also a peak in the around of the global financial crisis (2005–2009) in almost all countries of the sample.

[1]The smoothing-parameters are $\lambda = 400000$ for one-sided and $\lambda = 1600$ for two-sided HP filters. The Hamilton filter projection horizon of 20 quarters to reflect the long duration of credit cycles as in Hamilton [2018] and Drehmann and Yetman [2018].

[2]Austria (AT), Belgium (BE), Finland (FI), France (FR), Germany (DE), Greece (GR), Ireland (IE), Italy (IT), Netherlands (NL), Portugal (PT) and Spain (ES).

Before to identify credit-boom events, it is safer to test the assumption that credit cycles come from normal distributions, which justifies to calibrate the boom-threshold factor $\phi = 1.65$. The (one-sample) Kolmogorov-Smirnov test indicates to what extent the observed credit-cycles deviate from a normal distribution, so that if the null hypothesis is true this deviation is likely small. Table 1.4 reports the D-statistic[3] and the relative p-values for credit cycles obtained with the three filters for each country in the sample. In most cases a failure to reject the null hypothesis is recorded. Specifically, in all countries when credit cycles are obtained through one-sided HP filter. In 9 countries in the case of the two-sided HP and 8 in the Hamilton filter case.

By applying the threshold method of MT, the Hamilton filter is the one that identifies more credit booms (20 events), followed by the two-sided HP filter (18 events) and the one-sided HP filter (only 8 events). Though the two-sided filter by using past, present and future information provides a genuine representation of the long-run trend, the resulting credit cycles would be less useful for forecasting purpose. Therefore, for the purpose of predicting excessive credit dynamics through the EW model, in what follows the Hamilton-filtered credit cycle will be used as benchmark to identify credit-boom events. However the one-sided HP is taken as benchmark for Germany, Spain, Greece and Italy to meet the assumption of normality of the boom-threshold factor.

1.2.1 Stylized facts on credit dynamics within the Euro Area

In this subsection credit booms are identified in order to study their cross-country frequency and the behavior of macro-financial variables in the neighborhood of the event. The sample in object collects quarterly data for 11 EA countries from 1991:Q2 to 2017:Q4. The advantage of this sample is twofold: on the one hand, there are enough post-2008 observations to analyze the behavior of the main macro variables in the aftermath of the global financial crisis. On the other hand, since the focus is on countries adopting Euro convergence criteria, periods of exchange rates overheating are excluded for the most part of the sample period. The time-series used for the identification is the cyclical component of real private credit (deflated by the CPI) sourced by the Bank of International Settlements (BIS), that captures both loans and debt security instruments. In principle, there are two versions of this series: one is the private credit from domestic banking systems, the other is the private credit from the

[3] This indicates maximal absolute difference between the observed and the normal cumulative relative frequencies.

whole financial sector. These two series share a similar path up to the beginning of the global financial crisis, then the former slows down and the latter increases rapidly. They track almost the same boom episodes, but since the analysis keeps a close watch on banking crises and since EA countries are mostly bank-based, the focus will be on the first one.[4]

Overall, 20 credit booms are identified, ranging from 1 to 3 episodes per country with an average duration of 8 quarters. Nine countries experienced a credit-boom between 1996:Q1 and 2000:Q1, before the collapse of the dot-com bubble, while five between 2007:Q1 and 2008:Q3, before the collapse of Lehman Brothers.[5] The sample average standard deviation of credit's cyclical components, $\sigma(\bar{l})$, is 3% above the trend.

The event analysis shows cross-country means and medians of macro-financial variables (Figures 1.7–1.10). Of course, there is no causal interpretation for these figures, but they show that characteristic patterns around credit booms belong to both the time and the cross-sectional dimension. For the large part of the variables, average dynamics are not influenced by outliers since there are no significant differences from their respective median dynamics. The figures show a five-years window (21 quarters) centered at the peak of the credit boom ($\hat{t}$ is normalized to $t = 0$). Figure 1.7 shows real private loans and real GDP cycles. This suggests that credit booms are associated with a specific pattern of the business cycle across countries, which is the same regularity that MT find for advanced economies during the period 1960-2010.

Panel (a) shows that, on average, the credit cycle is symmetric around the peak and that it starts to cross the trend about a year and an half before the farthest deviation. The average peak is about 7% above the trend. In the following quarters, on average, the credit falls about 2 points below its trend. Panel (b) shows that the GDP cycle rises suddenly during the buildup of the boom, about 2% above the trend, and drops up to 1 point below it during the downswing. Notice that, less than 50% of credit booms are concomitant to GDP booms tracked through the same threshold method. However, the business cycle around the booms reveals also several differences among countries.

Figure 1.8 shows country-specific events occurred during the period 2007:Q1-2008:Q3, before the Lehman Brothers collapse. Also in this case the peak of the boom is centered at $t = 0$. Credit increases rapidly in Ireland, Greece and Belgium, while Spain

[4]By using loans from the whole financial sector three more episodes are identified in Portugal and an additional event in other two countries although they last no more than three quarters.

[5]Dot-com bubble: AT, ES, FI, FR, GR, IE, IT, NL and PT. Global financial crisis: AT, ES, FI, FR and IE.

and France experience a slower buildup phase (Panel a). Belgium and Ireland are also those countries that experience a severe bust phase up to 12 points below the trend. Almost all countries present large fluctuations of real GDP cycle, but Spain and Greece show an asymmetric pattern after the peak. Moreover, apart from Spain, all countries experience a severe GDP fall about 2% below the long-run trend within the two years that follow the peak.

Figure 1.9 presents the event analysis for lending margins of EA banking systems. These credit spreads indicate bank's profitability, and are calculated as the difference between the average lending rates and the average deposit rate to both households and non-financial corporations (NFCs henceforth). Figure 1.9 is split between lending margins to new loans/deposits and outstanding loans/deposits. Since these data are available from 2003, we can include only credit booms related to the global financial crisis and the sovereign debt crisis.[6] The analysis shows an average downward pattern before the peak and a sudden increase after the boom. However, margins on outstanding amounts have a deeper downward tendency also after the peak, while, margins on new businesses are flatter before the boom and jump suddenly at the peak date. Indeed, margins on new businesses are less sluggish and capture recent developments in bank interest income in a more timely fashion.[7]

Figure 1.10 shows the event analysis for other macro variables. The cycles of current accounts as percentage of the GDP, a stock index (deflated by the CPI), an house price index and the CPI inflation rate (quarter-on-quarter). The current account displays a deficit greater than 0.8% of GDP at the peak, but it gradually turns to a surplus up to 0.6% of GDP. The house price index records on average a 10% increase at the peak and a fall in the downswing about the same extent, showing a pattern similar to that of real credit cycle. The stock price index shows a similar pattern to the real GDP cycle: it increases about 20% during the buildup of the boom and it falls in the after the peak on a similar extent. The inflation rate has not particular tendency around the event since, showing only an above-trend pattern around the quarters close to the peak at median level.

Another important question is how frequently credit booms relate to crisis states. To study this relationship one need a clear definition of crisis states that clearly distinguishes financial from other types of crises. This paper follows the classification made

[6]Specifically, the following countries are involved (peak date): Belgium (2008:Q1), France (2008:Q4), Greece (2009:Q1), Ireland (2008:Q1), Italy (2011:Q3), The Netherlands (2011:Q2), Spain (2007:Q3).

[7]See ECB, Monthly Bulletin, Jan (2009).

in Duprey et al. [2017], which identify systemic financial stress dates using a Markov-switching model selection. One reason to use it is that the model captures on average 100% of the banking crises identified by Laeven and Valencia [2013] that is generally accepted as benchmark for crises identification. More specifically, the model selects financial stress episodes that are associated with prolonged declines in real economic activities. These are defined as at least six consecutive months of negative annual industrial production growth concomitant to a decline in real GDP during at least two quarters. Moreover, the model allows to construct an EU crisis simultaneity index that preserves cross-country comparability. Crises dates are reported in Table 1.3. The frequency analysis reveals that 70% of credit booms are associated with crisis states, of which 80% relates to banking crises, while the rest to equity crashes in the private sector. Almost 70% of credit booms start prior to the crisis, ranging from 2 to 9 quarters before. However, 30% of these do not end up in crises and they have a maximum duration of four quarters. Finally, on average, countries have more than 50% of probability of experiencing a credit boom (that in MT definition includes also credit downswings after a peak) once the starting threshold is crossed.

Summarizing, the analysis shows that banking credit booms in the EA are associated with specific patterns of many macro-financial variables. On average the event starts with a surge in the cyclical component of GDP, house price indexes, stock indexes, increasing deficits in current accounts and declining lending margins during the buildup phases, followed by an opposite pattern during credit downswings. These results confirm and reinforce MT analysis, notwithstanding their fluctuations result more accentuated around the peak, probably due to a larger sample — both in time and cross-sectional dimensions — that allows them to track many other episodes.

1.3 An Early Warning system to identify the booming nature of the credit cycle

This section focuses on the left-hand side of credit boom event as in Figure 1.7. The goal is to obtain a signal that predicts the buildup of the boom in order to provide policymakers with timely information to setup an ex-ante intervention. One caveat of MT's method is that a credit boom is qualified as such only when the credit cycle crosses its standard deviation times a threshold factor. This method, in fact, is such that credit cycle has to be un-normally far from its long-run trend, so as to avoid concerns about credit dynamics every time this is above its growth path, possibly also in a good shape. However, as the event analysis has shown, the credit cycle crosses its boom threshold about an year before it collapses, therefore contingent pre-emptive signals can be policy relevant. The setup of this section is a multivariate logistic EW model that assesses the power of several variables in predicting credit boom buildups. This section also tests the ability of the EW model to catch credit booms states rather than financial crisis states. As not all credit booms turn into financial crises, this can be a potential source of bias for policy makers that should be taken into account.

Thus, the same model is estimated for two different dependent dummy variables. Since the latter are binaries, the probability estimated on the left-hand side of the model is a non-linear function of the regressors on the right-hand side. The logistic model is described by the following equation:

$$P(Y_{i,t} = 1) = \frac{e^{\alpha_i + \beta_i X'_{i,t}}}{1 + e^{\alpha_i + \beta_i X'_{i,t}}} \tag{1.2}$$

The left-hand side variable is the probability of being in a given state for country i at time t. On the right-hand side, α_i catches the unobserved country-heterogeneity, while $X_{i,t}$ is a vector containing macro-financial regressors. The latter consists of growth rates of macro financial variables and other predictors in level.[8] The latter consists of real GDP, real credit from the banking system, real credit from all financial institutions, the CPI inflation, an house price index, a stock price index, the consolidated banking capitalization (defined as equity on total assets in levels), an average of lending rates and lending margins of consolidated banking systems. Alternatively, by splitting the real credit from the whole financial system, the model is regressed on credit to households and credit to NFCs.

All the specifications allow country fixed effects. The estimation does not include time dummies that would account for heterogeneity in crisis probability over time. Notice that, although time dummies would improve the ex-post fit of the model catching the global time factors— that drive the left-hand-side of the logit— they are unknown ex-ante. Thus, time dummies add little help to the EW evaluation, especially in the out-of-sample forecasting.[9] However, since the global financial crisis affected almost all

[8] As pointed out in Behn et al. [2013], Year-on-Year growth rates have much more predictive power than Quarter-on-Quarter growth rates. The analysis here takes YoY rates as benchmark and QoQ for robustness checks.

[9] See both Schularick and Taylor [2012] and Behn et al. [2013] on this point.

countries in the sample, robust standard errors clustered at quarterly level are employed in order to account for potential correlation in the error terms.

As clarified above, the first model specification uses two main dependent variables representing credit boom buildups and financial vulnerability states. As in Behn et al. [2016a], the latter is a binary variable that equals one between 7 and 12 quarters prior to a systemic crisis and zero otherwise. Again, systemic crisis states are identified following Duprey et al. [2017]. That way, the dependent variable allows to catch vulnerable states early enough without loosing accuracy. This is set so as to leave sufficient time to policymakers to implement adequate actions. In the same spirit, the second dependent variable anticipates credit downswings, and it equals one between 4 and 9 quarters before the boom threshold is crossed. Thus, on average, this dummy equals one between 7 and 12 quarters before credit cycle collapses after having crossed its boom threshold. As shown in the previous section, those phases are concomitant to the worsening of macro conditions and in many cases they are associated to financial crises. The credit boom dummy is chosen among four main specifications that take different upper bounds as reference points: the peak, the starting date and the whole event rather than the threshold-crossing date. However, the latter is preferred for two main reasons: first, it allows to avoid overlaps with crisis states and, second, on average it corresponds to the financial vulnerability dummy every time a financial crisis is anticipated by a credit boom.

Moreover, the estimation avoids the post-crisis bias that may arise when the dependent variable does not discriminate between tranquil periods (when economic fundamentals are sustainable) and crisis states (when macro series are much more volatile). Following Bussiere and Fratzscher [2006], this potential source of bias is addressed first by excluding quarters of crisis states from the estimation and then by performing a multinomial logit as robustness check. In the latter the dependent variables are specified so as to distinguish both tranquil, vulnerable and crisis states (see Section 1.4).

1.3.1 Model evaluation

The predictive ability of the EW models are measured following several evaluation criteria. The underlying idea is to compare the predicted probability with the actual outcome in the data, by defining a threshold above which the former signals that an event is about to occur. The signaling approach consists in finding this optimal threshold $\tau \in [0, 1]$, defined as a percentile of the distribution of predicted probability. The latter, $P(\widehat{Y_{i,t} = 1})$ is transformed into a binary predictor $\widehat{P_{j,t}}$, that equals one when the continuos predictor crosses the threshold and zero otherwise. Thus, signals issued by this binary predictor are compared with the actual outcome, $C_{i,t}$, that equals one for effective realizations observed in the data and zero otherwise. The latter has to be interpreted according to which dependent variable is considered. In the case in object, $C_{i,t}$ equals one if country i experiences a crisis within the following 7-12 quarters (i.e. from $t+7$ to $t+12$) and zero otherwise for the financial vulnerability dummy, while, $C_{i,t}$ equals one if the credit cycle crosses the threshold within the following 4-9 quarters (i.e. from $t+4$ to $t+9$) and zero otherwise for the credit boom dummy.

Each observation can be then classified in a contingency matrix reported in Table 1.5. There is a true positive (TP) when the model issues a signal and a realization in the actual class is observed, a false positive (FP) when the model issues a signal that does not correspond to a realization in the actual class, a false negative (FN) when the model does not signal a realization which instead is observed in the actual class, and a true negative (TN) for an observation to which corresponds both no signal and no realization in the actual class.

In order to find the optimal threshold, τ, the policymakers preference has to be set. The latter can be thought as a parameter $\mu \in [0, 1]$ denoting the relative aversion to Type I errors (i.e. the rate of missed realizations, $T_1(\tau) = FN/(TP+FN) \in [0, 1]$) and to Type II errors (i.e. the rate of false alarms, $T_2(\tau) = FP/(TN + FP) \in [0, 1]$). In general, μ is grater than 0.5, reflecting the fact that policymakers are more willing to issue a false alarm than missing a realization because crises are costly. In particular, in the baseline specification $\mu = 0.85$, but other calibrations are set as robustness checks. Therefore, the optimal threshold has to minimize the following loss function depending on the two errors (T_1 and T_2) weighted for the policymakers' preference (μ):

$$L(\mu, \tau) = \mu P_1 T_1(\tau) + (1 - \mu) P_2 T_2(\tau) \tag{1.3}$$

As in Sarlin [2013], equation (1.3) assumes that policymakers are concerned about the absolute number of misclassifications, so as to account for the relative frequencies of the actual class, which are $P_1 = P(C_{i,t} = 1)$ and $P_2 = P(C_{i,t} = 0)$.

A crucial evaluation instrument is the so called usefulness of the EW that can be obtained through the loss function. Alessi and Detken [2009] define the absolute usefulness of an indicator, U_a, as the difference between the minimum loss that the policymaker may reach by ignoring the indicator and the loss that the indicator produces by itself. This is defined as $U_a(\mu) = min(\mu P_1, (1-\mu)P_2) - L(\mu, \tau)$. The rationale underlying the latter is that policymakers may achieve a loss equal to $min(\mu P_1, (1-\mu)P_2)$ by either always issuing a signal ($T_1(\tau) = 0$) or never issuing a signal ($T_2(\tau) = 0$). Notice that, since in our sample tranquil periods are more frequent than crisis states ($P_2 > P_1$), setting an higher μ —which implies more interest in detecting vulnerable states— makes the indicator more useful in absolute terms.

However, the concept of relative usefulness is employed to compare different EW model specifications. This is defined as the share of $U_a(\mu)$ that policymakers can achieve through a perfectly performing model:

$$U_r(\mu) = \frac{U_a(\mu)}{min(\mu P_1, (1-\mu)P_2)} \tag{1.4}$$

where the denominator of the (1.4) is a perfect model achieving $T_1 = T_2 = 0$, so that $L = 0$.
The Hosmer-Lemeshow test (Lemeshow and Hosmer Jr [1982]) measures the general goodness of fit of the model, testing whether the actual realization rates match the predicted one in population subgroups.[10]

The receiver operating characteristics curves and its area (displays the optimal balance between the true positive rate and the false positive rate at any possible given threshold.[11]. This measure provides the accuracy of the signal, starting from a value of 0.5 which indicates that the discriminating ability of the model is like flipping a coin. In other words, the AUROC is the probability that the model ranks a randomly chosen realization $C_{i,t} = 1$ higher than a randomly chosen $C_{i,t} = 0$.

The adjusted noise-to-signal ratio (aNtS) measures the ratio between false signals rate and true signals rate: $aNtS = FPR/TPR = (FP/FP + TN)/(TP/TP + FN)$. An aNtS lower than one is a necessary condition for having a useful indicator (or model).[12]. Finally, the comparison between EWs is based also on the difference between the conditional and unconditional probability, defined as *(TP/TP+FP)-(TP+FN)/(TP+FP+TN+FN)*. The larger is this difference the better is the quality of

[10] In particular, this takes 10 subgroups. The subgroups are compared with a χ^2 to check the significance in the difference between expected and observed events. A *p-value* ≤ 0.05 indicates poor fit.

[11] Notice that, the true positive rate $TPR = \frac{TP}{TP+FN} = 1 - T_1(\tau)$, is the so called sensitivity, while the specificity is the true negative rate $SPC = \frac{TN}{TN+FP} = 1 - T_2(\tau)$.

[12] See Alessi and Detken [2009] for a discussion on this point.

the indicator.[13]

1.4 Empirical Results

The first two estimates assess the marginal effects of macro-financial variables on the probability of having a financial crises from 7 to 12 quarters ahead of the observed period and on the probability of having a credit boom from 4 to 9 quarters ahead of the observed period. By assumption policymakers have a strong preference in avoiding crises (or credit booms), at the cost of issuing false alarms, therefore $\mu = 0.85$. The estimates here give insights about the marginal effect of credit from non-banking institutions, credit to households and to NFCs, the effects of two lending margins, an average of lending rates and the effects of global variables. Results are reported in Tables 1.6–1.7. Notice that, the sample structure allows build the EW analysis on a balanced panel from 1998:Q1 to 2016:Q4. However, when lending rates and margins are included the sample size reduces, because these last are available from 2003:Q1. Thus, lending margins and rates enter the estimation just in two model specifications. The tables report also the *p-value* resulting from the Homser-Lemeshow test, the optimal threshold as percentile of the predicted distribution, the resulting Type I and Type II errors, the aNtS ratio, the AUROC, the relative usefulness, the percentage of correct predictions, the probability of having an event conditional to that of having a signal and the difference probability.

1.4.1 Sign, significance and predictive ability of the EW

Table 1.6 is divided in six columns for two dependent variables and three different model specifications. The credit growth from domestic banking systems has positive and significant sign in all specifications. Though this result was expected for credit booms (Model 2), it is worth noticing that the banking component of domestic credit growth is a significant source of financial instability also (Model 1).

However, one may argue that the inclusion of credit growth among the regressors (as well as the inclusion of GDP growth and inflation) can produce flawed coefficient estimates and it can be a source of reverse causality. This is not incorrect in principle, but even though the dummy is obtained from the credit cycle (or GDP in the case of financial vulnerability), the EW tells whether a regressors at time t, on right-hand

[13] Models with negative difference probability have to be discarded, because this implies that the indicator performs worse than an EW based on the simple unconditional probability.

side, helps to estimate the probability at time t that something happens in $t + n$, where $n = 4, ..., 9$ (or for vulnerable states $n = 7, ..., 12$). In fact, the EW here is about predictability of credit events, but it is poorly informative about causality, which would require a more specific experimental design. However, the estimates are robust even by excluding possible source of bias like that one of including credit itself in the estimation, though the predictive ability of the EW worsens.[14]

The credit growth from the all financial institutions has significant and negative sign in predicting financial vulnerability, but no significant impact on credit booms formation inasmuch the boom-events build upon banking loans cycles. Models 5 and 6 show that credit to households has a larger and significant impact on both states of financial vulnerability and credit-boom buildups, while credit growth to NFCs impacts negatively only on states before financial crises. On the one hand, this can be due to the fact that households, by using credit for mortgages to purchase existing homes, do not actually contribute to GDP and hence they boost house prices which feed credit booms. On the other hand, credit to NFC may contribute to GDP through investment and then it has a negative sign before crises.

The domestic real GDP growth has negative sign in all the specifications, but this is more significant for credit booms. Financial crises are hence strictly related with credit overheating that in its turn is likely to fall down dangerously in countries in which real GDP growth is weak. This is in line with the fact that the inclusion of credit-to-GDP ratio increases the predictive ability of EW models as highlighted in Alessi and Detken [2011] and Schularick and Taylor [2012]. Further results show that low inflation rates favor credit booms formation, but their effect is unclear on quarters preceding crises. Both stock index and house price growth have positive sign for both dependent variables, with weak magnitude of stock prices' log-odds for credit booms.

The consolidated banking capitalization has negative and significant sign for both dependent variables. This suggests that the more capitalized banking systems are, the less they are likely to experience credit booms and financial crises. This is in line with the idea that the more resilient banking systems are the less they are likely to fail, as their high level of capitalization lowers the probability of having a financial crisis.

The average lending rate on credit stocks has significant negative sign for vulnerable states. Thus, lower revenues for banks may trigger growing risks into the financial

[14] In particular, the AUROC drops on average to 75% and the relative usefulness to 40%. These results are available upon request.

system. This might be due, as instance, to some search-for-yielding mechanism. Even though lending rates have mixed effects in predicting credit booms, lending margins seem to play a non-negligible role. Their log-odds are negative and significant, which suggests that financial imbalances are favored in a low interest rates environment. One may think that as low margins increase the present value of banks' income, this allows for a greater risk bearing capacity of banks, that may lead to an expansion of the lending activity.

Models 6 log-odds are consistent with the previous estimates. All models present an aNtS significantly lower than one and the AUROC suggests that they are highly accurate in classifying observations. Indeed, the percentage of correct predictions is stably above the 80%. The results in Table 1.6 show that detecting credit booms is similar to detect financial instability, but the credit dynamics cannot be considered as a stand-alone warning indicator. Tranquil periods encompass fragility buildups in the credit dynamics which can become the driving force of the financial cycle.

Table 1.7 reports two models for credit booms regressed also on global variables. The latter include aggregate time-series of EA, US, UK and JP. The global variables enter the model in two versions, which are unweighted and GDP-weighted. The coefficients signs of the previous estimations are preserved as well as their significance, apart from domestic real GDP. Notwithstanding, global credit growth impacts much more than domestic one, while global GDP growth has a negative and significant sign. This confirms that slowdowns in the global growth could favor the buildup of domestic credit booms for highly integrated financial systems. The real credit to households has positive and significant sign, and its impact is stronger than the real credit to NFCs at both domestic and global level. This result, of course, could be driven also by the effect of the global financial crisis.

The EW analysis suggests that Model 7 is the best performing model for credit booms. It has the highest AUROC and its optimal threshold lies in the 74^{th} percentile of the distribution, that allows to obtain the lowest aNtS among these specifications. Model 7 predicts correctly 84.27% of the observations and it has the highest difference probability, suggesting that it is the best in terms of quality of the indicators. Moreover, Model 7 is the highest relative useful model. Therefore, this model is taken as benchmark specification for the following analysis. Finally, it is worth noticing that, the in-sample analysis is not helpful predict future states, which is the final goal of the paper. The out-of-sample analysis in the next subsection will reveal whether this EW can be used to set ex-ante actions by policymakers.

1.4.2 Out-of-sample analysis and the multinomial logit

In the out-of-sample analysis the estimation horizon is set to 2005:Q1 so as to see whether the model issues a signal before both the global financial crisis and the sovereign debt crisis. Furthermore, one may think that policymakers were less worried about credit booms in 2005, so the signal analysis is calibrated with $\mu = 0.85$ and 0.6. Through the second calibration policymakers are more willing to miss a crisis in order to improve the accuracy of the signals, still they have a relative aversion to Type I errors. The results are presented in the first two columns of Table 1.8.

The sign and the significance of the log-odds are similar to the in-sample analysis, confirming the stability of the parameters overtime. For $\mu = 0.6$ the optimal threshold rises from the 73^{th} to the 86^{th} percentile of the distribution, so it gives a signal for higher values of the predicted probability. This correctly classifies 87.1% of the observations and it has a lower aNtS, confirming a better predictive ability with respect to $\mu = 0.85$. At the same time the relative usefulness reaches 10% of the usefulness of a perfectly performing model against 64% when policymakers have $\mu = 0.85$.

Figure 1.12 shows country-specific predicted probabilities for credit booms (blue line), the real credit growth (red line), periods of financial crisis (vertical shaded area) and country-specific optimal thresholds for the two scenarios, $\mu = 0.85$ (horizontal black line) and $\mu = 0.6$ (horizontal green line). Greece is excluded from this estimation since it does not experience credit booms before 2005:Q1. The EW in the first scenario issues a signal by the end of 2005 in 9 of 10 countries considered. Only for Netherlands the predicted probability does not cross the optimal threshold before the global financial crisis, but it starts issuing a signal between 2008:Q3 and 2010:Q1, signaling the current and the subsequent financial crises. For $\mu = 0.6$, the EW misses the signal before the global financial crisis in Germany, Finland and Portugal, but it continues to issue a correct signal in the others. The signals reach the highest values between 2008 and 2010 in all countries, thus, the information available in 2005 would have signaled the boom which leads to the crises that hit the EA countries.

The remaining columns of Table 1.8 report the results for the multinomial logit models, which is the dependent variables is allowed to assume at least one specification more than zero-one values. The first model (second and third columns) addresses the post-crisis bias, so that the dependent variable equals 0 for tranquil periods, 1 for credit boom buildups, and 2 for crisis states up to 4 quarters after the crisis periods. So that the model accounts for the different dynamics of the regressors during crisis and recovery periods. Moreover, the comparison of the different realizations may reveal useful information about the end of credit booms[15]. The third column lists the marginal effects of changes in the regressors during pre-credit booms relative to tranquil periods, when the economic fundamentals are sustainable. The fourth column instead lists the coefficients relative to crisis and recovery states and tranquil regimes.

The log-odds for credit booms are consistent with previous specifications. Their sign and significancy are both preserved, but the reduction in their magnitude witnesses that the multinomial logit captures the post-crisis bias better than a binary logit which ignores crises states. Concerning crisis and post-crisis states there are important reversions in signs. Slowdowns in both domestic credit and GDP growth rates characterize crises states. Also, crisis states are characterized by falls in both house prices, global GDP growth and global credit growth.

The second multinomial (fifth and sixth columns) estimates credit booms leading to financial crises (the dependent variable equals 1) and booms that are not related with real losses (the dependent variable equals 2). The log-odds for booms leading to crises (crisis-boom) are significantly consistent with the baseline specification, even though there is a reduction in their magnitude. Most importantly, there are substantial differences of these from booms that are not followed by crises (tranquil-boom). For the latter, the log-odd of domestic GDP is positive and significant and, most of all, both domestic credit and banking capitalization are not significant anymore. This last result suggests that tranquil-booms are mostly driven by global dynamics rather than domestic determinants, as witnessed also from their larger log-odds.

1.5 Conclusions

This paper analyses credit booms within EA countries, their connections with financial crises and the predictive power of global and domestic macro-financial indicators in signaling these events. Credit booms identified through MT's threshold method correspond to specific patterns of real GDP, current account balance, house prices, stock prices and lending margins. Overall, 70% of these episodes are associated with financial crises in the quarters that following their starting date.

[15]See Bussiere and Fratzscher [2006] for a discussion on this point.

As in this paper, the latter is a well established finding of the empirical literature which motivates the identification of credit booms to set up ex-ante policy measures. However, measures flagging the credit dynamics can be costly for real economy, so that a timely identification combined with enough confidence about the detrimental nature of the boom, are two empirical challenges which are policy relevant.

In this paper real-time filtering techniques identify events detected through an EW system. The novelty is that the latter is used to detect credit boom buildups, rather than periods anticipating financial crises. The boom-buildups are defined as phases anticipating the date in which the credit cycle crosses the real-time standard-deviation-based threshold factor. The paper compares different EWs with models catching states of financial vulnerability (which are states that anticipate financial crises). Besides accelerations in the domestic credit growth, credit booms are likely to materialize when both real GDP growth and inflation rates are weak. This significant relation does not hold when the EW is set to predict financial vulnerable states.

Moreover, credit booms are more likely to occur in those banking systems with low capitalization levels and low lending margins, in contrast with the findings of Richter et al. [2017]. Also, expansions in lending to household is the leading component of credit booms in the EA, while lending to NFCs seems to play a marginal role. The inclusion of global variables improve the predictive ability of the EW. The global GDP and global inflation rates account much more than the domestic ones.

The predictive ability of the EW is then tested in an out-of-sample analysis. The model predicts credit booms related to the global financial crisis in 9 countries on 10 in the sample. Then, the model issues the highest signal in all counties between 2008 and 2010, that is just before the European sovereign debt crisis. This suggests that the information used would have been a precious signal of imminent crises since 2005.

However, two further challenges arise. One is that the estimation might be biased by the so-called post-crisis bias. Second, not all credit booms end up in crises as they might be economic responses to improved fundamentals. Two multinomial logistic models address these issues. The first controls for both crisis and recovery states: besides the stability of its log-odds, this model shows that real GDP growth remains significant only at global level.

The second multinomial logit distinguishes credit booms that do not lead to real losses from credit booms related to financial crises and also in this case its log-odds are stable. Moreover, the exercise provides relevant information for policymakers to distinguish EW signals: while tranquil-boom buildups are driven mainly by global macro dynamics, crisis-boom buildups are related to the domestic capitalization of the banking system and asset prices growth.

These findings are in line with the theoretical prescription that fluctuations in asset prices are source of financial instability that operates through adverse feedback loops across the financial market and banks balance sheets (Brunnermeier and Sannikov [2014]). The latter can be, as instance, a consequence of an improper incentive systems and a lack of constraints imposed to banking institutions (Mittnik and Semmler [2013]). Though any causal interpretation would be misleading, the results here suggest that, by using real-time macro-financial information, timely policies addressing the resilience of the banking system and stock-market overheating might actually lower the probability that credit growth turns to be dangerously excessive in the following years. Clearly, these ex-ante goals call two main policy tools in. On the one hand, the macroprudential capital regulation can improve the solvency of banks' balance sheets. On the other hand, a leaning against the wind of the central bank might aim at deflating financial bubbles. Further research should focus on whether the former policy, the latter or both would be successful in achieving credit and financial stability. In this sense, empirical and theoretical challenges are open to see "what's next" policies implemented after the EW signals.

Appendix

Data sources

Quarterly level data: bank credit, total credit, total credit to households and NFCs have been taken from BIS. All these are adjusted for the breaks. Nominal GDP is taken from OECD data, while Current Account-to-GDP from bloomberg. House and stock prices from mixed sources (BIS, National central banks, Eurostat, Bloomberg). Total assets of MFIs, the capital and reserves of MFIs, the lending rates and are taken from the Statistical Data Warehouse of the ECB.

Table 1.1: Summary of the variables

Variable	Obs	Mean	Std.Dev.	Min	Max
Real Credit Growth from Banks	1078	3.911	7.683	-22.87	35.77
Real Credit Growth from All	1078	4.706	6.838	-12.65	58.44
Real Credit Growth to Household	1003	5.237	7.799	-8.544	36.07
Real Credit Growth to NFCs	1003	3.996	7.579	-14.56	87.22
Credit-to-GDP	1078	2.217	6.708	-40.28	25.08
Real GDP Growth	1078	1.697	4.189	-17.23	37.55
Inflation	1078	2.242	1.989	-6.109	16.14
Stock Price Growth	1078	8.473	28.10	-66.2	167.2
House Price Growth	1055	4.823	7.516	-23.14	32.21
Banking Capitalization	789	2.917	13.92	-54.19	206.1
Avg. Lending Rates	605	3.995	1.101	1.450	6.390
Lending Margin (New Business)	605	1.624	0.633	0.308	4.122
Lending Margin (Outstanding)	605	1.800	0.789	0.195	4.375
Real Global Credit from Banks	1078	0.127	0.104	-0.116	0.313
Real Global Credit to Households	1078	0.160	0.114	-0.0346	0.363
Real Global Credit to NFCs	1078	0.131	0.116	-0.130	0.343
Real Global GDP	1078	0.117	0.0680	-0.183	0.215
Global Inflation	1078	0.0679	0.0370	-0.0289	0.198
Global House Price Growth	1078	0.0912	0.124	-0.261	0.373
Global Stock Price Growth	1078	0.207	0.518	-1.142	1.328

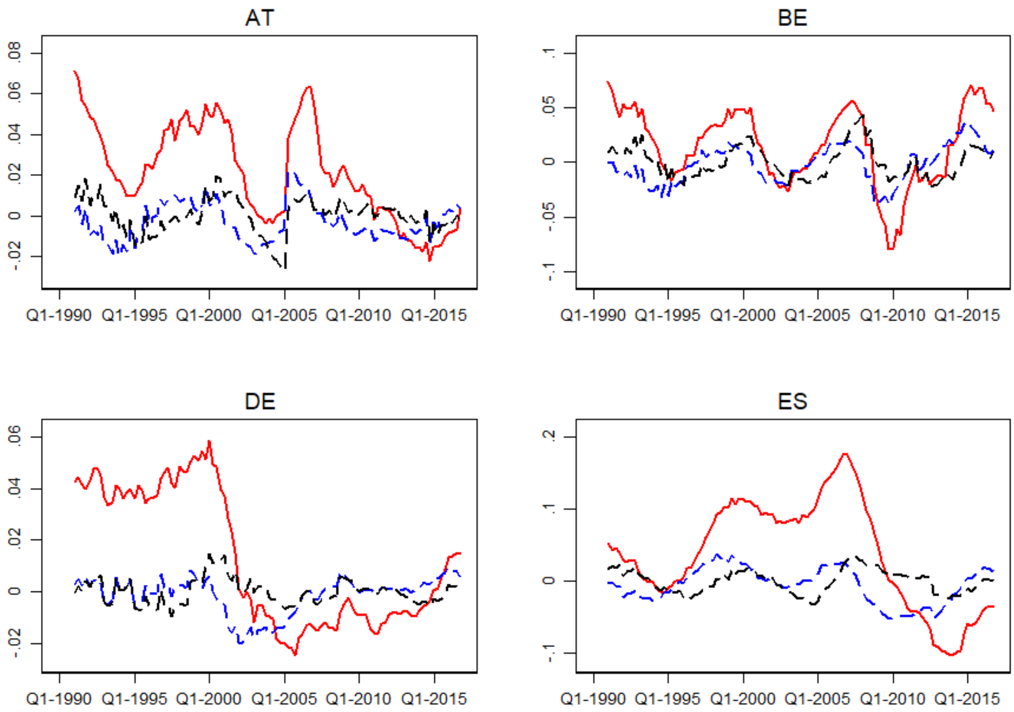


Figure 1.1: Credit cycles obtained through two-sided HP filter and $\lambda = 16000$ (black), one-sided HP filter $\lambda = 400000$ (blue) and the Hamilton filter (red). Credit is (log) CPI-deflated and it consists of loans and debt securities instruments of the domestic banking system.

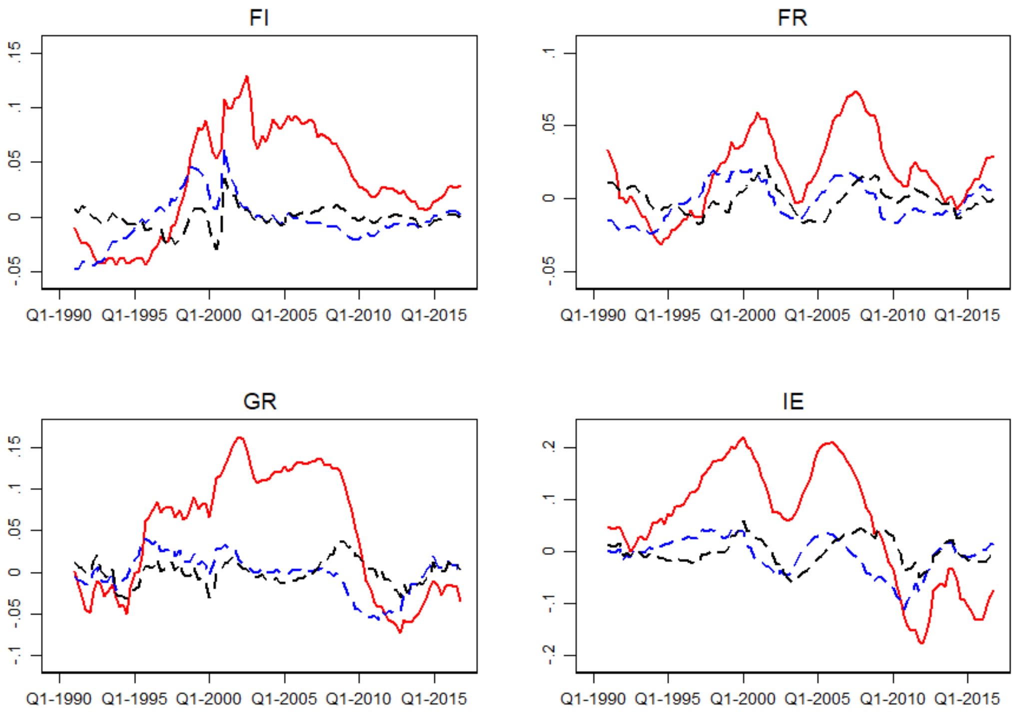


Figure 1.2: Credit cycles obtained through two-sided HP filter and $\lambda = 16000$ (black), one-sided HP filter $\lambda = 400000$ (blue) and the Hamilton filter (red). Credit is (log) CPI-deflated and it consists of loans and debt securities instruments of the domestic banking system.

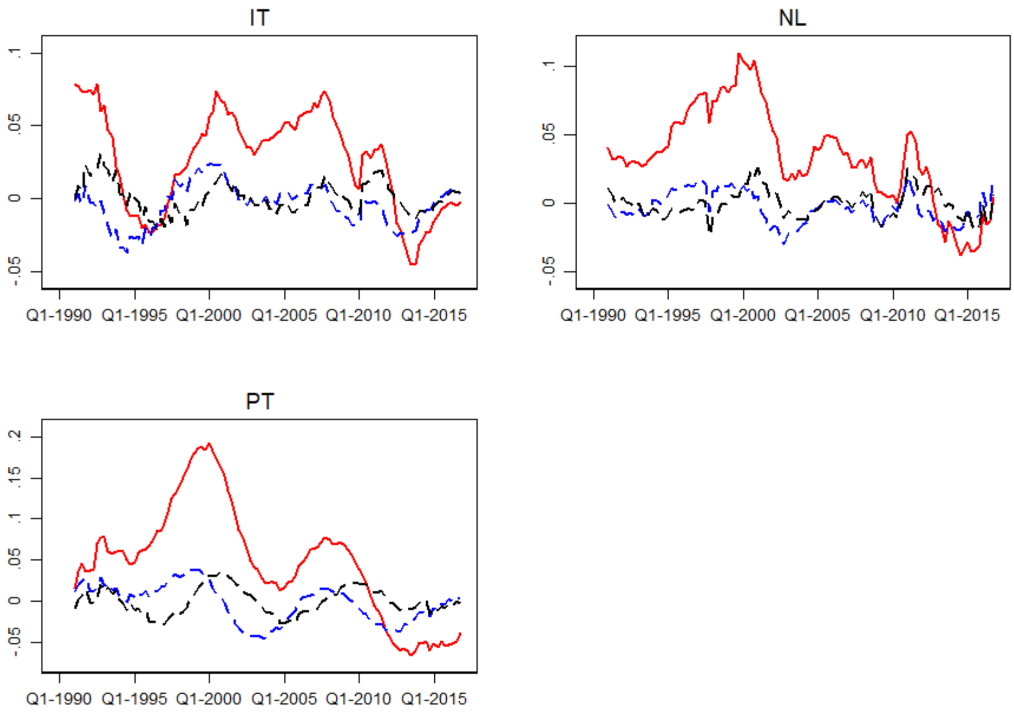


Figure 1.3: Credit cycles obtained through two-sided HP filter and $\lambda = 16000$ (black), one-sided HP filter $\lambda = 400000$ (blue) and the Hamilton filter (red). Credit is (log) CPI-deflated and it consists of loans and debt securities instruments of the domestic banking system.

	Hamilton	One-sided HP	Two-sided HP
AT	1990:Q3; 1998:Q3; 2000:Q1; 2006:Q4	2005:Q3	2000q4
BE	2015:Q2	2015:Q1	2000:Q3; 2008:Q1
DE	1991:Q2; 2000:Q1		2000:Q2; 2001:Q1
ES	1999:Q3; 2000:Q1; 2007:Q1		2007:Q3
FI	1999:Q4; 2001:Q2; 2002:Q3; 2004:Q3; 2006:Q1	1999:Q1; 2001:Q2	1990:Q3; 2001:Q2
FR	1990:Q1; 2001:Q2; 2007:Q3	1998:Q2; 2000:Q3	1990:Q1; 2001:Q3; 2008:Q1; 2009:Q1
GR	2002:Q2; 2005:Q2; 2006:Q2	1996:Q1	1990:Q1; 2009:Q1
IE	2000:Q1; 2006:Q1		2000:Q1; 2008:Q1; 2009:Q3
IT	1990:Q4; 2000:Q4; 2007:Q4	2000:Q2	1992:Q1; 2011:Q3
NL	1995:Q4; 1997:Q3; 2000:Q1		2001:Q1; 2011:Q2
PT	1999:Q3; 2000:Q1	1999:Q1	2000:Q2; 2001:Q1

Table 1.2: Peaks of credit cycles identified with Hamilton, one-sided HP and two-sided HP filters respectively.

	Crisis period
AT	1991:Q1-1993:Q2; 2008:Q1-2010:Q3
BE	1991:Q2-1993:Q3; 2007:Q4-2013:Q1
FI	1991:Q2-1996:Q2; 2001:Q1-2001:Q3; 2008:Q4-2010:Q3; 2012:Q3-2013:Q2
FR	1991:Q2-1993:Q1; 2002:Q3-2003:Q2; 2008:Q1-2012:Q3
DE	1992:Q3-1994:Q3; 2001:Q4-2003:Q3; 2008:Q3-2010:Q2
ES	1992:Q3-1992:Q3; 2008:Q1-2013:Q3
GR	2008:Q1-2013:Q2
IE	2007:Q3-2012:Q2
IT	1991:Q3-1996:Q3; 2008:Q1-2013:Q2
NL	2002:Q2-2004:Q2; 2008:Q1-2010:Q3; 2011:Q3-2012:Q2
PT	2008:Q1-2013:Q3

Table 1.3: Crisis periods. Crises dates are taken from Duprey et al. [2017]. These are periods of financial stress followed by significant losses on the real side.

	Hamilton		HP one-sided		HP two-sided	
	Difference	*p-value*	Difference	*p-value*	Difference	*p-value*
AT	0.072964	*0.187943*	0.039903	*0.574587*	0.025483	*0.797733*
BE	0.06992	*0.215444*	0.048926	*0.434744*	0.099553	*0.031781*
DE	0.134997	*0.003272*	0.077817	*0.121569*	0.05659	*0.328108*
ES	0.087448	*0.090611*	0.044522	*0.501684*	0.061525	*0.267868*
FI	0.066005	*0.254624*	0.083172	*0.090062*	0.123661	*0.004885*
FR	0.031536	*0.731787*	0.041241	*0.553296*	0.059196	*0.295395*
GR	0.146176	*0.00122*	0.067469	*0.205133*	0.049977	*0.419293*
IE	0.044301	*0.539967*	0.062117	*0.261125*	0.045187	*0.491374*
IT	0.10726	*0.026986*	0.046104	*0.47726*	0.055076	*0.347983*
NL	0.051835	*0.430126*	0.052313	*0.385844*	0.051543	*0.396728*
PT	0.086999	*0.092868*	0.065735	*0.222301*	0.055221	*0.346056*

Table 1.4: One-sample Kolmogorov-Smirnov test for normality. The table reports the D-statistic for each country in the sample and for three different filtered credit cycles.

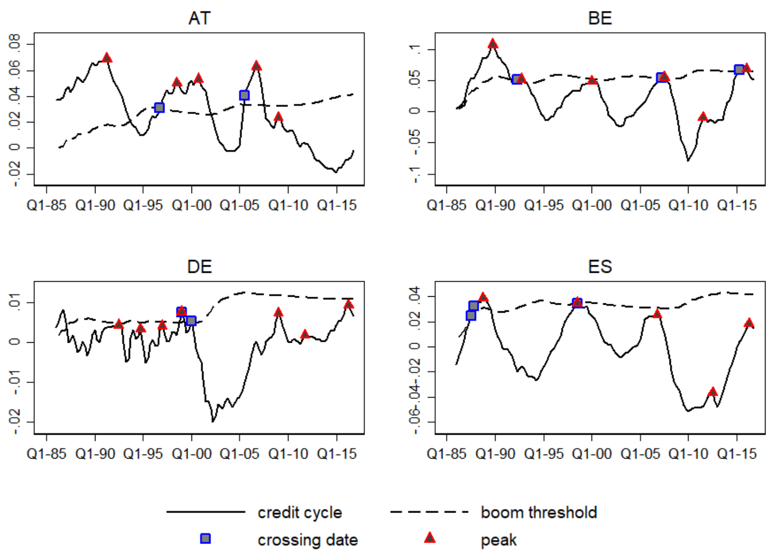


Figure 1.4: Credit Boom identification per country. The figure reports credit cycle identified with only the Hamilton filter.

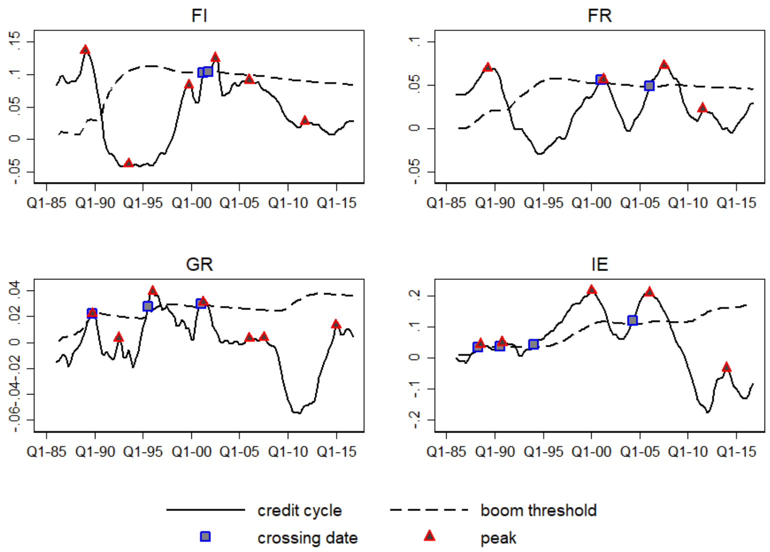


Figure 1.5: Credit Boom identification per country. The figure reports credit cycle identified with only the Hamilton filter.

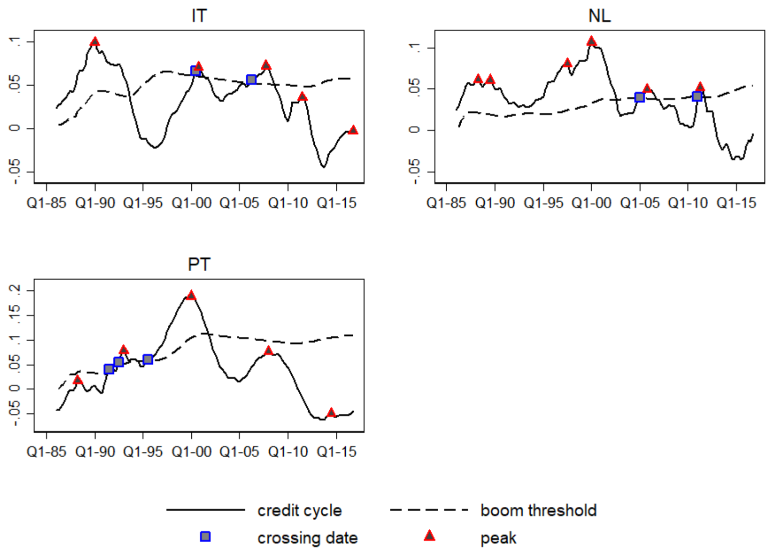


Figure 1.6: Credit Boom identification per country. The figure reports credit cycle identified with only the Hamilton filter.

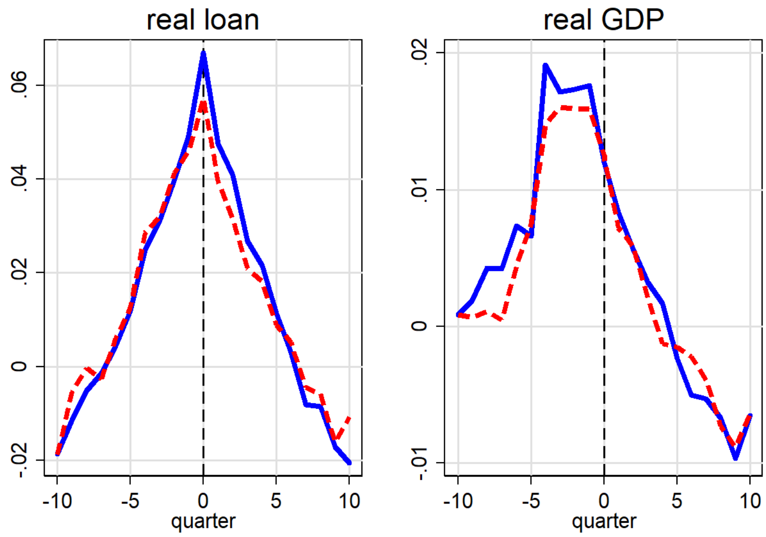


Figure 1.7: Credit Boom event: cross-country means (blue) and medians (red) of real loans and real GDP cycles. Long-run trend here are obtained through Hamilton filter.

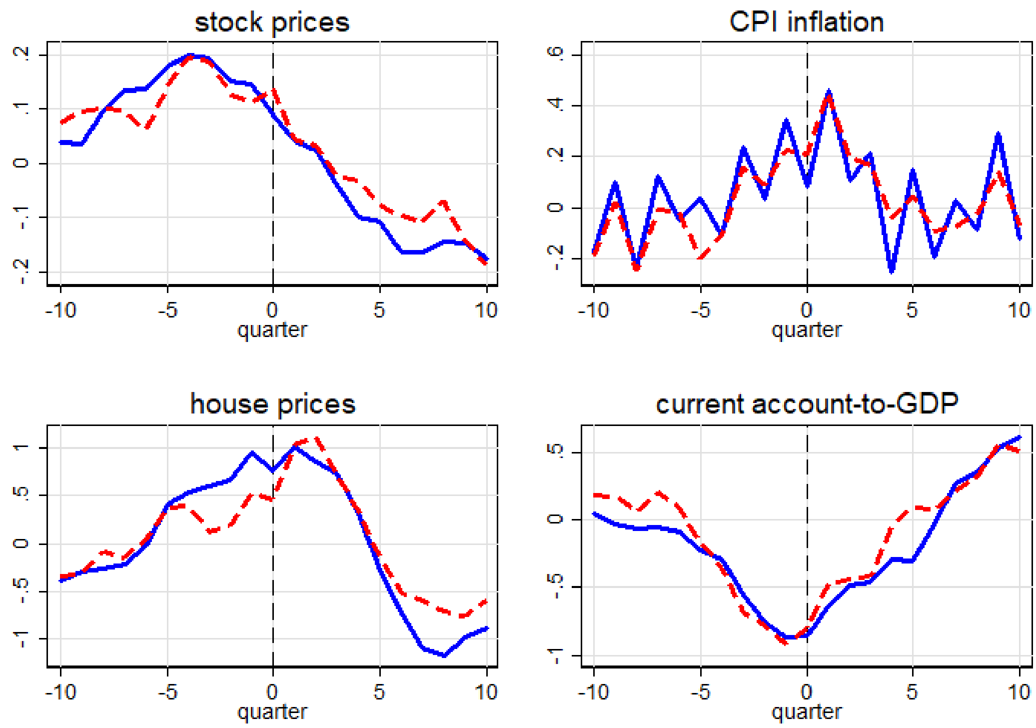
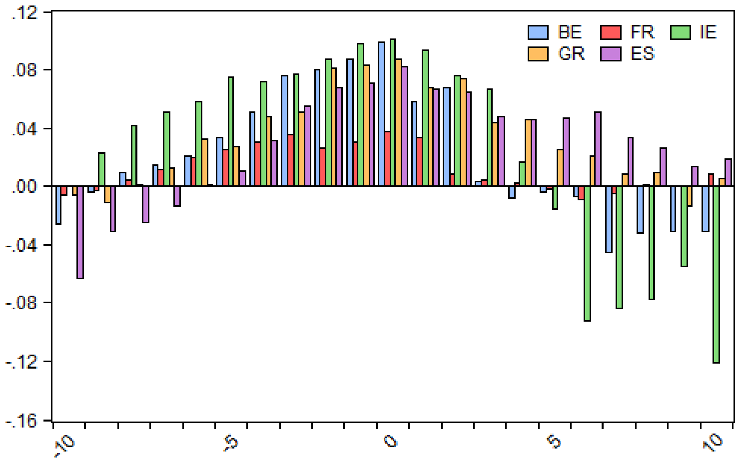
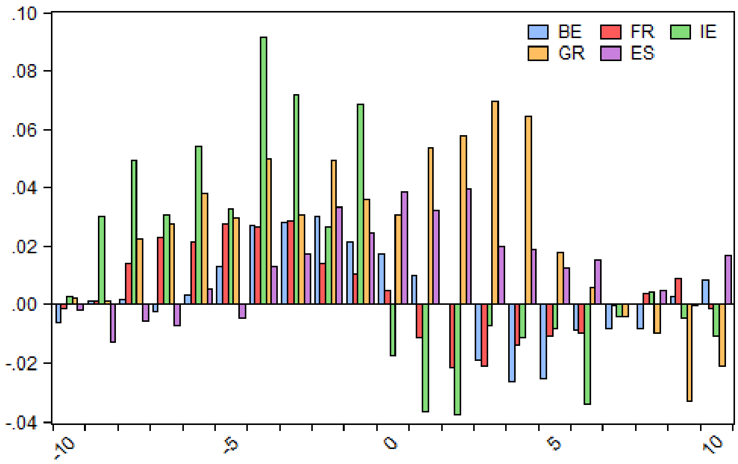


Figure 1.10: Credit Boom event for other macro variables' cycles. Long-run trends are obtained through Hamilton filter.

Figure 1.8: Credit Boom event before Lehman Brother collapse for selected countries



8.1. Deviations of Real Credit from long-run trend obtained through Hamilton filter.



8.2. Deviations of Real GDP from long-run trend obtained through Hamilton filter.

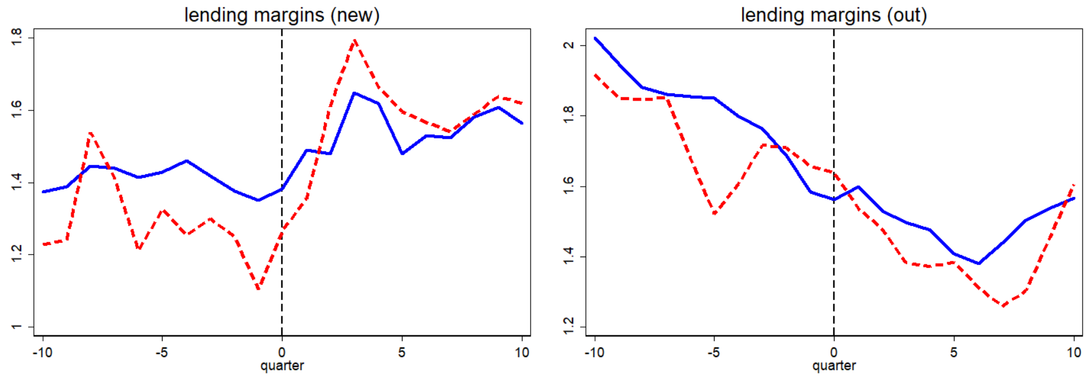


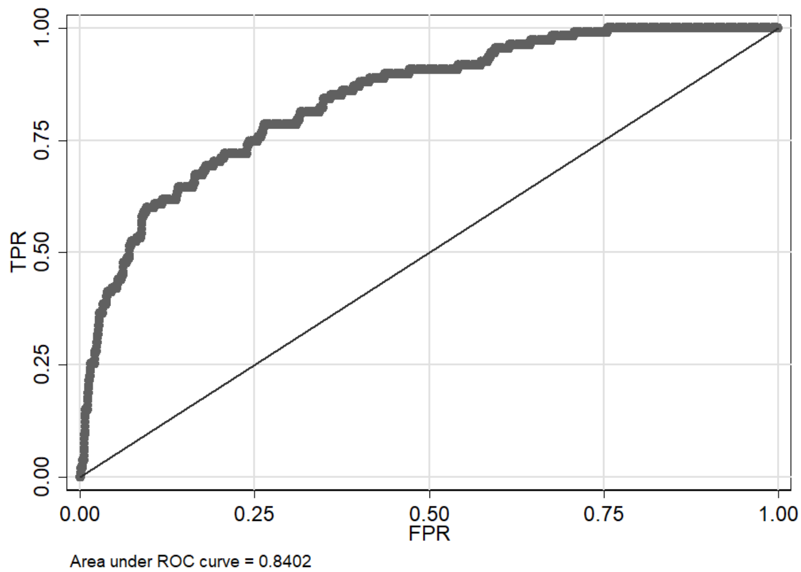
Figure 1.9: Lending margins on new loans and outstanding loans in correspondence of credit events.

		Actual Class	
		$C_{i,t} = 1$	$C_{i,t} = 0$
Predicted Class	$P_{i,t} = 1$	TP	FP
	$P_{i,t} = 0$	FN	TN

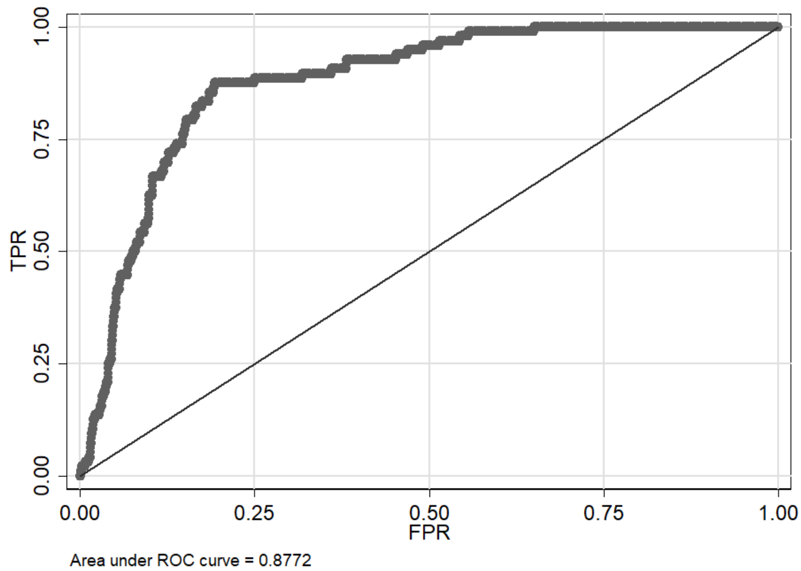
Table 1.5: Contingency Matrix. A TP when the model issues a signal and we observe an actual realization, a FP when the model issues a signal that does not correspond to an actual realization, a FN when the model does not signal an actual realization which instead is observed and a TN when there are no signal and no realization at all.

	Dependent Variable					
	Vulnerability	Credit Boom	Vulnerability	Credit Boom	Vulnerability	Credit Boom
	(1)	(2)	(3)	(4)	(5)	(6)
Real Credit growth	0.146***	0.253***	0.354***	0.344***		
	(0.0258)	(0.0337)	(0.0585)	(0.0737)		
Real Credit growth (non-banking)	-0.122***	0.0327*	-0.0848***	0.0113		
	(0.0193)	(0.0184)	(0.0246)	(0.0392)		
Real Credit to househ. growth					0.713***	0.216***
					(0.159)	(0.0477)
Real Credit to NFCs growth					-0.158***	0.0638
					(0.0591)	(0.0450)
Real GDP growth	-0.180*	-0.141*	-0.101	-0.539***	-0.187	-0.481***
	(0.0992)	(0.0855)	(0.125)	(0.135)	(0.153)	(0.0719)
Inflation	-0.277	-0.888***	0.860*	-1.271**	1.534***	-0.554**
	(0.185)	(0.238)	(0.445)	(0.507)	(0.482)	(0.224)
Stock Index growth	0.0217***	0.0195**	0.0464***	0.00571	0.0535***	0.0136
	(0.00689)	(0.00819)	(0.0154)	(0.0252)	(0.0138)	(0.0131)
House Price growth	0.190***	0.134***	0.206***	0.248***	0.0856	0.144***
	(0.0339)	(0.0346)	(0.0574)	(0.0859)	(0.0583)	(0.0386)
Banking Capitalization	-0.483***	-0.928***	-0.586**	-1.225	-0.668**	-0.387***
	(0.139)	(0.191)	(0.237)	(0.946)	(0.291)	(0.106)
Avg. Lending Rates (Stock)			-1.198***	0.471	-0.864**	1.025***
			(0.358)	(0.559)	(0.363)	(0.272)
Lending Margin (New Business)			-3.544***	-1.065	-3.423**	-1.616***
			(1.106)	(0.754)	(1.344)	(0.624)
Lending Margin (Outstanding)			2.910***	-2.121***	0.515	-0.726***
			(0.732)	(0.776)	(0.921)	(0.236)
Constant	0.792	3.415**	0.853	6.393	0.730	-1.997
	(1.192)	(1.363)	(2.626)	(6.760)	(3.005)	(1.353)
Observations	621	698	405	315	405	315
Pseudo R-Squared	0.279	0.358	0.457	0.336	0.489	0.338
Hosmer-Lemeshow	0.997	0.652	0.992	0.920	0.998	0.854
Opt. Threshold	68	73	77	75	74	84
Type I error	0.401	0.135	0.241	0.142	0.204	0.357
Type II error	0.095	0.192	0.145	0.191	0.170	0.116
aNtS	0.159	0.222	0.191	0.222	0.213	0.180
AUROC	0.840	0.877	0.857	0.880	0.885	0.871
Abs. Usefulness	0.052	0.060	0.071	0.045	0.072	0.023
Rel. Usefulness	0.484	0.613	0.609	0.561	0.618	0.393
%Predicted	86.54	81.39	84.13	81.36	82.48	86.78
Cond. Prob.	0.481	0.368	0.453	0.321	0.425	0.293
Dif. Prob.	0.353	0.253	0.315	0.225	0.287	0.223

Table 1.6: EW benchmark. The table shows the ability of the logistic model in estimating quarters before crisis states (Vulnerability) and quarters before credit events (Credit Booms). Robust standard error are clustered at quarterly level. The policymaker preference parameter is $\mu = 0.85$ for any specification.



11.1. Receiver operating characteristic curve. Model 1: dependent variable vulnerable state (before financial crisis).



11.2. Receiver operating characteristic curve. Model 2: dependent variable credit boom buildup.

	Dependent Variable			
	No Weights (7)	GDP Weights (8)	No Weights (9)	GDP Weights (10)
Real Credit growth	0.230***	0.192***		
	(0.0406)	(0.0304)		
Real GDP growth	0.0105	-0.0732	-0.0628	-0.197***
	(0.0748)	(0.0700)	(0.111)	(0.0728)
Inflation	-0.346	-0.779***	-0.344*	-0.686***
	(0.272)	(0.198)	(0.201)	(0.158)
Stock Index growth	0.0216**	0.0170**	0.0242***	0.0192***
	(0.00898)	(0.00725)	(0.00807)	(0.00725)
House Price growth	0.155***	0.168***	0.146***	0.136***
	(0.0336)	(0.0373)	(0.0329)	(0.0366)
Banking Capitalization	-0.981***	-0.822***	-1.246***	-1.116***
	(0.241)	(0.194)	(0.182)	(0.172)
Real Credit to househ. growth			0.152***	0.156***
			(0.0352)	(0.0340)
Real Credit to NFCs growth			-0.00522	0.0523*
			(0.0343)	(0.0293)
Global Credit growth	0.191***	0.941***		
	(0.0423)	(0.261)		
Global GDP growth	-0.261***	-0.558**	-0.147***	-0.175
	(0.0587)	(0.245)	(0.0507)	(0.187)
Global Inflation	-0.138***	-0.654***	-0.102***	-0.377**
	(0.0437)	(0.253)	(0.0347)	(0.176)
Global Stock growth	0.0106*	0.00303	0.00989*	0.00330
	(0.00615)	(0.00463)	(0.00569)	(0.00448)
Global House Price growth	-0.0392	-0.373**	0.0232	-0.114
	(0.0334)	(0.145)	(0.0356)	(0.163)
Global Credit to househ. growth			-0.0572	-0.123
			(0.0380)	(0.173)
Global Credit to NFCs growth			0.123***	0.594***
			(0.0251)	(0.202)
Constant	2.845	2.674*	5.402***	4.495***
	(1.787)	(1.411)	(1.275)	(1.137)
Observations	698	698	683	683
Pseudo R-Squared	0.523	0.428	0.460	392
Hosmer-Lemeshow	0.370	0.253	0.928	0.058
Opt. Threshold	74	80	71	71
Type I error	0.052	0.177	0.056	0.089
Type II error	0.174	0.118	0.203	0.206
aNtS	0.185	0.143	0.215	0.226
AUROC	0.932	0.904	0.917	0.893
Rel. Usefulness	0.712	0.673	0.656	0.630
%Predicted	84.03	87.52	0.812	80.64
Cond. Probability	0.415	0.475	0.366	0.355
Dif. Probabiblity	0.299	0.341	0.255	0.244

Table 1.7: EW and Global Variables. The table shows the ability of the logistic model in estimating quarters before credit booms. Robust standard error are clustered at quarterly level. The policymaker preference parameter is $\mu = 0.85$ for any specification.

	Out-of-sample		Multinomial Crisis		Multinomial Boom	
	$\mu = 0.85$	$\mu = 0.6$	Credit Boom	Crisis/Post-crisis	Crisis-boom	Tranquil-boom
Real Credit growth	0.168***	0.168***	0.0820**	-0.0546*	0.153***	0.122
	(0.0491)	(0.0491)	(0.0363)	(0.0283)	(0.0504)	(0.0777)
Real GDP growth	-0.241**	-0.241**	-0.0647	-0.206***	-0.248***	0.296**
	(0.0994)	(0.0994)	(0.0851)	(0.0695)	(0.0951)	(0.125)
Inflation	-0.841***	-0.841***	-0.637***	0.274*	-0.135	-3.065***
	(0.310)	(0.310)	(0.242)	(0.141)	(0.272)	(0.933)
Stock Index growth	0.0440***	0.0440***	0.0158	0.0143	0.0506***	0.00895
	(0.00776)	(0.00776)	(0.0103)	(0.00897)	(0.0137)	(0.0184)
House Price growth	0.291***	0.291***	0.218***	-0.0949***	0.135***	0.304***
	(0.0501)	(0.0501)	(0.0379)	(0.0294)	(0.0447)	(0.109)
Banking Capitalization	-0.531	-0.531	-0.990***	-0.0726	-0.705**	-0.708
	(0.514)	(0.514)	(0.270)	(0.0681)	(0.320)	(0.551)
Global Credit growth	0.362***	0.362***	0.297***	-0.0419*	0.187***	0.570***
	(0.0617)	(0.0617)	(0.0453)	(0.0218)	(0.0404)	(0.146)
Global GDP growth	-0.323***	-0.323***	-0.297***	-0.116*	-0.183***	-0.351***
	(0.0981)	(0.0981)	(0.0850)	(0.0677)	(0.0599)	(0.123)
Global Inflation	-0.183***	-0.183***	-0.0884*	0.132***	-0.132***	-0.240*
	(0.0529)	(0.0529)	(0.0511)	(0.0512)	(0.0472)	(0.123)
Global Stock growth	-0.00298	-0.00298	0.0133**	-0.000909	0.00283	0.0190
	(0.00572)	(0.00572)	(0.00656)	(0.00560)	(0.00695)	(0.0130)
Global House Price growth	-0.228***	-0.228***	-0.0507	-0.0478*	-0.0597*	0.0157
	(0.0836)	(0.0836)	(0.0451)	(0.0258)	(0.0357)	(0.102)
Constant	2.966	2.966	1.935	0.183	-16.80	-5.407
	(3.291)	(3.291)	(1.938)	(0.815)	(3,053)	(3.853)
Observations	317	317	833	833	833	833
Pseudo R-Squared	0.472	0.472	0.513	0.513	0.552	0.552
Opt. Threshold	73	86	—	—	—	
Type I error	0.111	0.500	—	—	—	—
Type II error	0.185	0.079	—	—	—	—
aNtS	0.208	0.158	—	—	—	—
AUROC	0.894	0.894	—	—	—	—
Rel. Usefulness	0.641	0.100	—	—	—	—
%Predicted	82.34	87.14	—	—	—	—
Cond. Probability	38.83	0.455	—	—	—	—
Dif. Probability	0.272	0.338	—	—	—	—

Table 1.8: The first two columns of the table report the out-of-sample EW for two values of policymarker preference, μ. The third and the fourth column report the results of the multinomial logit for credit boom buildups and crisis/post-crisis states. The fourth and the fifth columns is the multinomial logit discriminating credit booms leading to financial crises and booms not related with real losses.

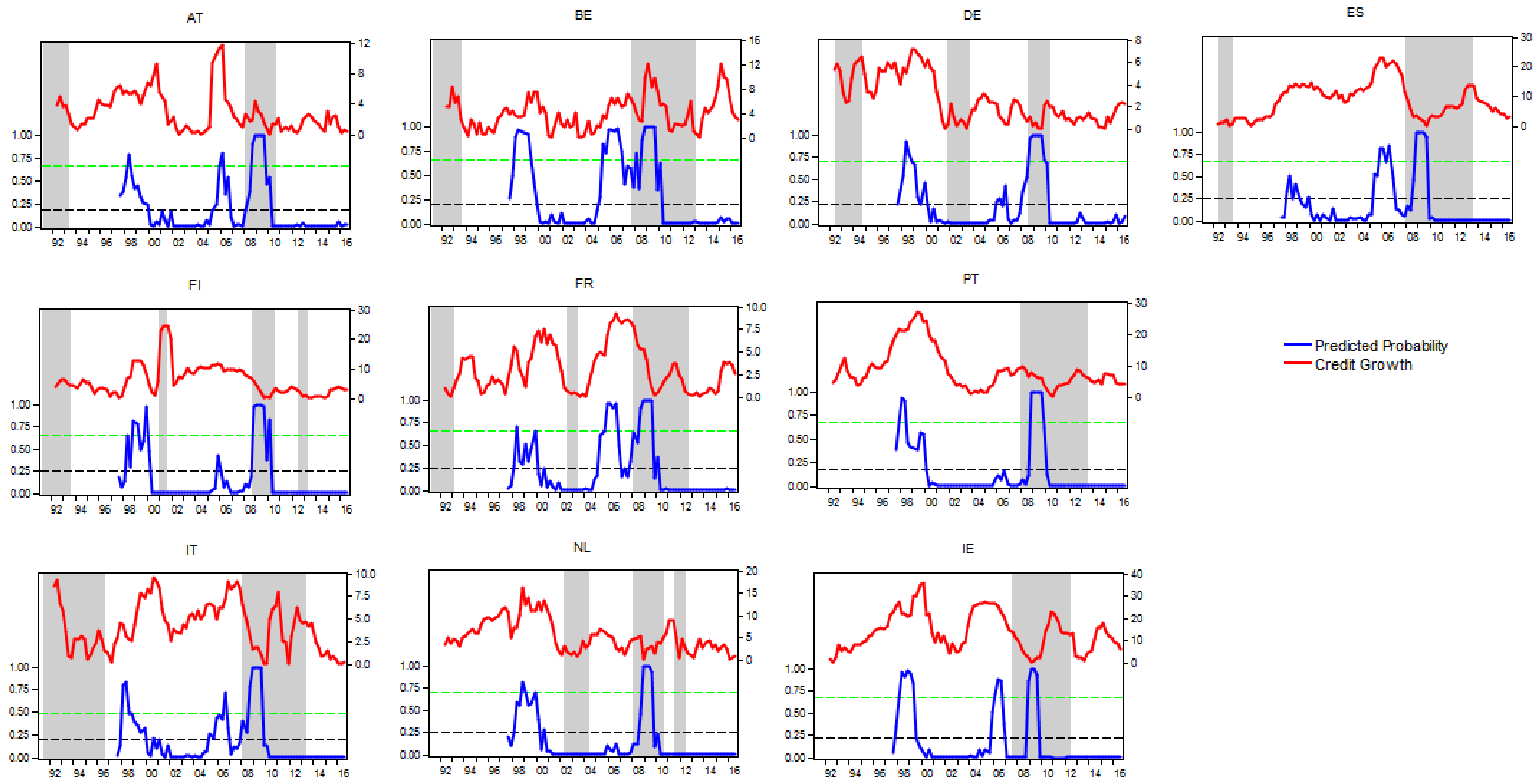


Figure 1.12: Out-of-sample forecasting 2008 Global Financial Crisis. The estimation sample goes from 1998:Q1 to 2005:Q1. EW optimal thresholds are country-specific.

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Chapter 2

Nonlinear credit dynamics and regime switches in the output gap

Joint with Willi Semmler

Over the last two decades the intensity of credit standards' tightening during economic contractions has exceeded their easing during expansions among euro area banks. This mechanism is fed by the boom-bust cycle of credit that, as much research has shown, is linked to financial instability with large effects on the real economy. We build a small scale nonlinear quadratic (NLQ) model to study how credit feedback can affect the overall adjustment path of the economy towards some steady state, when the central bank solve a finite-horizon decision problem where the policy rate is allowed to also be zero or negative. Then, we estimate local projections for a supervisory shock hitting banks' credit standards and propose a new external instrument to identify its dynamic causal impact on the real and financial sector. We find that the regime dependence reveals important information to policy makers to implement macroprudential measures.

2.1 Introduction

One of the main conventionally model which has been used as guidance for monetary policy before the Great Recessions was the inflation targeting model as put forward by Svensson [1997], usually characterized by a Phillips-curve, output gap dynamics and the Taylor rule for setting the policy rate. Financial market components, such as credit dynamics, were not included in those models. Yet after the Great Recession of 2007-9 many academics and policy makers reached the conclusion that the widely used linear monetary policy models are missing some financial market features and are not sufficient for monetary policy guidance. An early statement on the limitations of linear (for example LQ or linearized DSGE) macro models neglecting nonlinearities, in particular with respect to financial market-macro economy interactions, can be found in Mishkin [2011]:

> "The role of nonlinearities in the macro economy when there is a financial disruption implies an important flaw in the theory of optimal monetary policy that was in general use prior to the crisis....The financial crisis of 2007-9 demonstrates that although the linear-quadratic framework may provide a reasonable approximation to how optimal monetary policy operates under fairly normal circumstances, this approach will not be adequate for thinking about monetary policy when financial disruptions hit the economy"

The LQ approach[1] was useful since it allowed for studying effectiveness and long run impacts of monetary policy in normal times. Many central banks had by and large used LQ form models, augmented by the descriptive Taylor rule as the inflation targeting model before the Great Recession. Central banks have also employed DSGE models frequently. Usually these models were constructed in linearized form, allowing for the interaction of product, labor, and financial markets and a large number of shocks (one prominent example is the model by Smets and Wouters [2007]). This allowed for a more extensive assessment of macroeconomic and monetary policy performances.

Yet, given the large meltdown of the financial market in 2007-9 dominant macroeconomic forecasting models were not capable of predicting large scale output losses and the meltdown of the financial sector. Economists realized that these models were missing essential components, such as credit flows and financial sectors (asset prices and banking system) and their interaction with the real sector. Recent work has therefore focused on adding financial sector components, such as asset prices and financial intermediaries, to macro and monetary policy models.[2]

It is noteworthy that there was some earlier work on historical credit boom-bust cycles mostly related to economists such as Fisher, Minsky and Kindleberger.[3] In the tradition of small scale macro dynamic models, Svensson [2017], Ajello et al. [2016], and researchers at the IMF, see Antoshin et al. [2017], have pursued an analysis based on recent empirical research on credit cycles. In fact, it was important empirical work which triggered this new research agenda trying to add credit cycles to small scale macro models of the Svensson [1997] type. Such empirical research was put forward by Jordà et al. [2013], Schularick and Taylor [2012] and Borio [2014], to name a few. The time varying credit gap is now frequently used as measure

[1] The LQ model has also been interpreted as an approximation, using the first order approximation of the Taylor series, of more general equilibrium models (Woodford [2001]) and the New Keynesian version of the DSGE model (Galí [2008]). The lack of nonlinearities in DSGE models has recently also been pointed out by Gertler and Gilchrist [2018].

[2] See Brunnermeier and Sannikov [2014] and Gertler and Karadi [2015] to name a few.

[3] The Minsky view, by referring to credit flows, is also vividly expressed in Kindleberger and Aliber [2003] when they state: "...the cycle of manias and panics results from the pro-cyclical changes in the supply of credit; the credit supply increases relatively rapidly in good times, and then when economic growth slackens, the rate of growth of credit has often declined sharply".

for the credit cycle and the linkages of credit gaps with asset prices, real estate and banking sector as well as with other macro variables are studied in more detail now. Building on the empirical literature on credit cycles and gaps, small scale models can give relevant insight into the effectiveness of conventional and unconventional monetary policies (UMP). Recent reviews on the need and effectiveness of UMP, and responses to criticism of them, are undertaken by central banks' officials, current and former staff members, for example in Mishkin [2011], Bernanke [2017], Blanchard and Summers [2017] and Blinder et al. [2017]. Those recent evaluations take into account both, the stabilizing as well as destabilizing effects that UMP might have set in motion. Yet, those represent to a great extent central banks' views and academic evaluations from outsiders are still in progress.[4]

In order to study the issue of the stabilizing potentials of conventional as well as unconventional monetary policy we introduce an extended inflation targeting model that takes dynamic equations for credit flows and credit conditions into account. This equation helps in defining the crucial role of credit gaps during and after a crisis. We use short cuts and approximations which can be derived from more general macro models by employing (nonlinear) equations for the Phillips curve with an output gap, an intertemporal IS equation representing the dynamics of the output gap,[5] and a (nonlinear) credit flow equation, which resembles the recent work by Svensson [2017], Ajello et al. [2016], Antoshin et al. [2017] and others. Including those nonlinearities satisfies the Mishkin criticism and allows us to move from a LQ to a NLQ model. Further model variants, including credit flows and their interaction with credit spread and output, are introduced in Gross and Semmler [2017] and further detailed and estimated in Faulwasser et al. [2018].

The inclusion of credit feedback effects in the IS curve allows us to study the consequences of tighter credit constraints for the stabilization policy such as monetary policy. Through numerical solution method of our NLQ model we address the issue that monetary policy alone can hardly be sufficient to prevent deep contractions due to financial crises despite the implementation of unconventional measures (see Yellen [2011]). By focusing on credit standards for borrowers in different economic scenarios we explore how these are related to the stabilization policy. Credit standards are a measure that can be affected directly by financial authorities through the implementation of macroprudential regulation of the banking system. However, we do not

[4] Other dimensions are that the UMP might have generated imbalances arising from new credit bubbles, the impact of UMP on income and wealth distribution, and the international spillover effects of UMP, possibly giving rise to international vulnerabilities due to linkages between economies. Furthermore, there are tapering and exit risks. Employing models that include credit flows, asset prices, financial sector dynamics, the housing sector, fiscal policy, wealth and distributional effects, and open economy extensions with endogenous risk build up might be helpful for evaluating the negative long run effects of UMPs. Yet these aspects are outside the scope of this paper.

[5] For further derivations such approximations we are using above, see Zhang and Wu [2016] and Cúrdia and Woodford [2009].

model explicitly the financial market and the effect it may have on tighter or relaxed credit standards.

In order to see whether a supervisory change, orthogonal to the central bank action, affects credit dynamics and economic activity independently, we explore empirically the dynamic causal impact of a shock to credit standards among EA countries. We identify the exogenous shock through an instrumental variable that is used to estimate local projections (IV-LP) in the spirit of Stock and Watson [2018]. The new instrument we develop accounts for mandatory rotations of external auditors (MAR) that banks are forced to meet when the auditors tenure exceeds a given number of financial years. These rotations come from country-specific regulatory schemes that are set to preserve the independence of the external auditors of banking institutions. We show that this institutional idiosyncrasy is not only relevant for credit standards but also that it is distributed randomly among banks and than it can be used to study the effect of the shock as in a quasi-experiment.

The supervisory shock resembles the idea of capital framework effect as in Borio and Zhu [2012], that is how minimum capital standards affect the way in which banks perceive and manage risks. Then theoretical intuitions lead us to explore whether the shock has a non-linear impact on the economy. Macroprudential measures targeting risk-taking behavior of banks, might be beneficial in good times, but costly during downturns. Indeed, as risk tolerance tend to be lower during expansions and higher during contractions, measures like capital requirements tend to worsening lending activities more during bad times which amplifies the economic downturns (see Borio et al. [2001], Kashyap and Stein [2004] and Hanson et al. [2011]). We show that actually the shock does have a regime-dependent causal impact on the economy, with different implications for credit demand and supply. Therefore, we reconcile empirical findings with the simulation results of our theoretical framework.

The remainder of the paper is organized as follows. Section 2 introduces the NLQ model. Section 3 reports results from model scenarios. Section 4 introduces the econometric model. Section 5 reports the results from both linear and nonlinear local projections. Section 6 presents concluding remarks.

2.2 The NLQ model with credit flows

Following up on the above criticism of missing nonlinearities in the interaction of financial and real sectors, we consider the following system of nonlinear differential equations. The system contains two regime switches, one for the inflation rate in the Phillips curve, and one for credit flows and credit risk in the financial market. This setup is a sufficient approximation for policy purposes. The stylized NLQ model that allows for credit dynamics looks as follows:

$$\begin{bmatrix} \dot{\pi} \\ \dot{y} \\ \dot{l} \end{bmatrix} = \begin{bmatrix} \alpha_1 \pi + \alpha(y) y \\ \beta_1 y - \beta_2 (i + \delta(y) - \pi - r) + \beta_3 (l - l_s) \\ \gamma_1 l + \gamma_2 y + \gamma_3 (i + \delta(y)) - \gamma_4 \pi \end{bmatrix} \tag{2.1}$$

The nonlinear state equations comprise the dynamics of the inflation rate, π, output gap, y, and credit flows, l. What we are proposing is a NLQ model – a nonlinear quadratic model, nonlinear in the state space and quadratic in the objective function.

Note that the deviations from the standard inflation targeting models consist of regime switching behavior of the inflation dynamics, $\alpha(y)$, in the first equation and credit flows and credit spreads, $\delta(y)$, representing state dependent credit spreads, in the second equation. Gross and Semmler [2017] estimate the nonlinearity in the Phillips curve, and Faulwasser et al. [2018] highlight the empirical relevance of nonlinearities in credit flows and credit spreads.

Hamilton and Wu [2012] and Zhang and Wu [2016] define the double term $i + \delta(y) = s$, as the shadow rate, an expression for credit cost in the 2nd and 3rd equations. They derive the shadow rate as a summary variable, consisting of the interest rate (the policy rate) and a risk and liquidity premium, driven by the term spread and a bond risk premia.[6] As they show, though there is a lower bound for the interest rate, the ZLB, the shadow rate can be negative, due to UMP.

Compared to the standard LQ model, the term $\beta_3(l - l_s)$ in the IS equation is added. This term represents the impact of credit conditions on output gap dynamics and on the inflation. The enriched IS can also be derived from a more general NK model with credit constraints for households and firms.[7] This feature emerges in the microfounded works of Nisticò [2012, 2016] and Castelnuovo and Nistico [2010], in which households trading financial assets are replaced by agents with zero financial wealth in each period. As in Castelnuovo [2013], the fact that our β_3 is strictly positive implies that a lower (higher) credit gap leads to output bust (boom) due to tight (eased) access to credit market. Therefore, β_3 allows us to study the impact of credit volume, macro prudential policy, and selective credit policies on our macro dynamics.

The third dynamic equation represents the flow of new loans affecting the dynamics of the credit gap. Much effort has been spent to estimate and evaluate the parameters of the third equation, see Ajello et al. [2016], Svensson [2017] and Faulwasser et al. [2018]. Instead of modeling financial intermediaries explicitly, we may let the change of the flow of new loans to be driven by a feedback from loans, the output gap – for example a negative output gap co-varying

[6] See also Cúrdia and Woodford [2009] who define the credit spread as interest markup set by banks.

[7] A constraint could be given by a loan to value ratio (LTV) which will be relaxed when the LTV is allowed to rise. This ratio is usually impacted by macro prudential policies. With respect to the shadow rate, Zhang and Wu [2016] make also a distinction between normal times and crisis times. This distinction is important when evaluating the effects of UMP.

with nonperforming loans and reduced loan flows by banks[8] – and the shadow rate of the cost of loans $i + \delta(y) = s$, with $\gamma_3 < 0$, and $\delta(y)$, defined by an output gap. The inflation term appears here too, since we are considering real loan flows.[9]

What a typical credit boom-bust cycle and the corresponding credit spreads would look like in the context of our NLQ model, without monetary policy effect and with monetary policy effects (conventional and UMP), is demonstrated in Krishnamurthy and Muir [2017]. The interaction of inflation dynamics, output dynamics and credit dynamics is sketched in system (2.1). How monetary policy (conventional and UMP and their effects) can be introduced in our model is shown next.

Instead of spelling out the general equilibrium effects in a NK DSGE model which takes the mentioned nonlinearities into account, we use our NLQ model of system (2.1) that exhibits some shortcuts, but uses an optimal Taylor rule. The quadratic objective function for the domestic central bank – with nonlinear state equations – is equivalent to the minimization of a sum of weighted quadratic losses:

$$\min_{i(\cdot)} \int_0^T \frac{1}{2} e^{-\rho t} \|\Delta(\tau)\|_\Lambda^2 \mathrm{d}\tau \tag{2.2}$$

with

$$\Delta(\tau) = \Big[\lambda_\pi(\pi(\tau) - \pi_s), \lambda_y(y(\tau) - y_s), \quad \lambda_l(l(\tau) - l_s), \quad +\lambda_i(i(\tau) - i_s)\Big]^\top \tag{2.3}$$

$$\text{subject to (2.1)}$$

with $\lambda_\pi, \lambda_y, \lambda_l, \lambda_i$ being the weights for the targets. The target points are $[\pi_s, y_s, l_s]$, possibly the steady state of of the system. Note that we us a finite horizon model here.[10]

The nonlinearities refer to inflation dynamics, output gap and credit dynamics in a NLQ model. The essential nonlinearities we want to track in our NLQ model are also frequently employed in regime switching models such as Markov switching and threshold models.[11] In general these nonlinearities may be stylized by using some kind of step function such as:

$$\tilde{H}_c(x) = \frac{1}{1 + e^{-c_1 \cdot (x - c_2)}} \tag{2.4}$$

The nonlinearity in our PC curve depends on such a function of equation (2.4) as follow:[12]

[8]There is much recent research on this issue, see Henry et al. (2017)
[9]For further evaluation of the parameters of third equation in system (2.1), using a Bayesian approach, see Ajello et al. [2016], see also Faulwasser et al. [2018] who use the Marquardt algorithm for system estimation.
[10]For a criticism of infinite horizon models, see Korinek and Simsek [2016].
[11]See Granger et al. [1993] and Mittnik and Semmler [2018].
[12]This function resemble the logistic function used in STAR models, see Granger et al. [1993].

$$\alpha(y) = \alpha_{21} + (\alpha_{22} - \alpha_{12})\tilde{H}_c(y) \tag{2.5}$$

The function $\delta(y)$ represents the rise of credit spread depending on the output gap. The latter is depicted in Figure 2.1 based on the following approximation:

$$\delta(y) = \mu_1 \arctan(\mu_2 y - \mu_3) \tag{2.6}$$

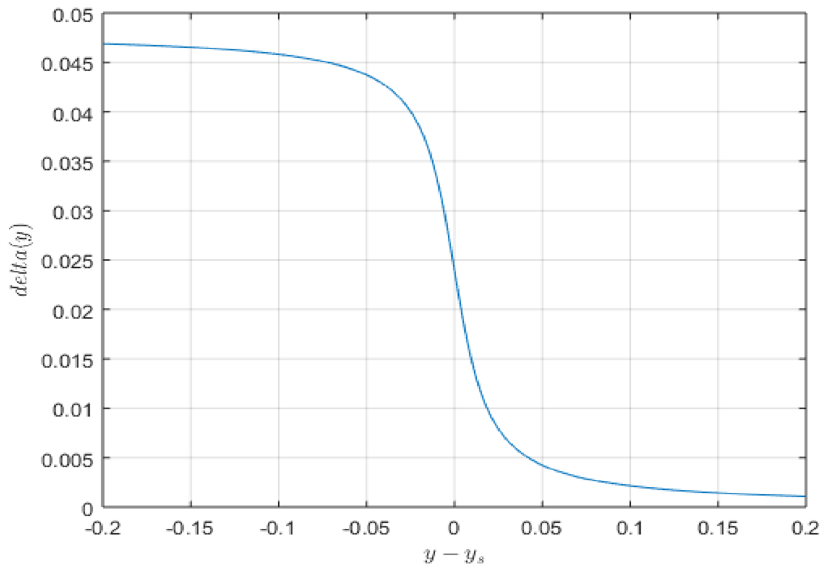

Figure 2.1: $\delta(y)$ function. Note that the credit spread jumps up, as output gap declines below the threshold of $y - y_s = 0$, or near zero. The shape parameter parameters $\mu_1 = -0.1$, the slope $\mu_2 = 5$ and the shift parameter $\mu_3 = 0.05$.

Using estimated parameters, that we borrow from Faulwasser et al. [2018], we can get an approximation of such a function as shown in Figure 2.1 for the output dependent credit spread $\delta(y)$ – or, equivalently, for the shadow rate, s.[13] In other words corresponding to the Okun output gap there is likely to be found a credit spread gap.

[13] Note that we could also use a double sided heavy side function instead of using only the contractionary part of the credit spread $\delta(y)$, or the shadow rate s. The shadow rate and credit spread stays low for some period in the expansion, but the risk premia (and shadow rates) may move up again, due to the rising leverage and rising risk perception, accompanied by a rise in the vulnerability of banks and financial market risk. This case could be econometrically explored by using the ESTAR model suggested by Granger et al. [1993] instead of an LSTAR model as shown in figure 2.1.

Moreover, as to the impact of the output gap and its impact on inflation dynamics – the regime switching of the inflation rate in the Phillips-Curve – we can use an approximation similar to figure 2.2.

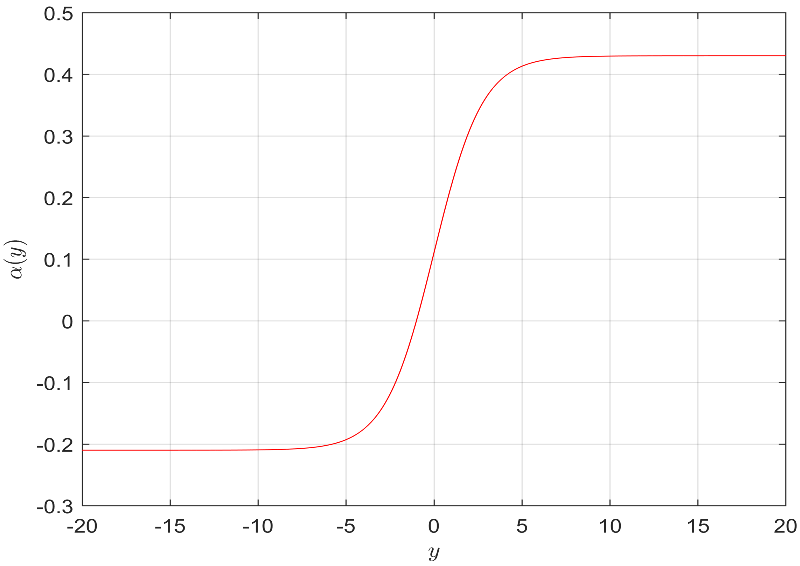

Figure 2.2: $\alpha(y)$ function based on the basis function $\tilde{H}_c$; note that $\alpha(y)$ moves up beyond a certain threshold of the output gap y, note also that such a function produces different inflation dynamics in the recession than in the expansion.

In the following two regimes will be studied. We define the expansionary regime as $R1$ with $y > 0$, and the contractionary regime $R2$ with $y < 0$. For those two regimes the changed credit standards, credit flows, interest rate spreads, the output gap and inflationary dynamics will be studied. To this end we solve system (2.1) globally, by employing estimated parameters, as reported in the numerical solutions. Appendix 1 provides a sketch of the solution method. Faulwasser et al. [2018] employ a full information maximum likelihood (FIML) estimation for the NLQ model, based on EA countries in the period 2003:Q1-2017:Q4. Table 2.1 reports the empirical estimates. As in the previous studies, the parameters related to credit flows signal absence of relationship, which suggest to explore nonlinear dynamics arising from regime dependent credit dynamics and then to consider alternative parametric setting to explore the robustness of our simulations.

	Parameter	Estimate	p-value
PC	α_1	0.67	0%
	α_{12}	-0.21	0%
	α_{22}	0.43	0%
	α_{21}	0	-
	c_2	0.72	11%
	c_1	-0.001	0%
IS	β_1	0.18	0%
	β_2	0.45	0%
	β_3	0.03	3%
Credit	γ_1	0	85%
	γ_2	0.81	0%
	γ_3	0.48	41%
	γ_4	-0.61	52%

Table 2.1: FIML estimation of the NLQ system on EA countries in the period 2003:Q1-2017:Q4

2.3 Results from model scenarios

We explore policy effects in the context of some relevant scenarios for $R1$, with $y > 0$, and the contractionary regime $R2$, with $y < 0$, where credit flow has an initial value below its steady state. For each of those regimes normal as well as tightening of credit standards are considered. Credit standards in general arise from the banking system, as a result of credit constraints, for example by collateral requirements, implementation of changing loan-to-value ratio (LTV) in real estate mortgages, margin requirements in equity markets, banking competition, financial regulations and supervisory guidelines. Therefore, many measures that fall into the area of macroprudential regulation impact the overall level of credit standards of domestic banking systems.[14] However, in the context of our NLQ model, β_3 captures credit constraints for borrowing of households and firms. The more β_3 approaches zero the more credit constraints tighten the availability of new loans to the private sector. In other words, the size of β_3 indicates how much credit standards set by banks constraint borrowers and, hence, it is also a measure of the credit channel of monetary policy.[15]

[14]See Section 2.4 for a detailed description on how credit standards are determined in EA countries.

[15]Implicitly, here we are assuming that only a fraction of agents is eligible to obtain a collateralized loan. For a derivation of such a term in the context of a NK modelt see Zhang and Wu [2016].

Though credit policies that impact banking institutions affect the supply side of credit, the demand of credit by households and firms will be affected too, since their credit constraints are relaxed or tightened. Central for both sides is the credit spread that we define here in our context as the difference between loan interest rate charged by banks and the money market rate. As mentioned we do not model explicitly the asset market and the balance sheets of the banking system. Negative credit shock in the credit market has recently been studied in many papers where it is pointed out that a negative credit shock can come from a decline in asset prices, affecting the banks balance sheets, in the form of reducing their net worth, triggering maybe a fire sales of assets, reducing asset prices further, and so on, for such a mechanism sketched, see Brunnermeier and Sannikov [2014], De Grauwe and Macchiarelli [2015], Schleer and Semmler [2016] and Gross et al. [2018].[16]

Expansionary regime R1 with $y > 0$: Normal loan standards

Next we consider an expansionary regime moving the initial values of the inflation and output gap into a positive region, above their steady state, but allowing for normal credit standards. We consider a initial inflationary environment and positive output gap such as $\pi(0) = 0.03$; $y(0) = 0.05$; $l(0) = 0.18$, with $\beta_3 = 0.15$. We work with normal credit standards, but we set set $l(0) = 0.18$, which is below its steady state. The credit supply is given by banks operating in a expansionary macro economic environment, but here we can think that it is affected, for instance, by a negative shock to asset prices. Figures 2.3–2.4 show how macro variables readjust towards the steady state due to central bank optimal policy.

In the expansionary regime the central bank increases the policy rate at time zero.[17] However, this affects credit flow that goes down suddenly, driving real variables towards a downward dynamics too. The central bank then sets a negative rate that reaches its ELB, and by doing so it manages to drive the economy along the steady state path. Notice that when the output gap turns to be negative both inflation rate dynamics (in Figure 2.3) and credit spread (Figure 2.4) switch into a new regime.[18] Because the credit feedback is sizable, the output gap is more responsive to credit dynamics and the policy influence to the second dimension spreads into the first one. In this scenario, the central bank is able to fully stabilize the economy.

[16] In the latter work a mechanism is also econometrically estimated in a regime change model where banks reduce their loan supply when they are highly leveraged and are in a bad regime.

[17] Notice that our NLQ captures that the central bank's optimal problem incorporates forward-looking expectations about real variables along the overall time horizon.

[18] Here we by-pass to model the slowly recovering banking system and improving asset markets which are likely to aid to reduce the risk premia supporting this way the recovery of the output gap and the success of inflation targeting.

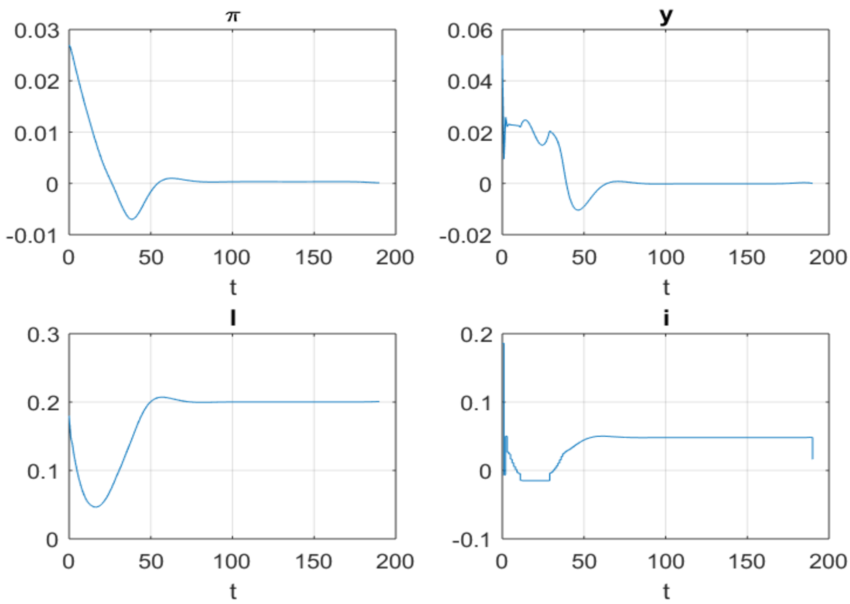

Figure 2.3: Results for $\pi(0) = 0.03$; $y(0) = 0.05$; $l(0) = 0.18$; $\beta_3 = 0.15$. Expansionary regime with positive inflation and output gap.

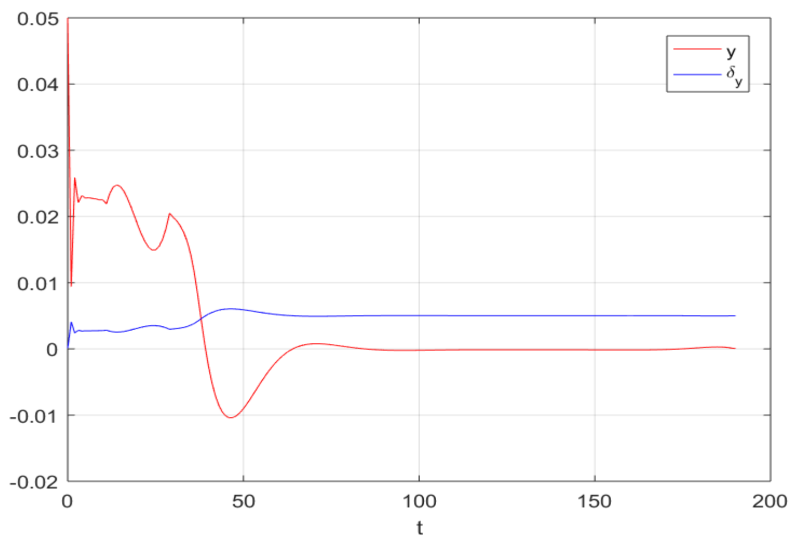

Figure 2.4: The output gap expansion and normal credit standards allow the credit spread to come down, both output and inflation stabilize and credit gap closes

Expansionary regime R1: Tightening of credit standards

Next we consider a scenario where the initial value of real variables is the same as before, but credit standards are tighter. We can think that some financial authority may aim at flagging the build-up of financial risks into the system. In other words, some macroprudential measure, such as higher capital requirements to banks or lower LTV to borrowers, has been activated. In our NLQ model this is reflected in a lower value of the parameter β_3 so to diminish the credit feedback into the IS curve, though we do not model directly any constraint on credit supply. Therefore, the initial conditions are such as $\pi(0) = 0.03$; $y(0) = 0.05$; $l(0) = 0.18$ and $\beta_3 = 0.03$. The results are shown in Figures 2.5–2.6.

Also in this case the central bank is able to fully stabilize the economy, but with a substantial difference. Yet real variables turn into a bad shape as credit flow diminishes, but this time the policy rate does not reach its ELB and stabilizes to a lower level than before. Since the credit feedback has been lowered, the output gap is less responsive to credit dynamics and the monetary policy impact on credit flow transmits less into the real economy. On the one hand, this means that the central bank can avoid to employ UMP when the economy contracts. On the other hand, when credit flow recovers the central bank manages to reach the equilibrium path through a lower policy rate, reducing its optimal "leaning against the wind" strategy. The latter has been formalized in a linear quadratic framework in Svensson [2017], where the inflation targeting regime is adjusted so as to target financial crises.

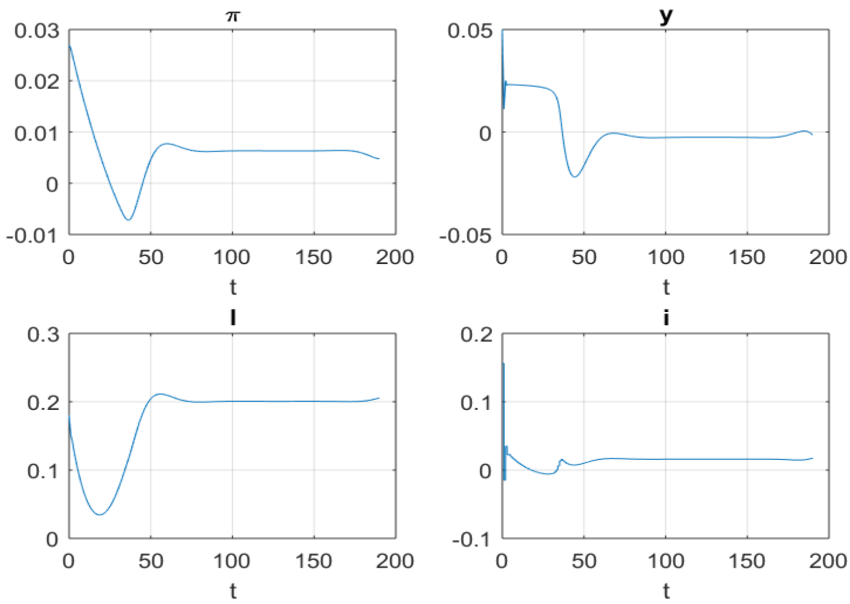

Figure 2.5: Results for $\pi(0) = 0.03$; $y(0) = 0.05$; $l(0) = 0.3$; $\beta_3 = 0.03$; here too both output and inflation stabilize and credit gap closes

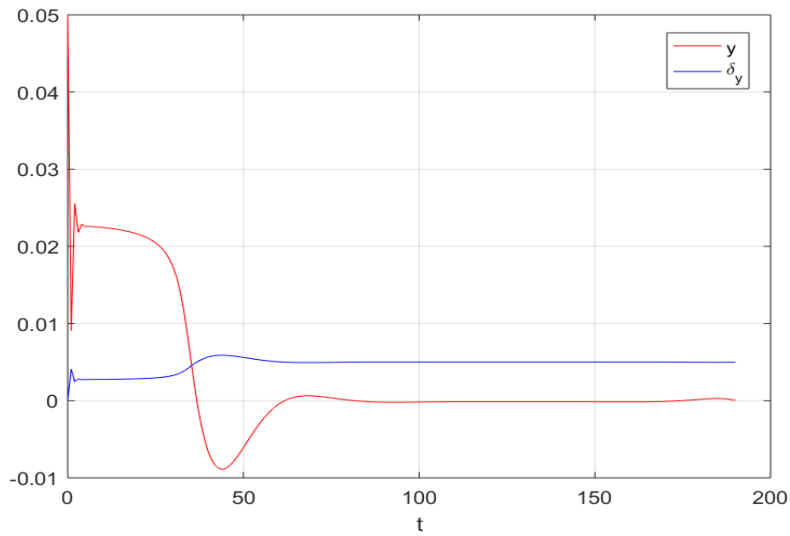

Figure 2.6: For $\pi(0) = 0.03; y(0) = 0.05; l(0) = 0.3$,$\beta_3 = 0.03$; here too, even with stricter credit standards credit spread stabilizes

Contractionary regime R2: Normal credit standards

Next we consider output and the inflation rates moving further away from the steady state, into the negative region. We still allow for low credit flows below the steady state. Initial conditions are then $\pi(0) = -0.027$; $y(0) = -0.2$; $l(0) = 0.18$, with $\beta_3 = 0.15$. In this case of $\beta_3 = 0.15$ and credit demand constraints are relaxed, for example by reducing collateral requirements, allowing for a higher LTV in real estate mortgages, or relaxing borrowing standards through financial regulation. The results are shown for our macro variables in Figures 2.7–2.8. The central bank fully stabilizes the economy within few periods. In this case, since all real variables are below their steady state, the central bank sets the monetary rate at its ELB. The credit spread passes from an higher to a lower regime in less than ten periods. Real variables expand quickly and approach their steady state. The model suggests that UMP works appropriately to respond to macro downturns.

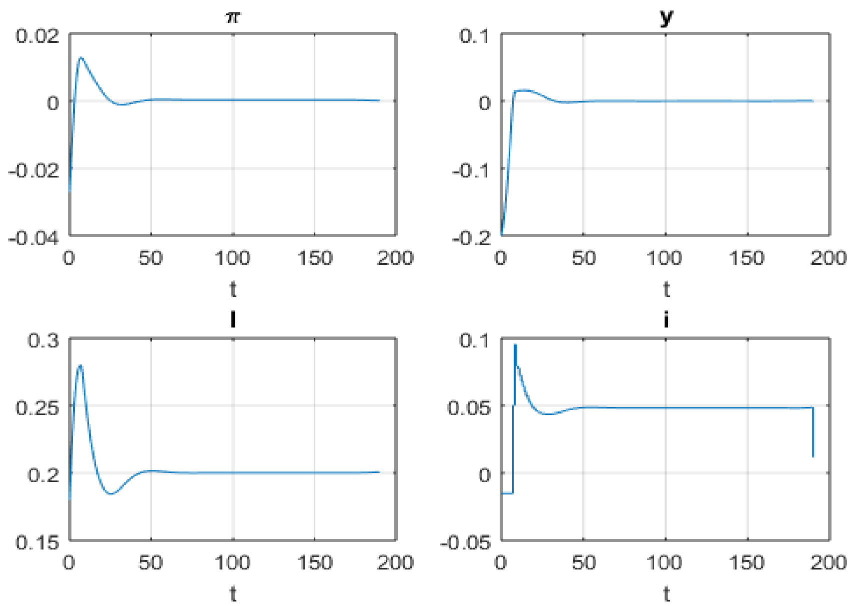

Figure 2.7: Results for $\pi(0) = -0.027$; $y(0) = -0.2$; $l(0) = 0.18$ and $\beta_3 = 0.15$; deflationary regime with negative output gap, but normal credit standards

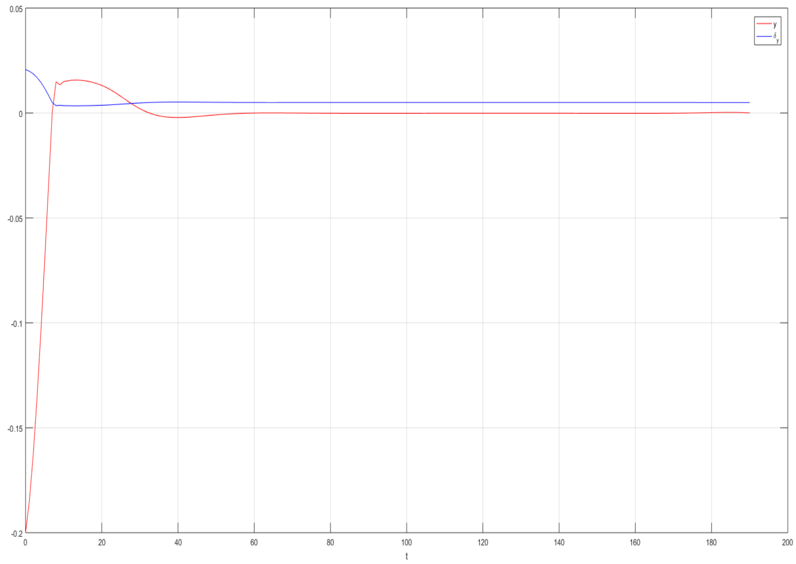

Figure 2.8: Normal credit standards still allow for a convergence; the favorable credit standards make output gap closing and credit spread moving down.

Contractionary regime R2: Tightening of credit standards

Next we assume initial conditions $\pi(0) = -0.027$; $y(0) = -0.2$; $l(0) = 0.18$ but with $\beta_3 = 0.03$, which is a contractionary regime with tighter credit standards. We can think of this case as a financial crisis where the economy faces a recession, accompanied by a weaker credit supply due to a high level on non-performing loans and higher credit spreads. This is what many economies experienced during the global financial crisis. In this context credit standards might be tighter because banks are not willing to undertake new risks on their balance sheets because of the high uncertainty in the system or banks relative exposure.

Credit standards might be tighter also because some macroprudential policy has been activated, like capital requirements or borrowing constraints, to contain the spreading of financial risks though the economy is in a contractionary regime. Figures 2.9–2.10 show the simulation results. This time the central bank is not able to adjust the economy towards the equilibrium path over its decision's horizon. Despite several attempts to stimulate the economy by bringing the monetary rate below zero the central bank fails to stabilize real variables on their steady state. Notice that with respect to the previous case we have changed only the value of β_3.

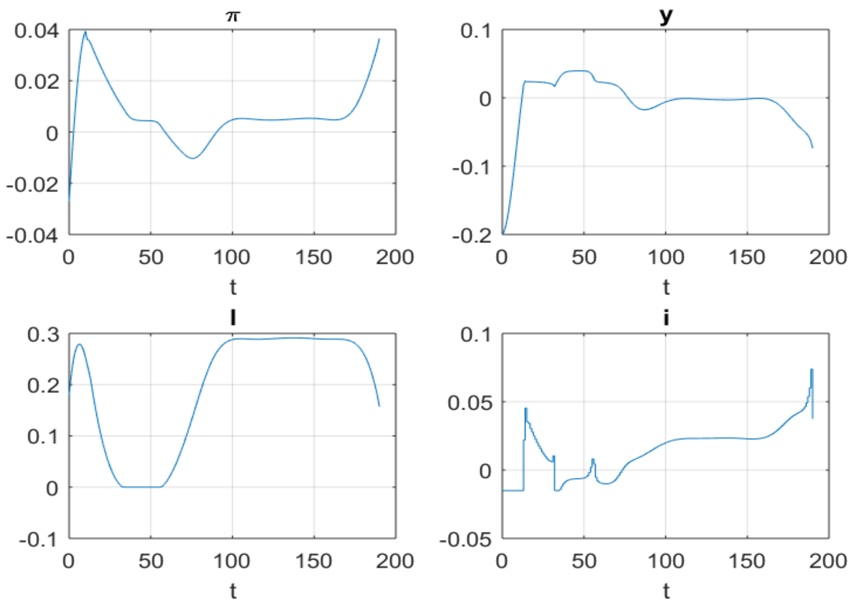

Figure 2.9: Results for $\pi(0) = -0.027$; $y(0) = -0.2$; $l(0) = 0.18$; tightening of credit standards, entailing decline of credit supply and demand, with $\beta_3 = 0.03$

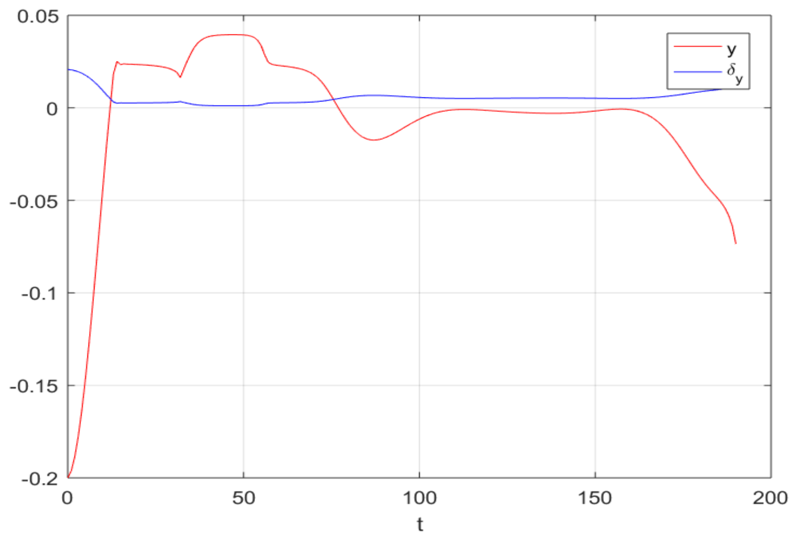

Figure 2.10: Output gap and credit spread, credit spread after falling stays positive and rises, making output gap falling and credit flow falling, finally credit spread rising, interest rate rising and output gap becoming strongly negative

Overall, the model demonstrates that credit feedback, here represented as direct effect of credit supply on credit demand (what we call here credit standards), plays a substantial role for the effectiveness of monetary policy (and UMP) especially when the economy is in a phase of negative output gap. The model shows that a central bank working in an NLQ framework with finite horizon can achieve the stabilization of inflation and output gap. Though changes of credit standards and credit spread compression at the banking system level play an important role too. Yet a tightening of credit standards in a contractionary regime is likely to generate more instability through jumps in credit spreads and negative output gap. This analysis might also point to the limits and the benefits of macroprudential policies as tuning policies.

Others have expressed doubts whether macroprudential policies are available and sufficient. Gourio et al. [2018] state with respect to the US: "Many countries such as the United States have a limited set of macroprudential tools, and suffer from dispersion of regulatory authorities. The tools are difficult and slow to adjust, and their effects remain fairly uncertain". However, as our NLQ model has shown, tighter credit standards flags the credit channel of monetary transmission. This can help the central bank to readjust the economy when an adverse negative shock hits credit supply in an expansionary regime. A direct policy influence on credit standards is more likely to come from macroprudential tools and financial regulations. This is the starting point for our empirical analysis presented in the next session. In the following we try to isolate the effect of a prudential shock that exogenously affects credit standards and study its effects on the economy in the two different regimes of our theoretical model.

2.4 The dynamic causal effect of shocks to credit standards

Our NLQ model has shown that credit feedback effects, interpreted as credit standards that banks set to create new loans, have an important role in the stabilization of the real economy. Broadly speaking, credit standards summarize all those conditions relative to both credit supply, credit demand and competition that affect banks' lending activity. This measure normally builds upon surveys that central banks conduct periodically at bank level. The Bank Lending Survey (BLS) of the ECB is collected every quarter among loan officers of over 140 representative banks of EA countries. The questionnaire is made on credit supply and demand items with reference to both past three months (backward looking) and the next three months (forward looking) relatively to the bank where loan officers operate.[19] More specifically, credit standards are part of credit supply items and represent the internal guidelines or loan approval criteria that banks establish prior to loans negotiations (see Köhler-Ulbrich et al. [2016]).

We take this measure expressed as a net percentage, that is the difference between answers in the questionnaire that indicate tighter standards and the ones indicating easer standards. Positive values correspond to a net percentage of tighter credit standards, while negative values indicate a net easing. In principle, credit standards can be affected by both credit demand factors, such as the economic environment, the creditworthiness of borrowers or the competitive conditions, and credit supply factors, such as the cost of funds, balance sheet constraints or risk-taking tolerance on bank's balance sheet. Our interest on credit standards is because they reflect the willingness of banks to create new loans.

An exogenous shock to credit standards, orthogonal to any other disturbance in the economy, may reveal amplifying effects of credit dynamics that passes exclusively through the banking system. Figure 2.11 displays cross-country averages (red lines) and medians (blue lines) of both credit standards and annual growth rate of total loans from banking systems of nine EA countries. We report also different percentile intervals 35th-65th (30%), 20th-80th (60%), 5th-95th (90%), indicating how these measures are dispersed among countries. Before 2008 EA banks presented low credit standards, that were associated with a turbulent credit growth in a majority of countries.

[19] This forward looking measures are available from 2015 only.

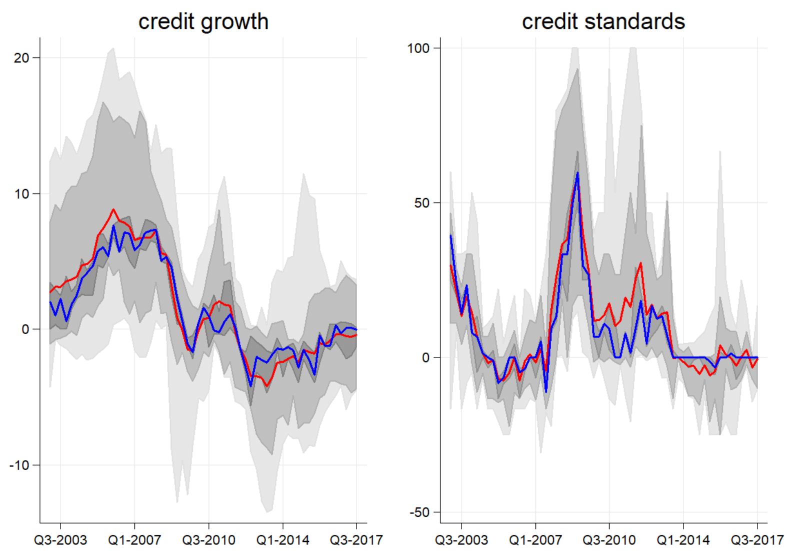

Figure 2.11: credit standards and credit growth. *Note*: cross-country averages (red lines) and medians (blue lines) of the quarterly growth rates of credit growth and credit standards over time. The bands show different percentile intervals, 35th-65th (30%), 20th-80th (60%) and 5th-95th (90%).

The rapid drop of credit growth after the Lehman's collapse was accompanied by a large tightening of credit standards, while the slight recovery of credit growth in the period 2009:Q4-2010:Q4 was associated with eased credit standards. The latter show a negative correlation with the credit cycle. In the recent history of the *credit easing policies* (Draghi, 2015), this negative correlation appears overall weaker although sizable, in view of an higher dispersion of credit growth among EA countries. Changes in credit standards are by construction endogenous to economic conditions in particular to credit dynamics of the banking system.

Yet, exogenous variations in credit standards may help to understand which mechanisms come at play when a shock emerges within banking institutions. However, the identification of a shock to credit standards is not an easy task. Bassett et al. [2014] and Altavilla et al. [2015] build a credit supply indicator upon credit standards in order to identify a credit supply shock. As to our knowledge this is the first attempt to identify a shock to credit standards through an external instrument. In the Appendix 2 we present and explain the construction of the instrument in detail.

Exploiting IV to identify local projections

The external identification in macroeconomics borrows from microeconometric tradition of instrumental variables employed in policy evaluation, and it relies on the use of an external variable that is correlated with the shock of interest but not to any other shock in the economy. In fact, the instrument is aimed at catching an external source of variation in the shock of interest that mimics an as-if randomness, orthogonal to any other macroeconomic shock. This way, one can exploit a quasi-experiment setting to study the effects of some policy treatment.

Jordà et al. [2015, 2017] use the "trilemma" instrument to identify monetary policy shocks. Ramey and Zubairy [2018] estimate state dependent fiscal multipliers using a military news variable. Despite a wide use of external instruments in macro research also in the VAR tradition,[20] the above mentioned authors show that the dynamic causal effect of the shock of interest can be obtained by estimating structural direct multistep forecasts with a IV-LP approach, where LP are local projections of Jordà [2005].

Stock and Watson [2018] (SW, henceforth) highlight that IV-LP allows to estimate the dynamic causal effect without assuming invertibility, according to which the structural shocks must be recovered from current and lagged value of observed data, that is at the ground of structural VAR.

This advantage comes at the condition of meeting the lead-lag exogeneity that is the instrument must be uncorrelated with past and future shocks. Suppose we have an IV, Z_t that we wanted to use to instrument a given shock $\varepsilon_{1,t}$, then, this condition requires $E(\varepsilon_{t+j}Z_t') = 0$ for $j \neq 0$. The latter adds to the standard IV's assumptions of both contemporaneous exogeneity, $E(\varepsilon_{2:n,t}Z_t') = 0$, and relevance, $E(\varepsilon_t Z_t') = \alpha' \neq 0$[21]. We focus on these conditions in the Appendix 2. Once the consistency of the instrument is ensured, then the dynamic causal effect of the shock can be obtained through local projections in a two-stages least squares estimation (TSLS).

Therefore, our IV-LP estimation can be summarized through the following equation:

$$Y_{i,t+h} = \alpha_i^h + \gamma_t^h + \beta^h \widehat{\varepsilon_{i,t}} + \Gamma^h W_{i,t} + \phi^h(L) X_{i,t-1} + u_{i,t+h} \tag{2.7}$$

where $Y_{i,t}$ contains both real and financial variables of interest for country i at time t, while α_i^h and γ_t^h are respectively country and time fixed effects. For each variable's projection we add respective contemporaneous, $W_{i,t}$, and lagged, $X_{i,t-1}$ controls (where L is the lag operator), including the lags of the shock, in order to avoid any serial correlation problem.

We also add other variables to control potential sources of unobserved heterogeneity. This is particularly relevant to ensure the validity of our instrument, that we explore in the first stage of the estimation. Since in the second stage the shock is orthogonal to any other control variable

[20] See, Olea et al. [2013], Ramey [2016], Mertens and Ravn [2013], Gertler and Karadi [2015].

[21] As in the SW's notation $\varepsilon_{2:n,t} = (\varepsilon_{2,t}, ..., \varepsilon_{n,t})'$ denotes the elements of the shock's vector other than the first row.

by construction, we do not include any specific restriction, so that any variable can influence the others, contemporaneously and with lags. At any horizon $h = 0, 1, 2, ...$ a regression is run. The point estimates of the shock at any h represents the dynamic causal effect of the shock $\widehat{\varepsilon_{i,t}}$. Though local projections are more suitable for panel data analysis and allow to easily accommodate nonlinearities, they suffer a lack of efficiency of the estimates at longer forecast horizons.

This cost is also associated to the use of heteroskedastic and autocorrelated consistent (HAC) variance-covariance matrix.[22] Consistently with equation 2.7, we therefore allow for nonlinearities estimating the following equation:

$$Y_{i,t+h} = I_{i,t-1}\Big[\alpha_i^{R1,h} + \gamma_t^{R1,h} + \beta^{R1,h}\widehat{\varepsilon_{i,t}} + \Gamma^{R1,h}W_{i,t} + \phi^{R1,h}(L)X_{i,t-1}\Big] + \tag{2.8}$$
$$(1 - I_{i,t-1})\Big[\alpha_i^{R2,h} + \gamma_t^{R2,h} + \beta^{R2,h}\widehat{\varepsilon_{i,t}} + \Gamma^{R2,h}W_{i,t} + \phi^{R2,h}(L)X_{i,t-1}\Big] + u_{i,t+h}$$

where $I_{i,t-1}$ is a dummy indicating whether the economy is in state $\{R1, R2\}$ in the period before the shock occurs. The dummy I equals one for expansionary observations of the (one-sided) Hodrik-Prescott cyclical component of real GDP (at very low frequency, with smoothing parameter $\lambda = 10,000$).

As in Auerbach and Gorodnichenko [2013], the dummy is taken at $t-1$ so to avoid simultaneity problems between the shock and the state of the economy.[23] As for equation (2.7), the point estimates of $\beta^{R1,h}$ and $\beta^{R2,h}$ coefficients of equation (3.2) at each horizon h provide the state dependent dynamic causal effect of the shock.

[22] In particular, we implement the STATA command *ivreg2* followed by options *cluster* and *bw(3)* giving HAC standard errors computed with Driscoll Kraay correction, which takes into account the potential residual correlation across countries, as well as serial correlation and heteroskedasticity among the residuals over time.

[23] See also Bernardini and Peersman [2018] on this point.

External audit rotations as an instrument

In order to identify the effects of a shock to credit standards, we introduce a novel instrument that takes into account the mandatory rotations of external auditors (MAR) in the biggest banking groups of EA countries. The latter have adopted some rotation scheme in their regulation on bank auditing in order to preserve the independence of external auditors and avoid any risk of material misstatement in the financial information provided to bank's stakeholders.[24] The instrument is built first at banking level and then is aggregated at country level by weighting for the total assets of the single bank over country total assets. We find that this institutional idiosyncrasy has a sizable impact on credit standards, and that it can be seen as a random assignment of a "supervisory" treatment, exogenous to the economic conditions.

The main idea is that, as external auditors need to mature an intimate knowledge of the specific bank functioning, and as their supervisory role has improved since 2000 (mostly due to the guidelines coming from Basel Accords), the change of external auditors implies a radical change in the risk management of the bank that can have relevant effects also on lending activity. In particular, we argue that, because of absence of personal relationships between new external auditors and the bank management, at the beginning of the new tenure the entrants are more prone to adopt a tighter audit strategy in order to enforce their supervisory role. This may affect banks management's decisions and then credit standards. With this shape, our supervisory shock reproduces in fact to what Borio and Zhu [2012] call capital framework effect. While the capital threshold effect would describe how banks readjust their portfolios following a prudential measure, the capital framework effect gauges the impact that supervisory measures have on banks' risk management framework, which is their attitude towards risk. Though banking loans are impacted by banks management decisions, volume measures can hardly be decomposed to identify this effect univocally. Nevertheless, this information is separately contained within credit standards by construction and, therefore, they can be used to retrieve that source of variation.

Notice that despite the possibility of sizable measurement errors, the variable that we build would not lead to any bias in the estimation since we treat this as an instrument rather than a true shock. The rationale and the construction of the instrument are explained in detail in Appendix 2.

[24] From 2014/16 a regulation on external auditors rotation for credit institutions has been adopted at European level. See Appendix 2 for details.

2.5 Shock to credit standards and state dependent impulse responses

Next, we show the dynamic causal impact of a shock to credit standards. The shock is identified through our IV, $Z_{i,t}$ (see Appendix 2). Since this external source of variation stems univocally from an institutional variation at banking level, we interpret our shock as an unexpected change to banking supervision. We take a balanced panel of 9 EA countries in the time period 2003:Q1–2017:Q4 to estimate both equations (2.7) and (3.2). Our dependent variables in $Y_{i,t}$ includes real GDP, the GDP deflator, real total credit from domestic banks, real stock prices and house prices, the lending rate and its difference with the money market rate (what we refer in the model also as credit spread). We use also the seasonally adjusted cumulation of loans as financial transactions, taken by the MFI data of the ECB, which is our measure of credit flow.

As explained in the methodological note of the MFI statistics, the outstanding amounts at the end of each period include not only the cumulative effect of financial transactions, but also reclassifications, breaks in the series, price and exchange rate fluctuations and write-offs/write-downs. As in our theoretical model, we believe that a pure flow measure related to new lending is directly linked to consumption and investment flows, therefore we use the latter as a benchmark for credit. The dependent variables in $Y_{i,t}$ are expressed as the log differences between the variable at horizon $t+h$ and $t-1$. The vectors $W_{i,t}$ and $X_{i,t-1}$ contain respectively contemporaneous and lagged controls expressed in log first difference[25]. Each variable in $Y_{i,t}$ is used as control for the others from $t=0$ up to lag 4. The lags of the shock of interest, $\varepsilon_{i,t}$, are also added to control for serial correlation of the shock. Moreover, the ratio between equity (capital and reserves) and total assets of EA monetary financial institutions is added to control possible heterogeneity arising at banking system level.

Linear dynamic impact. Table 2.2 reports the estimates for equation (2.7) at different horizons for four key variables of interest. We report the Kleibergen-Paap F-statistics for weak instruments at different horizons. These results allow us to reject the null hypothesis that the maximum bias of the TSLS due to weak instruments relative to OLS is higher than 10% (see Stock and Yogo [2005]. Figures 2.12–2.13 show the impulse responses of variables in the linear case at time horizons $h = 0, ..., 20$.

Notice that in local projection's literature most authors hold the sample constant over horizons by using the longest horizon H. However, in this application a reduction of the sample to horizon $H = 20$ would create a shortage of IV's observations so that the resulting F-statistics at the first stage would be too low. Therefore, we allow the sample size to change as the horizon

[25] For robustness we run the model with log level controls also, in order to take into account possible cointegration relationships. We found sizable differences in the linear responses, while not in the nonlinear responses.

increases (see Table 2.2). However, robustness checks have been made and the estimated dynamic multipliers remain consistent.[26]

In each graph the solid lines represent the point estimate, whereas the bands show the 68% and the 90% confidence intervals based on Driscoll Kraay standard errors. The shock to credit standards at $h = 0$ corresponds to a one percent increase as the unit effect normalization, as explained in Stock and Watson [2018], and its effect slowly decays below zero within ten quarters. Real credit drops at the impact about 1% within 20 quarters, while the real credit flow falls about 2%. Both the real GDP and its deflator lower significantly to –0.2%, with more persistent effects for the latter.

These effects on real variables are not dissimilar to the macroprudential shock due to a 1% tightening of LTV, studied in Richter et al. [2018]. Figure 2.13 shows the dynamic effect of the shock for financial variables. The shock has zero impact on the lending rate but then it rises up to 0.5% starting from quarter 5. This result, combined with the permanent decline in the real credit, suggests that the shock implies a credit supply decline. A similar interpretation can be found in Altavilla et al. [2015] who study a tightening shock to credit standards. Accordingly, the credit spread increases about 4 base points within 8 quarters, then the effect vanishes around quarter 18. Apart from a downward tendency we do not find significant effects on house prices, whereas stock prices fall to –0.5% between quarters 5 and 10.

Nonlinear dynamic impact. Figures 2.14–2.15 show the impulse responses of variables in the nonlinear case, which are the point estimate of the shocks in equation (3.2). We study the dynamic causal effect of a marginal tightening to credit standards in two regimes of positive (R1) and negative (R2) output gap. We report also the significance level of the impulse responses when they pass from a contractionary to an expansionary regime, i.e. the difference between R2-R1 point estimates (DIFF).

Policy tools addressing the time-dimension of financial stability are macroprudential measures that try to capture the procyclicality of risk. Whereas measures like countercyclical capital buffers are thought to be effective during economic expansions (see Kashyap and Stein [2004] and Hanson et al. [2011]), other measures like capital requirements or loan loss provisions might be activated also during business cycle downturns, because of an higher perception of risk (Borio et al. [2001]). As shown in Figures 2.14, both credit standards and real total credit respond to the shock with no significant differences in R2 and R1. This means that the nature of the shock and its overall effect on credit are not regime dependent. However, the flow of new lending responds more promptly in R1 than R2, although on a similar extent (about 2% within 20 quarters).

In R1, the lending rate first responds negatively (–1% within 10 quarters) and then turns positive at longer horizons about 1%, but in R2 it responds positively at the impact above to 1% within 15 quarters. These results suggest that during expansions (R1) the shock implies

[26] Results are available upon request.

an immediate downward shift in the credit demand, whereas during contractions (R2) credit supply reduces. A sizable difference is found also in the response of the real GDP (Figure 2.15), that lowers 0.2% more in R2 than in R1 in the 5 quarters after the shock, while inflation reacts slower in R2. Consistently to our model assumption that the output gap drives the credit spread towards an higher regime when negative, the latter increases significantly in R2 about 4 bases point after 5 quarters, while the same effect cannot be observed in R1. Another sizable difference is found in response of the systemic stress index that lowers more in R1 than in R2. No significant difference is found in stock prices responses, while house prices lower about 1% more in R2 within 15 quarters (Figure 2.16).

Overall, in the view of seeing our shock as a macroprudential intervention implemented through a tighter banking supervision, our results suggest that the measure significantly impacts the dynamic of the credit flow and that the latter one transmits the policy impulse to both real and financial variables. The dynamic causal effects of credit standards on real variables estimated through IV-LP is conform to the dynamics that we have observed by simulating the NLQ model with different values of β_3.

The supervisory shock estimated in nonlinear case seems to be more beneficial when implemented during business cycle expansions than during contractions. Indeed, during downturns the shock is transmitted immediately to credit supply with a more negative effect on both real GDP, house prices (at a longer horizon) and stock prices (at a shorter horizon). Moreover, the overall financial risk in the system, represented by the systemic stress index, decreases more during expansions than during contractions. This suggests that macroprudential tools can be effective in good times, but also they can have substantial side effects if still activated during downturns.

2.6 Conclusions

Given the recent empirical evidence on the relevance of credit cycles for macro dynamics and monetary policy, we build a small scale nonlinear quadratic (NLQ) model to study how credit flows and credit spreads and their feedback effects can impact, in quite a nonlinear way, the overall adjustment path of the economy towards some steady state. We pose those nonlinearities as a challenges to central banks' monetary (conventional and unconventional) policy. Then we solve such a model as a finite-horizon decision problem where the policy rate is the control variable and is allowed to become zero or negative.

Monetary policy effects in regimes, such as expansions or contractions of business cycles are studied from the perspective of relaxing or tightening of credit standards. The latter are showed to be crucial for stabilization policy. In particular, tighter credit standards seem to ease the leaning against the wind of the central bank during economic expansions, while they exacerbate macro instability during contractions. The insights from studying the effects of different credit standards in different regimes are then further explored empirically.

In the empirical part the effects of an exogenous shock to credit standards –arising from supervisory changes originating within the banking system, but orthogonal to monetary policy actions– are then studied to see their impact on credit dynamics. We simulate a shock on credit standards as they reflect the willingness of banks to create new loans or, in other words, the degree of access to the credit market for private borrowers. Given a quasi-experimental setting, our analysis shows that changes to credit standards causally impact both real and financial activities.

However, as in our theoretical model, their effects are regime dependent, in particular, local projections are different according to the real business cycle being in an expansionary or a contractionary regime. This non-linear estimation suggests that the dynamics triggered by supervisory shocks, orthogonal to economic conditions, deserves a separate cost/benefit analysis about the timing of the implementation of such a measure. It is noteworthy that our shock identification relies upon an IV that we build starting from mandatory changes of the external auditors within single EA banking institutions. Therefore, the nature of our instrument allows to conceive the shock as a supervisory change that tightens credit standards, like a macroprudential measure aimed at discouraging banks' risk-taking behavior.

A natural interpretation of this shock is what Borio and Zhu [2012] name capital framework, which is the impact of supervisory measures on banks' attitude towards risk. During expansions the supervisory shock lowers credit demand at the impact, while during contractions it reduces credit supply. As noticed in Kashyap and Stein [2004], during contractions banks' balance sheet structure is threatened by loan losses, thus for tighter macroprudential rules banks are forced to shrink further their lending activity, with amplifying effects on both real and financial side. In line with these prescriptions, our results show, on the one hand, the negative impact of the shock on real growth and on financial variables such as credit spreads, stock and house prices, is more pronounced and long-lasting during contractionary regimes. On the other hand, the supervisory shock reduces systemic stress more during expansions than in contractions, which it can be interpreted as a successful outcome of the supervisory measure.

Therefore, our policy notice is that the side effect of banking supervision, in terms of dampening banks' lending activity, is stronger when banks face economic contractions because of a different risk-sensitivity over economic regimes. At the same time, macroprudential policies targeting risk-taking behavior can be beneficial during good times, though with significant, but lower, real costs. As for our NLQ model, this conclusion is in line with the idea that macroprudential policy should embrace a time-varying structure of the risk.

Kleibergen-Paap weak IV	h=0	h=4	h=8	h=12	h=16
Real Total Loans	14.04	11.4	10.67	10.74	17.7
Loan Interest Rate	14.25	11.86	10.84	11.59	19.13
Real GDP	14.52	12.14	10.9	11.28	18.71
GDP deflator	14.41	11.82	11.15	11.53	18.78
Observations	469	435	399	365	331

Table 2.2: IV-Local projections. *Note:* IV-LP over 2003:Q1–2017:Q4. The table reports the Kleibergen-Paap F-statistic for weak instruments

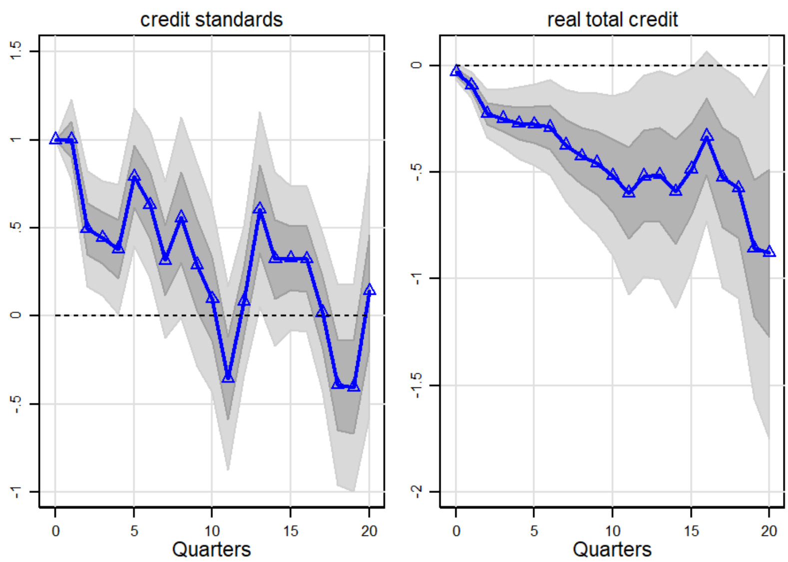

Figure 2.12: Credit standards shock, linear case.*Note*: the figures show 68% (dark) and 90% (light) confidence bands with HAC consistent standard errors.

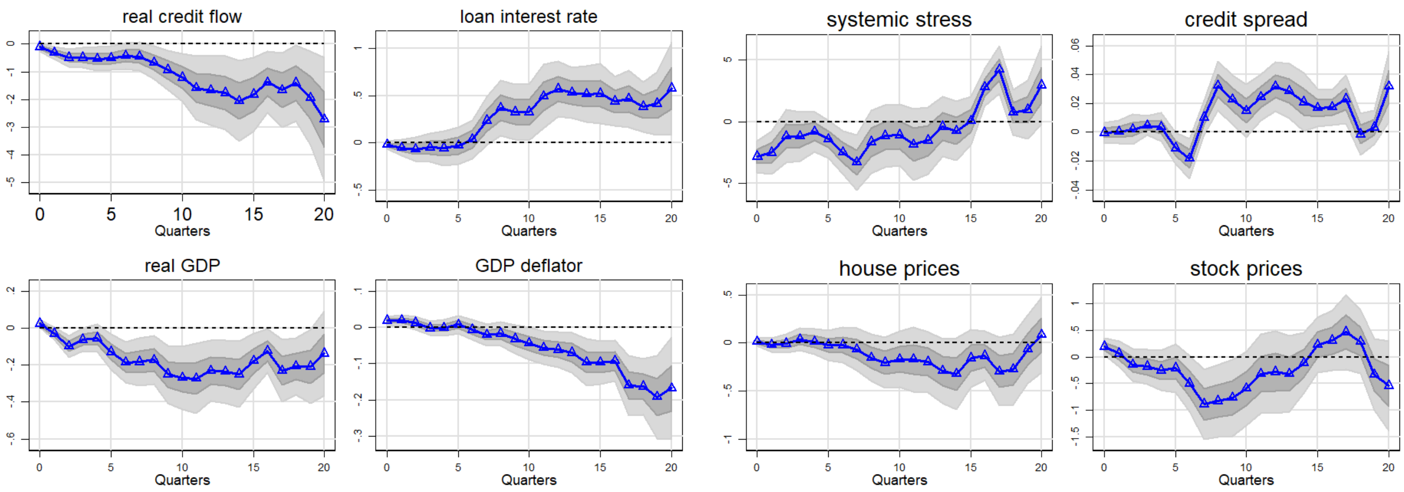

Figure 2.13: Credit standards shock, linear case. *Note*: the figures show 68% (dark) and 90% (light) confidence bands with HAC consistent standard errors.

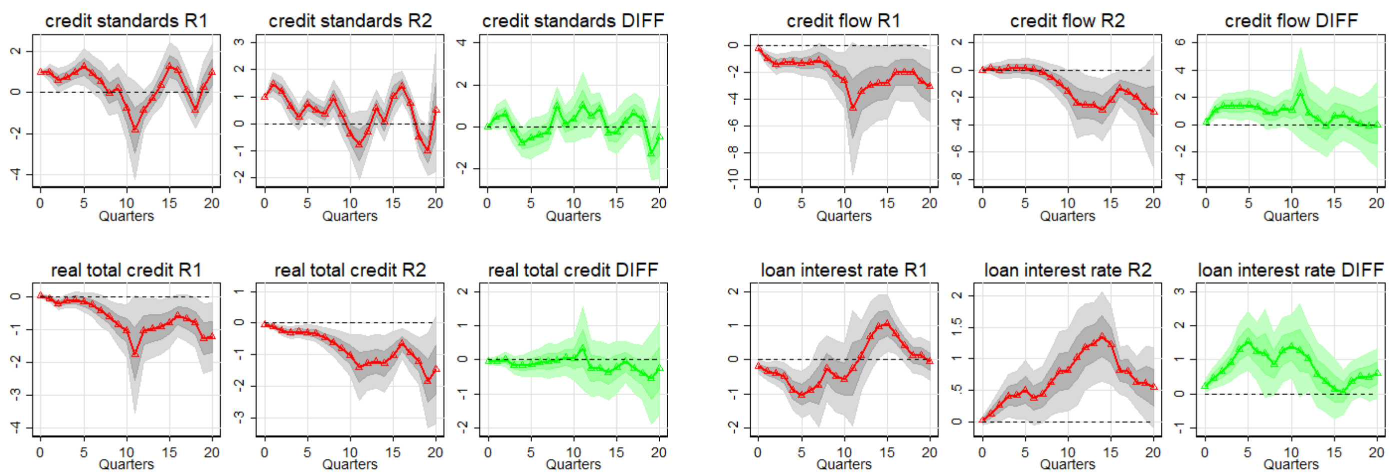

Figure 2.14: Credit standards shock, nonlinear case. *Note*: the figures show 68% (dark) and 90% (light) confidence bands with HAC consistent standard errors. R1 and R2 are regimes of output expansion and contraction, respectively. DIFF is the difference R2-R1 of the dynamic multipliers.

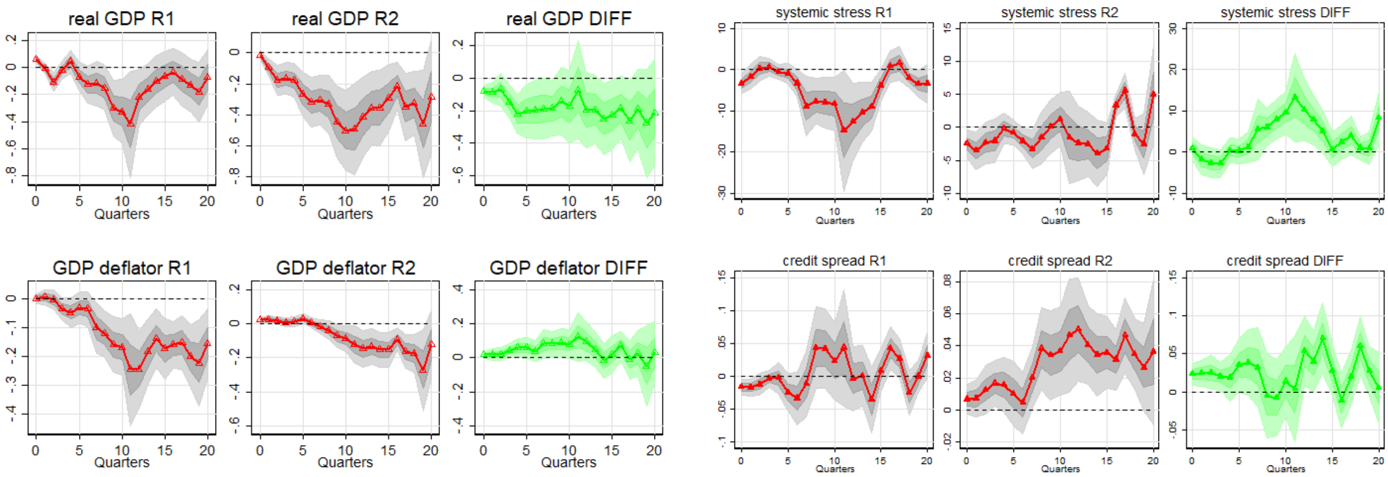

Figure 2.15: Credit standards shock, nonlinear case. *Note*: the figures show 68% (dark) and 90% (light) confidence bands with HAC consistent standard errors. R1 and R2 are regimes of output expansion and contraction, respectively. DIFF is the difference R2-R1 of the dynamic multipliers.

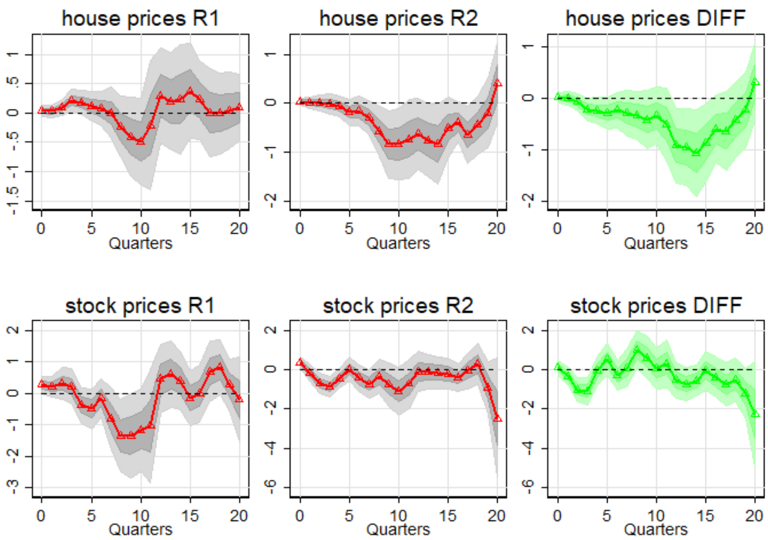

Figure 2.16: Credit standards shock, nonlinear case. *Note*: the figures show 68% (dark) and 90% (light) confidence bands with HAC consistent standard errors. R1 and R2 are regimes of output expansion and contraction, respectively. DIFF is the difference R2-R1 of the dynamic multipliers.

Appendix 1: Solution algorithm

Details of the solution algorithm can be found in Faulwasser et al. [2018]. Here only a sketch is provided such as the computational strategy to find steady states and the dynamics. Parameter estimates used in the computational strategy can also be found in Faulwasser et al. [2018]. First, we need to compute a steady state for the proposed model with two switches of the NLQ system (2.1). To this end, we introduce a state vector $x := (\pi, y, l)^\top$ which allows writing the latter at the steady state as

$$f(x, i) = 0,$$

where $f : \mathbb{R}^3 \times \mathbb{R} \to \mathbb{R}^3$. This is a nonlinear system of three equations and four unknowns.[27] We compute economically meaningful steady states solving the following simple problem numerically

$$\min_{x_s, i_s} \|x_s - x_{ref}\|^2 \text{ subject to } f(x, i) = 0 \text{ and } (5b - 5g).$$

Here, x_{ref} is a chosen economically reasonable reference value. This problem is solved using CasADI (Andersson [2013]) and IPOPT (Wächter and Biegler [2006]). This way we obtain

$$\pi_s = ..., y_s = ..., l_s = ..., i_s = ...$$

which are used then in the penalty function (5a). Solving OCP (5) entailed the following challenges:

- Smoothing out the discontinuities in $\delta(y)$ and $\alpha(y)$.
- Dealing with a possible instability of the dynamics of some differential equations, for example l (for instance for $\gamma_1 > 0$).
- Requiring long horizon and discounting
- Dealing with multiple equilibria of the system

While the first challenge is addressed via smooth approximations form, the second one requires care in choosing the numerical algorithms for OCP discretization. The third and fourth challenge are treated in Faulwasser et al. [2018]. As to the multiple steady states, though we can state that - since our system is nonlinear– there are likely to be multiple steady states, this challenge is not so easy to handle. This issue is preliminary explored for a simplified system in Faulwasser et al (2017) that shows the possibility of multiple steady states for reasonably chosen parameters.

[27] Note that the interest rate is here a control variable that helps to reduce the macroeconomic imbalances through (5a). We are not applying the descriptive Taylor rule as in Galí [2008] (sect. 4.3.1.1) where then in a New Keynesian linearized version the issue of determinacy and indeterminacy is discussed, an issue that is not coming up in our NLQ model.

To solve our system (2.9) we are interested in solving the OCP for (**??**) for horizons of $T \approx 50 - 60$. As the dynamics (2.1) can be unstable, we employ a direct discretization using the open-source tools CasADI (Andersson [2013]) and IPOPT (Wächter and Biegler [2006]), all used in Matlab.

The ODE is discretized using a fixed-stepsize Runge-Kutta scheme of order 4/5 with 15 integration steps per shooting interval. The input i is discretized as piece-wise constant function. For the different present results, we consider equidistant shooting intervals of length $\Delta T = 10$, i.e. the number of shooting intervals equals the horizon length T.

In other words, the OCP is discretized in both control and state variables such that the NLP to be solved reads as follows

$$\min_{i_k, x_k} \sum_{i=0}^{N-1} \rho_k \|x_k - x_s,\, i_k - i_s\|_\Lambda^2 \tag{2.9a}$$

subject to, for all $k = 0, \ldots, N-1$,

$$x_{k+1} = f_d(x_k, i_k), \tag{2.9b}$$

$$x_0 = x(0) \tag{2.9c}$$

$$x_k \in \mathcal{X}, i_k \in [-0.015, 3], \tag{2.9d}$$

where $x_k := (\pi(t_k), y(t_k), l(t_k))^\top$ is the discretized state variable, $i_k := i(t_k)$ is the discretized input, $\rho_k := e^{-\rho t_k}$, and $f_d : \mathbb{R}^3 \times \mathbb{R} \to \mathbb{R}^3$ is the state transition map arising from the employed fixed-stepsize Runge-Kutta scheme.[28]

As for the considered parameter values, the horizon length is limited, we do not employ a receding horizon approach as suggest in Grüne et al. [2015]. Instead, we solve NLP (2.9) directly. However, as the construction of feasible initial guesses is some times challenging, one may need to solve simplified instances of NLP (2.9) to construct those guesses.

Appendix 2: The effects of external audit rotations on credit standards

Before entering the construction of the instrument, we explain the rationale behind its functioning. In other words, we answer to why changes in banks' external auditors should matter for banks' credit standards. Figure 2.17 layouts the flow of financial information relative to new loans' formation. The bank's management establishes the internal guidelines leading the

[28] A detailed and in-depth description of the employed numerical solution method is beyond the scope of the present paper. We refer the interested reader to standard references from the engineering literature, see (Diehl et al. [2006]). Moreover, we remark that we have neglected the multiple-shooting constraints for sake of a simplified exposition, for details see (Bock and Plitt [1984]).

approval of new loans (i.e. credit standards) according to its risk management strategy. These criteria are then settled by loan officers of the banks to borrowers that ask for a new loan according to their investment plans.[29] At the same time, new loans decisions must be consistent with the banks' risk profile: the BIS and the Basel Committee [2000] emphasizes that the management must ensure that bank's credit exposure adheres to prudential standards and internal limits.

Accordingly, the external auditors inform bank's stakeholders on whether all this financial information is genuine or there is a risk of material misstatement through the exercise of their professional judgment. The bank's management is then committed to provide the external auditors with reliable financial information in a timely manner. However, the role of external auditors is more than a mere reporting function: as supervisory authorities are considered part of banks' stakeholders, the role of external auditors has become particularly important for prudential purposes and then for financial stability.

Over the last two decades, the BIS and the Basel Committee [2000, 2002, 2008, 2014] have designed several principles and expectations that are meant to improve this prudential function. In particular, on the one hand, this set of recommendations defines a prolonged and direct collaboration between the authority and auditors that |in case of concrete risk of material misstatement| may also transmit confidential information.[30] On the other hand, the authority stressed that a substantial improvement in the prudential function passes through the exercise of professional skepticism by auditors.

This attitude consists in challenging management's assertions about their accounting choices, especially for those auditing areas affected by management bias, like accounting estimates and instruments' classification, relevant for regulatory capital measures. The willingness of banks to create new loans reflects on its credit standards, but these depend in turn on the bank's capacity to undertake new risk on its balance sheet. The assessment of the risk-bearing capacity and its acceptance by all the stakeholders, is considerably affected by the judgment of external auditors, whose role becomes crucial in a risk-based approach to financial regulation.[31]

At the same time, it seems clear that the success of the audit functioning hangs on the coordination between the central actors involved in Figure 2.17. The relationship between external auditors and bank's management is also a regulatory matter when the independence of the former is jeopardized by the latter, inasmuch external auditors must be independent *in fact* and *in appearance*.

[29] Credit standards can relate to both housing or households consumption purposes or loan demand by non-financial corporations. We are not able to disentangle the effect of the instrument on these different sources, therefore, we take the average of the three sources of credit standards as benchmark.

[30] See BIS and the Basel Committee [2014], *Principle 7*, pg. 20.

[31] In a book published by the World Bank, Van Greuning and Brajovic Bratanovic [2009] consider this approach at the ground of a good assessment and valuation of bank's risk-management.

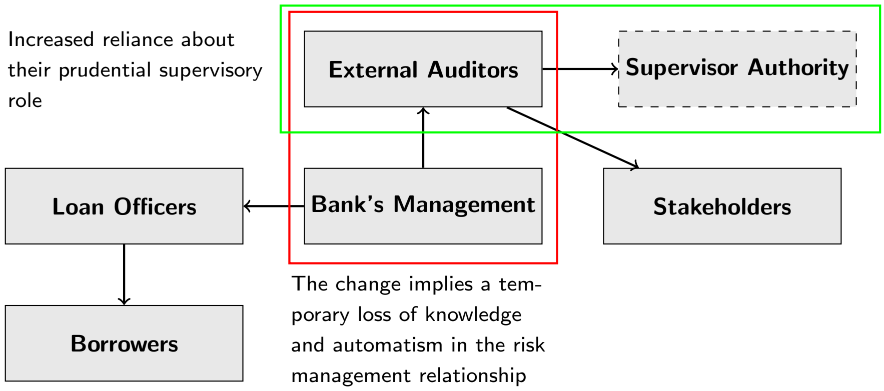

Figure 2.17: credit standards, risk management and bank's supervision

However, a controversial issue is whether long-term tenures favor familiarity and self-interests in the auditors-management relationship, rising concerns about the independence of external auditors. In order to avoid this risk, several countries adopt some scheme of mandatory rotation of external auditors (MAR), that consists in the rotation of the audit firm or of the key audit partner after a maximum of financial years.[32] Whether the MAR implies a trade-off between audit quality and independence is an empirical question of the management literature.

Several studies build cross-sectional analyses on firms or surveys to auditors and managers to study the MAR's effects on estimated measures of financial reporting quality, such as discretionary accruals or other implied measures of earnings quality.[33] However, our instrument is agnostic regarding the effectiveness of the MAR, our interest is whether and how single external auditors changes in big banking groups affects on a small extent the overall willingness of the banking system to issue new loans. On the one hand, for the single bank, the end of the previous audit relationship implies a temporary loss of knowledge and automatisms in the financial reporting process.

At the very beginning of the new tenure, the entrant external auditors would spend a time window to set its audit strategy, so to improve her understanding about the essence of bank's transactions and the financial engineering used by the management. On the other hand, we have seen that more in general external auditors fulfill a supervisory function that has become prominent over the last decades. For these reasons, it seems reasonable that regarding our sample of 30 EA banking groups over the period 2003-2017, for any new tenure observed, the new external auditor that is still not involved in the relationship with the management, is more likely to set a stringent audit strategy than the previous one, at least at the very beginning of

[32]In general, the key audit partner is a representative of the firm that is in charge for the audit and signs the audit report enclosed in the financial report of the bank.

[33]See, among the others, Johnson et al. [2002].

the new tenure. This can pass, for instance, by stringent loan classification criteria, asking for higher loan loss provisions and reserves, or revaluation of past loans.

This in its turn can be reflected in tighter bank's credit standards. Because of the mandatory nature of the rotation, this external source of variation is likely to be exogenous, in the sense that its effect cannot be captured by any other shock of interest. Although in principle the effect of any change of external auditors may result in small positive variations of credit standards, we cannot exclude that a new tenure appointed before the maximum time allowed is correlated with economic or bank-specific conditions, which would violate the exogeneity assumption.

We aggregate the country-specific MARs for supervised banking groups, specifically, the first three biggest supervised entities listed by the ECB in terms of total assets. For each banking group of Table 2.3 we collect the name of the external audit firm and its key auditor partners. We take this information from the annual reports and financial statements of banks in the time period 1999-2017. The banks are chosen so to represent not less than one third of total assets of the country's banking sector over time. The country-specific rules about external auditors rotations (for both partners and firms) have been elaborated and classified in Barth et al. [2013] allowing us to extrapolate MAR rules for banking institutions since 2002, reported in Table 2.4.

The instrument identifies MAR changes on the two quarters following the start of a new tenure only if the previous tenure lasted the maximum amount of time allowed.[34] This choice stands on the fact that, although the tenure starts with the financial year, the first semestral report is signed by former auditors due to the accrual principle. Therefore, for each bank $k = 1, 2, 3$ the MAR variable is:

$$MAR_{k(i),t} = \begin{cases} 2/3 & \text{if firm rotation} \\ 1/3 & \text{if partner rotation} \\ 1/6 & \text{if "cooling-off" rotation} \\ 0 & \text{otherwise} \end{cases} \tag{2.10}$$

where we assign different scores for audit firm, key auditor partner and "cooling-off" rotations. The latter indicates that the new tenure lasts just for the cooling-off period, so we cannot exclude that the change is steered by the audit committee to circumvent the MAR. For country i, we aggregate equation (2.10) and obtain our instrument:

$$Z_{i,t} = \sum_{k=1}^{3} w_{k(i),t} MAR_{k(i),t} \tag{2.11}$$

[34] In principle, we cannot exclude that even in this case the change is linked to bank-specific reasons. However, audit committee decisions (which are normally in charge of appointing external auditors) reported in the annual report, rarely explain in details the reasons behind the new appointments. Then, we assume that if a tenure lasts the maximum amount of time allowed than the only reason to appoint new external auditors is the MAR.

where $w_{k(i),t}$ is the ratio between the total assets of bank k and total assets of the banking system of the country i. The instrument $Z_{i,t}$ is pictured against credit standards in Figure 2.19 for each country and year of our panel. The distribution of the MARs seems independent from credit standards.

Being aware that the presence of MARs during the quarters following the financial crisis (when credit standards were particularly high) may rise some concern about the relevance of the instrument, we rely on time fixed effects to control for such an unobserved heterogeneity. Figure 2.18 shows the scatter plots of our MARs, that seem to distribute randomly around values of real GDP and real total credit growth rates.

In order to test the relevance of our instrument we perform the first stage of equation (2.7). Table 2.5 reports the coefficients for both generic audit rotations and MARs estimated through standard OLS. The regression contains the same controls that we use to estimate equation (2.7) (see Section 2.5), as well as country and time fixed effects. By considering only mandatory rotations the coefficient remains positive and significant and also its t-statistic improves. The F-statistic is fairly higher than 10 and improves in the MAR case. However, in Section 2.5 we provide further tests for weak instruments.

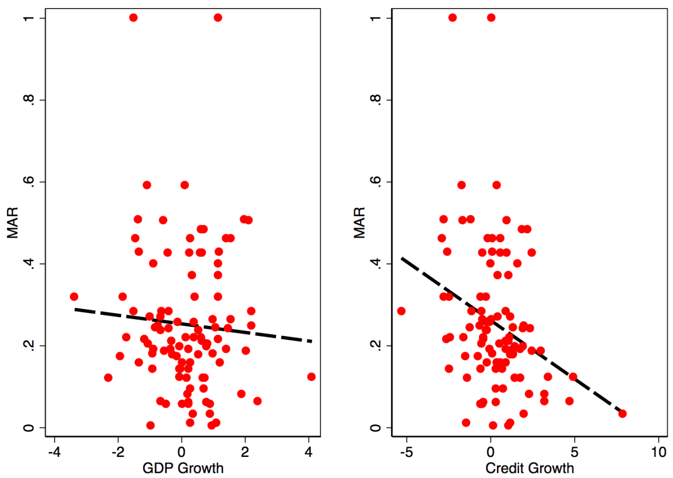

Figure 2.18: MAR distribution. *Note*: scatter plots of the IV against real total credit and real GDP growth.

Credit Institution	Avg. Tot. Assets	Credit Institution	Avg. Tot. Assets
Austria		Germany	
Erste Group Bank	20.17%	Deutsche Bank	19.64%
Raiffeisen Zentralbank Osterreich	12.22%	Commezbank	8.16%
Volksbank Wien	2.01%	DZ Bank	6.13%
Total %	34.41%	Total %	33.93%
Belgium		Spain	
KBC Group	25.40%	Banco Santander	32.67%
Belfius Banque (Dexia until 2012)	37.00%	BBVA	20.75%
ING Belgique	15.36%	Criteria Caixa	12.69%
Total %	77.76%	Total %	66.11%
France		Italy	
BNP Paribas	22.19%	UniCredit	19.81%
Credit Agricole	18.20%	Intesa Sanpaolo	16.43%
Societe generale	14.06%	MPS	5.43%
Total %	54.46%	Total %	41.67%
Greece		Netherlands	
Piraeus Bank	11.36%	ING Groep	43.65%
National Bank of Greece	24.83%	Coop. Rabobank	27.83%
Eurobank Ergasias	14.19%	ABN AMRO Group	12.49%
Total %	50.39%	Total %	83.97%
Portugal			
Caixa Geral de Depositos	21.97%		
Banco Comercial Portugues	17.95%		
Novo Banco (Espirito Santo until 2014)	13.65%		
Total %	53.56%		

Table 2.3: IV-banks. *Note:* over time average (1999-2017) of IV-banks' total assets on total assets of domestic MFIs.

Country	MAR Firm	MAR KAP	Cooling-off
Austria	No (10y from 2016)	No (7y from 2016)	No (3y from 2016)
Belgium	No (9y from 2016)	6y	3y
Germany	No (10y from 2016)	7y	4y
Spain	No (10y from 2016)	5y	3y
France	No (10y from 2016)	6y	No
Greece	No (10y from 2017)	7y	No
Italy	9y	No	No
Netherland	No (10y from 2014)	7y (5y from 2014)	3y
Portugal	8-9y	7y	3y

Table 2.4: MAR scheme. The country-specific rules (for both audit partners and firms) have been classified in Barth et al. [2013] and are valid since 2002.

Credit Standards	AR	MAR
Δ Ext. Audit	21.23**	18.66***
	(8.801)	(6.247)
F-test	16.77	16.94
Country FE	yes	yes
Time FE	yes	yes
R-squared	0.732	0.734
Observations	495	495

Table 2.5: First stage. Non-mandatory (AR) vs mandatory audit rotations (MAR). The estimation includes the controls used for estimating equation (2.7).

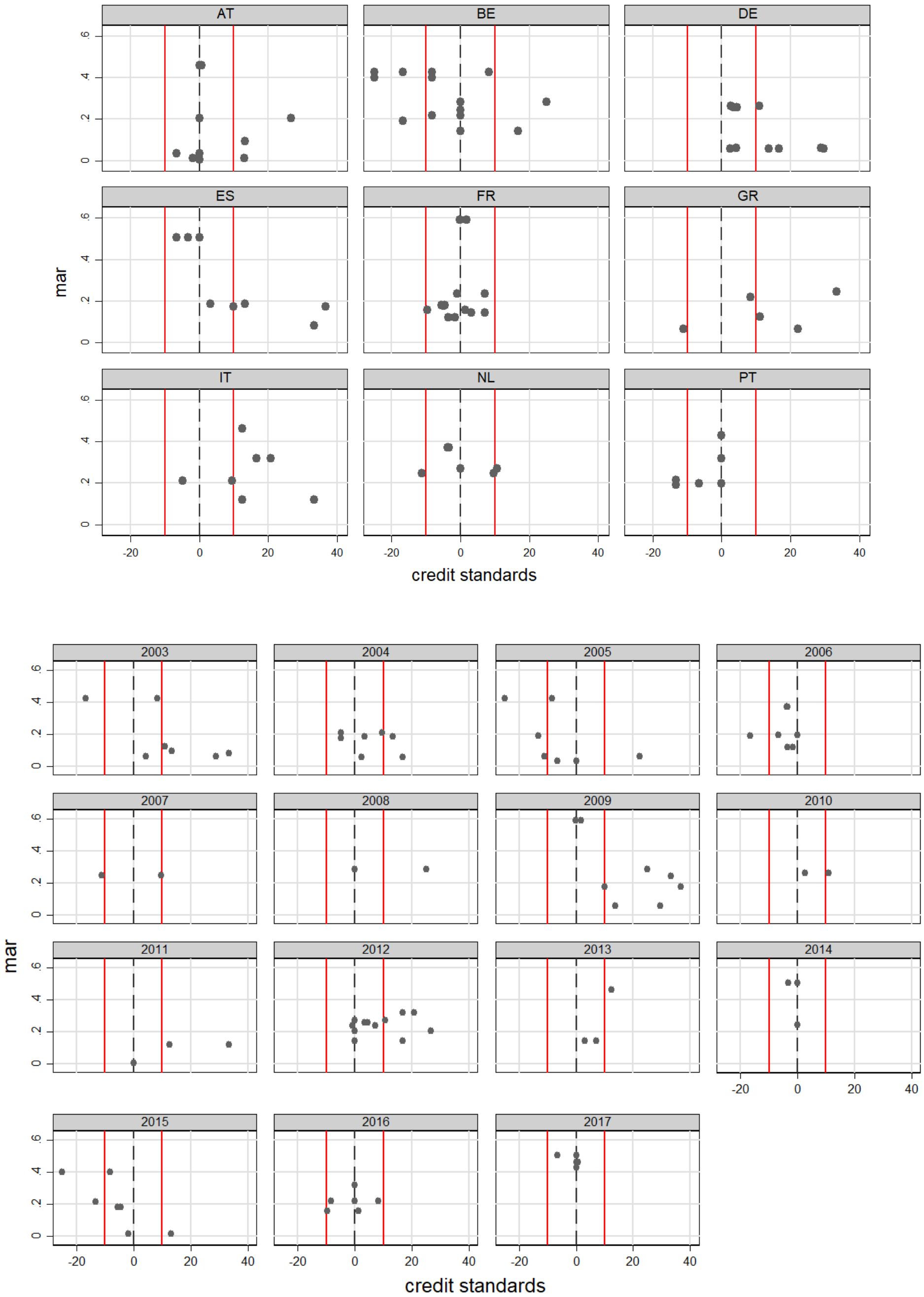

Figure 2.19: Scatter plots of credit standards and MAR by country and year. *Note*: vertical red lines indicate the threshold for significant net tightening/easing (±10).

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Chapter 3

Capital requirements shocks in Euro-Area countries: macro impacts and procyclical implications

Macroprudential policies like capital requirements have become a crucial tool to ensure stability and solvency of the banking system. However, their effects are potentially detrimental for real economy, inasmuch they may discourage banks' lending activity. This paper sheds light on the macroeconomic effects of changes in capital requirements. In the light of the European experience with capital regulation, I identify an exogenous shock to capital requirements by means of sign restrictions in a panel VAR for several EA countries. The structural shock is conceived to have a positive impact on capital ratios and lending rates, while it features a negative impact on bank loans. These effects are negatively transmitted to the industrial production and price level. However, by allowing dynamic multipliers to change with the state of the economy, a capital requirements shock seems to exacerbate the economic downturn by inducing an higher downward pressure on the credit dynamics.

3.1 Introduction

The stability of the banking system is a primary concern for policy makers. In Europe, a bunch of authorities and rules constitute the supervisory framework that pursues banking stability and try to avoid social costs to governments and taxpayers through the implementation of policy instruments.[1] Macroprudential capital requirements to banks are the core instrument of this framework. They have been implemented mostly through European and national regulations that endorsed the decisions made by the Basel Committee on Banking Supervision (BCBS). The final goal of capital requirements is to prevent banks to compress lending activity during recessions while maintaining higher capital ratios to assets in good times (Kashyap and Stein [2004])[2]. However, whether capital requirements are effective to sustain the stability of the banking system and their transmission to the real economy are two empirical questions without conclusive answers.

From a macro perspective, the empirical identification of macroprudential capital requirements struggles with two main problems. The first concerns the cross-sectional dimension, which is how banks adjust their balance sheet in response to changes in capital requirements. Banks may achieve higher capital ratios by both increasing regulatory capital and/or reducing asset exposure, in particular the one to risky assets. In the last case a deep deleveraging in the banking system may spread to credit supply with adverse effects on the real economy. In particular, capital requirements would affect aggregate credit supply of regulated banks when their equity is relatively expensive to rise and when the requirement continuously binds bank capital choices, i.e. banks are forced to change their behavior when the regulatory minimum requirement changes (Aiyar et al. [2014]).

A second hardship relates the time dimension of the policy measure. Though capital requirements should rise during economic upswings – they are thought to be countercyclical – the fact that banks overrate risk perception around turning points of the business cycle rises their procyclical implications are debated. As instance, Jackson et al. [1999] claim that the introduction of Basel I capital requirements during the recession in the US and Japan may have limited bank lending activity and contributed to the economic downturn. This concern has been deepened in the literature by Borio et al. [2001]; Kashyap and Stein [2004]; Hanson et al. [2011], to name a few.

For these reasons in this paper the following questions are posed: (1) Can capital measures be conceived as exogenous policy shocks? (2) Do those policies have a relevant macroeconomic impact? (3) Are their effects state-dependent? Or, in other words, do capital-policy announcements exacerbate the procyclicality of credit growth?

I argue that, looking at the recent European experience with capital requirements, the answer to question (1) is yes. Hereby two main empirical challenges motivate the investigation. The first concerns the identification of a structural shock to banking capitalization due to an exogenous change to capital requirements, in order to assess its macro dynamic impact. The

[1] In the European Union and in particular for the Euro Area, most notably the ECB, other national CBs, the EBA and SSM and SRM for the banking union, are the main authorities in charge for banking regulation and supervision.

[2] In what follows I refer to capital-to-asset, equity-to-asset and capital ratio as synonymous. Notice that this measure is unweighted for the risk.

economy is described by a panel VAR of 9 Euro Area countries, which is estimated following a bayesian approach as in Jarociński [2010]. The capital-policy shock is identified by imposing both zero and sign restrictions following the recent developments of Arias et al. [2018]. The restrictions relies upon both theoretical grounds, the empirical evidence and exploiting time-discrepancy regarding contemporaneous effects due to the monthly frequency of the data. The impulse response analysis shows that the answer to question (2) is yes too, but also that the short-run effects of capital requirements shock present a non-negligible country heterogeneity.

The second challenge is to investigate more in detail the consequences of the shock for credit conditions and the real economy in different economic states. The analysis proposed here is still at an early stage, but I consider these preliminary results as a good starting point to further explore the issue in the future. Passing from a linear to a non-linear framework, the structural shock is then employed to estimate local projections (Jordà [2005]), so to obtain state-dependent impulse responses for different measures of credit and lending rates. In this setting, preliminary results suggest that the answer to question (3) is yes too. Capital requirements shocks seem to exacerbate the procyclicality of credit dynamics. At the same time, the results lead to further policy implications in terms of costs and benefits of macroprudential capital measures. Notice that the strategy implemented in this preliminary investigation.

This paper relates to the empirical literature investigating the dynamic effects of capital requirements. Aiyar et al. [2016] estimate a panel VAR to study the effects of changes in capital requirements on UK bank lending. They assume a lower triangular identification scheme, which is capital requirements do not respond to credit innovations. Another similar example for the Euro Area can be found in Behn et al. [2016a] who estimate a global (panel) VAR where capital ratio shocks are identified via sign restrictions under different scenarios. However, those shocks are not directly linked to macroprudential policy actions. This work encompasses both the direct link to macroprudential policy –due to inclusion of an macroprudential index in the panel VAR estimation– and, the identification via sign restrictions that allows to exclude that the shock results from an endogenous response to macro-financial innovations.

A more close related work is Eickmeier et al. [2018] that build a capital requirement index with a narrative approach and estimate the effects of exogenous changes in capital requirements through local projections. The present work also use a narrative index, but the latter takes into account many other macroprudential tools and it is used directly in the VAR to catch the exogenous shock related to capital requirements. Moreover, the panel setting allows to estimate country-level structural shocks and to see whether actually they match capital requirement tightenings in EA countries. Though EA countries employ harmonized capital requirement rules, those rules have been implemented in different dates, at different level of legislation and with a different magnitude. In other words, I argue that some of those measures have an unexpected component, orthogonal to any other macro-financial innovation, that have an independent effect on the economic system.

This paper relates also to the literature that investigates the macro impact of macroprudential policy, like Cerutti et al. [2017]; Akinci and Olmstead-Rumsey [2018]; Richter et al. [2019], to name a few. Moreover, the first part of the paper borrows from the approach of Gambacorta et al. [2014] and Boeckx et al. [2014] who estimate an unconventional monetary policy shock in EA by means of sign restrictions.

The paper is structured as follow. Section 3.2 provides an overview about capital requirements implementation in European countries. Moreover, by arguing the relevance of exogenous changes in capital requirements, it reviews part of the theoretical and the empirical literature related to those measures. Section 3.3 presents the empirical strategy adopted, with focus on the panel VAR model employed and the rationale of the identification scheme. Furthermore, it presents the impulse responses and the structural shocks for each country in the sample. Section 3.4 shows preliminary results on state-dependent local projection technique employed and the resulting estimated impulse responses. Section 3.5 presents concluding remarks.

3.2 The European regulatory framework and exogenous changes of capital requirements

The core of this paper is to analyze the effects of capital requirements in EA countries. In this section I describe the main regulatory changes concerning capital requirements that took place in EA and the main concerns about this macroprudential measure emerged in the literature.

During the past two decades, the banking regulatory framework in Europe has changed radically through the release of Capital Requirements Directives (CRD) that translated the BCBS guidelines into European law. In June 2004, through the so-called Pillar I, the BCBS presented the new regulatory parameters for banks capitalization that characterized the transition from Basel I to Basel II regime. The completion of Basel II within the EU law ended in January 2007 and –differently from the standard approach of the Basel framework– it legally binds all Members States and types of credit institutions.

The fundamental change with respect to Basel I regime relates the improvement of the risk methodologies applied by banks in evaluating their assets. While minimum solvency ratio (which is the ratio between bank's capital and risk weighted assets) stayed overall unchanged to 8%, both market and operational risk corrections enriched the evaluation of banks' total assets. Moreover, banks have been allowed to gauge capital adequacy through internal risk methodologies. This fact has risen some concern about capital requirements as a tool that exacerbates credit procyclicality when the economy is slacking, since risk managers tends to overestimate borrower's probability default during recessions. Discouraging the creation of new loans may result in a further breakdown in the credit market which amplifies the economic downturn (Kashyap and Stein [2004]).

Concerns about the procyclicality of capital requirements are clearly reflected in the words of Yellen [2011]:*"Policymakers need to establish that countercyclical policy tools address cyclical vulnerabilities more effectively than simpler tools that are constant over the course of the cycle do"*. In some country, like in Spain, the procyclicality issue has been addressed by setting dynamic provisioning during credit expansions. Jiménez et al. [2017] recently have found that this kind of countercyclical measure helped to mitigate the credit crunch.

On the one hand, financial authorities addressed this issue with the introduction countercyclical capital buffers in Basel III, which, however, have become fully effective from January 2019. On the other hand, the general approach of Basel III to capital requirements was aimed at improving the resilience of the banking system to financial shocks in general. A better quality and a higher quantity of capital would allow banks to absorb losses during downturns while continuing to finance economic activities (BCBS [2010a]). Those goals to capital base were pursued by introducing and increasing minimum common equity to risk-weighted assets (RWA) from 2% to 4.5%, minimum Tier1 capital on RWA from 4% to 6%, minimum total capital (Tier1 and the supplementary Tier2) to RWA at the same level of 8% and an additional capital conservation buffer up to 2.5% to hold on top of the minimum capital requirement. Moreover, it has been imposed an additional loss absorbency requirement ranging from 1% to 2.5% of common equity for systemically important financial institutions (BCBS [2011]).

The CRD IV package, that characterized the European transition from Basel II to Basel III standards, has been published by the European Commission in July 2011, and enforced through the Directive 2013/36/EU and the Regulation (EU) Nr. 575/2013. The implementation of the latter regarded a set of countries representing about 50% of world's banking assets, with a system of national rules deeply heterogeneous. Policy needs, existent macroprudential frameworks and institutional settings were significantly different among EA countries at that time. Indeed, CRD IV's measures have been implemented through different level of legislation, with different magnitude and timing. This suggests that their introduction have had also country-specific peculiarities. Moreover, starting from 2011, the stability of the EA's banking system has been threatened by the sovereign debt crisis. This has led to a heavy phase of capital requirements and stress tests that, possibly, impacted countries with a different extent, according to relative exposure of their banks to risky countries.

At the first sight, it may seem that macroprudential actions are systematic reactions to periods of financial fragility. However, the general spirit of Basel Accords was aimed at addressing the fundamental fragility of the financial system, so that capital requirements were not conceived as an explicit countercyclical policy tool (Elliott et al. [2013]). Therefore, to differentiate regulatory changes that are driven by macro-financial fluctuations from potential exogenous sources may have important policy implications about the conduct of macroprudential policy. Eickmeier et al. [2018] build a capital requirements index for the US, based on narrative readings of legislative documents. They identify dates in which banks were asked to raise capital ratios simultaneously, in order to address long-run features of the banking system. Those changes were likely to have an exogenous nature. The latter is one of the few example that examines capital requirement changes by using macro level data along the time dimension.

Bank-level analyses are much more prone to achieve this goal, because micro-data allow to face less severe endogeneity problems and to build up policy experiments. One prominent example can be found in Aiyar et al. [2014], who exploit the fact that the Financial Services Authority (FSA) in UK has taken capital requirements decisions through the so-called "trigger ratios", which are based on firm-specific reviews and judgment about market conditions, quality of risk management and banks' system and controls. They show that changes of these ratios are not associated with past and future changes in the credit risk of loans, but more with bank-specific characteristics such as size, reliance on retail deposits and sectoral loan concentration. Therefore, the institutional setup allows them to exclude reverse-causality between credit growth and changes in capital requirements.

Concerning the European experience, capital requirements have been used as a policy instrument with a potential degree of exogeneity. An example is the capital exercise of the EBA, that has been set to test the solidity of the European banking system. In October 2011, the EBA asked to 61 banking groups to "strengthen their capital positions by building up a temporary capital buffer against sovereign debt exposures". More specifically, it asked to reach 9% Tier1 ratio by the end of June 2012. The exercise came just before the implementation of Basel III and few moths after the EBA's EU-wide stress testing. Moreover, the eight-months horizon to meet the new requirement was relatively shorter compared to Basel standards. The exercise was perceived as unexpected also because none of the banks failing the stress test were involved. Therefore, the resulting increase of banking capitalization observed in EA that period was likely an exogenous response to this episode. However, whether the exercise has had some side-effects on macro dynamics is something that is debated in the literature.[3]

The role of the EBA capital exercise has been studied through bank-level data by Mésonnier and Monks [2014] and Gropp et al. [2018], and is a good example where capital requirements can be conceived as a policy shock for EA countries. The identification of such a kind of shocks can be helpful in understanding the propagation of macroprudential capital measures to the real economy. In the next section I identify a capital requirements shock in EA countries by mean of zeroes and sign restrictions. Before of doing that, I build a country-level macroprudential index (MPIX) from the Macroprudential Policies Evaluation Database (MaPPED) of the ECB. This database reports the implementation of macroprudential measures such as capital requirements, capital buffers, risk weights, leverage ratios, provisioning systems, lending standards restrictions, limits on credit growth, taxes on financial activities, limits on large exposures, liquidity

[3]Mario Draghi on January 2012 stated: *"I think there are usually, by and large, three reasons why banks may not lend. (...) One is a lack of capital. (...) Now, the EBA exercise was in a sense right in itself, but it was decided at a time when things were very different from what they are today. (...) So in itself under these circumstances the EBA exercise has turned out to be pro-cyclical"*.

requirements and limits on currency and maturity mismatch.[4] The database covers the period 1995-2017 for EU countries and the policy dates are available at monthly frequency for both announcement and enforcement dates.

I select nine core-EA countries in the period 2003-2016 and build the MPIX. The left-hand-side panels of Figures 3.3–3.5 show the MPIX (dashed lines, right axis) against capital ratios of MFIs (solid lines, left axis). The right-hand-side panels report the percentage contribution of single measures to the MPIX in three main macroprudential regimes.[5] Single measures include minimum capital requirements (green), capital buffer (blue), limits on concentration and exposure (red), loan loss provisioning (gray) and leverage ratio (orange). The MPIX in the figure reports the announcement dates. Overall, the index increases in the periods of the adoption of Basel II (2006-2008) and Basel III (2011-2014) within the EU law. In the second period, the MPIX is strongly accompanied by an increase of capital ratios for the large part of countries. However, the overall cross-country correlation between the two of the two is weak. The figures offer also an insight about the heterogeneous experience of countries with macroprudential tools.

Limits on concentration and exposure (red bars) are active since 2003 in all countries as well as minimum capital requirements (green bars) apart from The Netherlands. Across the three-macroprudential periods the latter increase progressively in all countries, reflecting the introduction of CRDs in Europe. Although entered in force from 2016 with Basel III, Germany is the only country where capital buffers (blue bars) are still inactive. With a different timing, capital buffers have been activated elsewhere. In the Netherlands and Portugal capital buffers have been activated in 2014. France, Italy and Greece are the only countries which activated capital buffers before the CRD IV was enforced. From 2008, the Bank of Italy imposes minimum Core Tier1 on case-by-case basis. Since 1951, Greek's law foresees restrictions on profit distributions for credit institutions, in order to strengthen their capital base. Here, a sort of capital buffer that has been deactivated in 2007. France has activated capital buffers in 2009 by setting the effective Tier1 minimum ratio to 6% for major banks, as a consequence of the EU wide stress testing. Loan loss provisions (gray bars) are active in Spain, Greece and Portugal since 1999. In these countries central banks activated loss provisions in response to the strong growth of consumer and residential loans. Finally, Belgium is the only country which has had leverage ratios (orange bars) from 1991 until the recent introduction of the one in Basel III. Beside minimum capital requirements, all these other measures also have an independent effect on banking capitalization. Therefore, to hold the MPIX in the analysis may help to find those changes in the system-wide capital ratio that are related to capital-related macroprudential measures.

[4] See Budnik and Kleibl [2018] for details about MaPPED.

[5] I compute the country-specific MPIX medians in Pre-Basel II period (2003-07), Basel II (2007-13) and Basel III (2013-17).

3.3 Shock to capital requirements in Euro Area countries

The panel VAR employed here is developed by Jarociński [2010]. The main idea is that the VAR parameters for individual countries are similar across the region, since all countries considered are special cases of the same underlying economic model. Differently from mean-group and pooled panel VAR estimated through OLS, this model takes into account cross-sectional heterogeneity, that is the economic innovations are allowed to have unit-specific slope, intercept and variance, and it allows to compare impulse responses of different countries while dealing with short time series.

However, the model does not take into account static interdependency, that is the innovations are not allowed to be correlated across units.[6] This can be a potential threat since capital requirements entered into force through EU-level laws. At the same time, as explained in detail in the next subsection, national regulators have adopted capital requirements in different dates and through different level of legislation.[7] The panel VAR is estimated through the following equation:

$$Y_{i,t} = \alpha_i + A(L)_i Y_{i,t-1} + B_i \epsilon_{i,t} \tag{3.1}$$

where $Y_{i,t}$ is a vector of endogenous variables for $i = 1, ..., N$ countries, $A(L)_i$ is a matrix of polynomial in the lag operator L, and B_i is the contemporaneous impact matrix of vector ϵ_i containing error terms which are i.i.d. $N(0, \Sigma_i)$. Notice that the assumption of cross-subsectional heterogeneity implies that, for each $t = 1, ..., T$, $A_i \neq A_j$ and $\Sigma_i \neq \Sigma_j$ when $i \neq j$, that is the coefficients and residual variances are unit-specific. Jarociński [2010] uses this model to estimate a monetary policy shock to core EA countries and new monetary union's members. The estimation procedure follows a Bayesian approach where an exchangeable prior is used in a hierarchical linear model (Gelman et al. [2003]). The estimation is performed by using the BEAR toolbox of the ECB[8]. The posterior distributions are obtained through Gibbs sampler for a total of 20000 iterations with 2000 burn-in iterations[9].

[6] Canova and Ciccarelli [2013] provide a survey on panel VAR's literature and explain in detail these differences and their implications.

[7] This can still be a limitation of the analysis when the MPIX accounts for announcement dates rather than enforcement dates. Since the announcement dates of macroprudential policies in EA countries are mostly the same and the observed innovations are allowed to be independent from each other, the error bands can still result underestimated.

[8] Further information about the estimation procedure can be found in Jarociński [2010] and Dieppe et al. [2016].

[9] A more detailed explanation about the estimation procedure will be provided in a technical note in the Appendix.

3.3.1 Data in the panel VAR

Data are at monthly frequency covering the period 2003:M1–2016:M12 and the estimation includes twelve lags. The VAR includes the macroprudential index discussed in the previous section, the capital-to-asset ratio of MFIs (banking system-wide capital ratios), the notional stock of loans of MFIs expressed in real terms, the lending rates of MFIs, the country level index of financial stress of the ECB (CLIFS), the monetary policy rate (MRO of the ECB), the index of the industrial production expressed in real terms and the harmonized CPI index. One possible criticism is the use of a non-risk weighted measure of banking capitalization such as capital ratio, since –as highlighted by Gambacorta and Shin [2018]– this is structurally higher than risk-weighted measures. However, this choice rests on two considerations: first, the capital-to-asset ratio is available for longer time series which allows to consider the period of Basel II capital requirements in the estimation. Second, non-risk weighted measures allow to avoid possible distortions resulting from banks' manipulation of risk weights.[10] Data sources and the plot of time-series (Figure 3.2) are reported in the Appendix. All variables are expressed in log-levels apart from lending rates, the CLIFS and the MPR that are in levels. Notice that, the estimation of the VAR with level variables allows for implicit cointegration relationships in the data (Sims et al. [1990]). In the next subsection I describe in details the sign restriction scheme adopted for the identification of the capital requirement shock.

3.3.2 Capital requirement shock's identification

The aim of this subsection is to catch exogenous shifts to banking capitalization that relate to macroprudential capital measures, which I call for the sake of brevity capital requirements (CR) shocks. However, as explained in the previous section, in principle these shifts can be associated also to other macroprudential measures that implicitly affect banking capital. Notice that the analysis focuses mostly on short-run effects of capital requirements, therefore I identify their effects at the impact.[11] I use macro variables of consolidated banking systems being aware of the limitation of not having cross-banking variation, which is, I do not distinguish between banks subject to new capital requirements and banks capitalized enough that are not subject to new requirements.

In order to identify the structural shock, I use both sign and zeroes restrictions following Rubio-Ramirez et al. [2010] and Arias et al. [2018]. Restrictions are imposed by following both the economic theory and the empirical evidence.[12] Moreover, besides the economic literature, I use also the results of the Quantitative Impact Studies (QIS) made by the BCBS about Basel

[10] See Mariathasan and Merrouche [2014] and Behn et al. [2016b] on this point.

[11] An interesting macro analysis about long-run effects of capital requirements and countercyclical capital buffers can be found in Angelini et al. [2015]. Their analysis moves from the theoretical representation of the Basel III framework into a DSGE model to an empirical exercise that assesses the long-run costs and benefits of capital tightenings. The latter builds on a VECM representation.

[12] As entry point of the sign restrictions literature see Faust [1998]; Peersman [2005] and Uhlig [2005].

II, and the Basel III monitoring exercises as guidelines.[13] The advantage of using the latter is that they provide a specific notes for a group of EU banks, so their results are more consistent with the macro data observed in the sample here.

The MPIX is the first variable that I restrict to have a positive reaction to the CR shock. The MPIX counts each loosening policy with -1 and tightening policies with $+1$. All the macroprudential capital measures included in MaPPED are kept in the index so to take into account that also other tools different from minimum capital requirement can affect banks capitalization and credit supply. Therefore, by restricting the MPIX to respond positively, I associate the occurrence of the shock to a macroprudential tightenings. A possible concern with macroprudential policy-shocks regards the anticipation effect. Since macroprudential policies are implemented on average two years after their announcement, banks can adjust their balance sheets before the measures are actually implemented, so that using the enforcement date may distort the estimation of the structural shock, while by taking announcement dates would help to attenuate the bias arising from anticipating behaviors.

At the same time, more of the announcements dates are the same for all countries, because they relates to the BCBS decisions. Notably, capital requirements contained in the CRD IV have been announced around June 2013 for all the countries of the sample. This would distort the error bands of the responses estimated in the panel VAR, since the latter does not allow shocks to be correlated among cross-sections. However, to consider announcement dates is more suitable to catch the unexpected effects of capital measures and, therefore, I use the latter for the benchmark specification and enforcement dates as a robustness check.[14]

Notice also that a consistent part of the measures reported in MaPPED were undertaken for microprudential and EU harmonization reasons rather than to address contingent systemic-financial risks. As explained in the previous section, this also motivates the investigation of such exogenous shocks. However, the fact that countercyclical macroprudential policies can be actually endogenous responses to both business and/or financial cycle is something to control for in this analysis. For instance, the BIS indicate credit-to-GDP ratio as an explicit measure to target countercyclical capital buffers. However, Aiyar et al. [2016] address explicitly the concern about possible reverse causality between capital requirement and bank lending. They employ a panel VAR by combining bank lending with CR changes, and find that the latter do not respond to shocks to both loan growth and loan quality.

There are two main theoretical frameworks about the implications of capital requirements. The standard theory builds upon the Modigliani and Miller [1958] theorem, which claims that bank's total risk depends only on the composition of its assets. This implies that higher capital

[13] In particular, the BIS published on March 2003 the results of the exercise QIS3 about the impact of Basel II minimum capital requirements. The release of Basel II in June 2004 was based on this QIS3. While, the results of the first monitoring exercise were published on April 2012 and they are currently updated on a semestral basis.

[14] Although impulse responses are unchanged the peaks of structural shocks present some differences. Results are available upon request.

makes equity and debt funding safer and, thus, that capital requirements reduce the cost of fundings. A similar approach can be found in a more recent work of Admati et al. [2010]. A second strand of the literature assumes that equity markets are intrinsically imperfect instead, and thus that equity is a relatively costly source of banks' finance. New equity issuance can increase the downside risk for banks' shareholders (Myers [1977]) and require higher premium from the market (Myers and Majluf [1984]). Also, it can be relatively costly because debt financing allows for tax deducibility (Miles et al. [2012]). According to this view, capital requirements increase the cost of funding. As a consequence of this, on the one hand, capital requirements may discourage credit demand of some category of borrowers (Thakor and Wilson [1995]). On the other hand, it may negatively affect credit supply of regulated banks, which may choose to meet new requirements through deleveraging. However, the overall effect on credit supply might be (partially) offset by other non-regulated sources of credit supply (Aiyar et al. [2014]). As highlighted over this subsection, this second strand of the literature is the one that finds a more solid empirical support.

With regard to the benefits related to capital measures, the rationale to increase capital requirements is that they reduce banks' probability default and loss given default. A strand of the theory shows that capital regulation would actually reduce the incentive of banks to undertake risk (Furlong and Keeley [1989]; Rochet [1992]; Santos [1999]). On a similar track, others show that higher banks' capital level improves the overall financial stability (Diamond and Rajan [2000] and Admati et al. [2010]).

The effects of changes to capital requirements highlighted from the theoretical literature that find also solid empirical bases are summarized in Figure 3.1. An increase in capital requirements increase the overall capital ratios of the banking system –with increasing equity and/or lower total assets– with beneficial effects for financial stability. At the same time, it increases the cost of equity, that pushes up lending rates, discouraging credit demand. Moreover, the change of capital requirements can have a direct effect on lending activity, discouraging banks credit supply. I incorporate these restrictions to identify the CR shock by following up on the empirical evidence.

Therefore, I impose that the shock impacts the banking system-wide capital ratio with a positive sign. Studies such as Aiyar et al. [2014] and Francis and Osborne [2012] confirm that this is the case for the UK banking system. There is also evidence that aggregate banks' capital ratios rose significantly in other european countries the years following the implementation of both Basel II and Basel III.

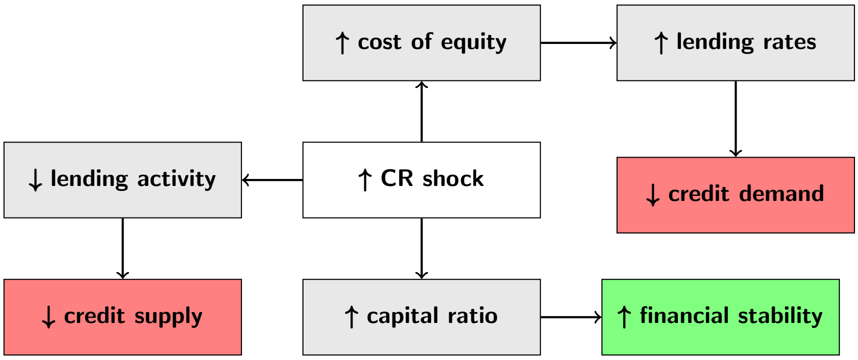

Figure 3.1: Short-run effects of change in banking capital requirements

More specifically, Tier1 (common equity) in EA increased about 1.4% (1.2%) in the period 2006-2009 (Slovik and Cournède [2011]). The QIS by BCBS shows that weighted average capital ratios of large (small) banks have risen from 5.7% (7.8%) to 9.2% (9.4%) in the period 2009-2012.[15] More consistently with the approach of this paper, Eickmeier et al. [2018] find that a shock to their narrative CR index increases permanently the bank capital ratio in US. The restriction on the MPIX and capital ratio, taken together, characterize the macroprudential nature of the shock that tightens capital requirements. However, in order to exclude that these responses emerge from other kind of shocks such as real, credit, equity or asset price shocks, I need to impose further restrictions to the contemporaneous impact of the CR shock.

Consistently with the theoretical assumptions presented earlier, I assume that the CR shock has a positive impact on lending rates and a negative impact on banks' lending activity, which is changes in capital requirements do negatively affect credit supply at the impact. A large part of the empirical literature confirms that these effects are sizable and significant on aggregate. Results well suited for this work are the one of Budnik and Kleibl [2018], who find that on average bank lending growth in EA declined notably with the introduction of new minimum capital requirements, capital buffers or new loan-loss-provisioning standards. The Macroeconomic Assessment Group (BCBS [2010b]), by calibrating a target capital ratio for the banking system, gauges that a marginal increase in capital requirements leads to an increase in lending spreads and a decrease in lending volume. Some different result emerges mostly from the empirical literature that builds upon bank-level data. Cohen [2013], as instance, finds a marginal increase to capital ratio is associated with a 3% increase in asset growth over three years adjustment. This work, however, focuses on a longer horizon effect and thus it has a little to do with the impact effect of the CR shocks explored here. Similar results can be found in Gambacorta and Shin [2018], where a one percent increase in capital ratio reduces the overall cost of debt funding

[15] They assumed that, starting from a benchmark common equity ratio of 5.7%, capital ratio needed to increase by 1.3 percentage points to achieve Basel III targets.

with an increase in the annual credit growth, but they do not address macroprudential capital measures directly.[16]

Among many others, two works that are in line with the assumptions highlighted earlier are worth to mention. These are Mésonnier and Monks [2014] and Gropp et al. [2018]. Both studies found the the EBA capital exercise has had a procyclical nature and induced a credit crunch in the EA. More specifically, the former find that forcing a banking group to increase its Core Tier1 capital by 1% of RWA led to a decrease of 1.2% points in credit supplied over nine months after the capital exercise. The latter concludes that a short notice exercise such as the EBA one implies that banks will deleverage by reducing assets rather than issue new equity. The two studies are used as a benchmark for the restrictions here not only because their analyses develop on EU banks, but also because they both focus on the unexpected effects of the EBA capital exercise on those banks' lending decisions, that is what this section aims at identifying.

Furthermore, I exclude that the CR shock is an endogenous policy response to specific financial stress or crises episodes. A good candidate that may embed the movements in the overall probability of default and loss given default of banks at macro level is the country level indicator of financial stress (CLIFS) developed in Duprey et al. [2017]. I choose this indicator because its model-based predictions about systemic banking crises fit the large part of episodes documented in EA countries.[17] Therefore, the CLIF is assumed to respond zero as the shock impacts. This restriction implies that the responses of capital ratios, lending rates and loans do not emerge from any other kind of adverse asset price shock, which would increase the CLIFS. Notice also that, although macroprudential CR would improve the overall financial stability, it is hard to say whether such a beneficial effect is envisaged as capital requirements are announced. Therefore, I stay agnostic about this assumption, and assume that the shock has only a lagged impact on the CLIFS.

MPIX	Capital ratio	Loans flow	Lending rate	CLIFS	MP rate	Output	Prices
+	+	−	+	0	0	0	0

Table 3.1: CR shock identification. Sign and zero restrictions on the variance-covariance matrix B_i of Equation 3.1.

[16] I try an alternative specification of the panel VAR, where I take lending margins instead of lending rates to proxy the banks' cost of funding as in Gambacorta and Shin [2018]. Here the identification scheme assumes lending margins respond negatively as the CR shock impacts. Surprisingly, the impulse responses provide similar results as in the benchmark specification. Results are available upon request.

[17] In particular the one reported in Laeven and Valencia [2013]; Reinhart and Rogoff [2009] and Babeckỳ et al. [2012].

However, the exogenous increase to capital ratios that affects credit supply can arise somewhere else in the economic system, as an endogenous response to monetary policy and real activity innovations. Therefore, I impose that the increase of capital ratios and lending rates, and the decrease in bank loans are not endogenous responses to the monetary policy actions. In other words, I need to exclude that the shock arises from the activation of both the bank lending[18], and the bank capital channel[19]. At the same time, given the monthly frequency of the data, I exclude that the monetary authority may respond to the CR shock within the period it occurs. Therefore, I restrict the monetary policy rate to be zero at the impact. Finally, for the same reason, I assume that there is only a lagged impact of the CR shock on output and consumer prices so that the contemporaneous impact on these variables is restricted to be zero as well.

Summing up, the shock is identified through zeroes and sign restrictions. This occurs as a macroprudential action that rises capital ratios and depress credit supply, while financial stress in the system does not respond within the period. The next subsection presents the impulse responses and the structural shock estimated in the panel VAR.

3.3.3 Estimation results

Before to comment the effects of the estimated structural CR shocks, I conduce a country-inspection in order to see whether there is a correspondence with actual announcement of macroprudential capital measures. Figures 3.6-3.14 show country-specific standard deviations of the innovations, which by construction sum zero over the whole sample period. A rise in these series reflects a tightening CR shock, while a decline reflects a loosening one, relative to the average endogenous responses to the other shocks. I cross-check whether peaks of these series correspond to specific capital measures (the dotted vertical lines in the figures). I consider tightening capital measures only when no loosening policy is observed within the same month. The notes to the figures report also the date, the type of measure and the type of institution that implemented the measure. The figures show that the shock catches the most important announcement dates of changes in capital regulation, that are for the larger part the CRDs related to the implementation of Basel II and Basel III. Among the latter, country-specific CR measures also are caught for the larger part, and they are ofter related to minimum CR and capital buffers.

Examples are multiple. In Austria on March 2012, the FMA issued the supervisory guidelines that were aimed at improving the core capital base of credit institutions, requiring them to anticipate to the beginning of 2013 their compliance with Basel III requirements. An equivalent

[18]A rise of the MP rate would contract credit supply so long as it affects the availability of loanable funds and banks are liquidity constrained. See Bernanke and Gertler [1995].

[19]A rise of the MP rate would negatively affect bank profits, which can deteriorate banks' capital adequacy. If banks are bind to issue new equity, this can cause a further decline in bank lending. See Blum and Hellwig [1995] and Van den Heuvel et al. [2002].

measure was undertaken in Spain on March 2011 to reinforce the solvency of banking institutions. Thus, the Bank of Spain introduced a stricter definition of core capital and set RWAs to 10% (instead of 8%) for banks which wholesale funding was above 20%. In Italy from May 2008, Bank of Italy has been allowed to impose a minimum Core Tier1 requirement to specific banks. On May 2015, in order to prepare Portuguese banks for the ECB's comprehensive assessment exercise, Banco de Portugal recommended the reinforcement and maintenance of the minimum total solvency ratio of 10.5% and Tier1 ratio of 8.5% for all banking groups excluding the eight largest banking groups, and the minimum total solvency ratio of 11.5% and common equity Tier1 ratio of 8% for largest groups. Likely all these measures have had an unexpected component that the CR shock is able to catch. Apart from Austria and Portugal, the announcement of the EBA capital exercise[20] also is caught by the CR shock as a tightening innovation (not reported in the figures), though the measure is not reported by the MPIX. This suggests that the CR shock is well identified and capture the large part of macroprudential capital measures observed in the sample.

The country-impulse responses to the CR shock are reported in Figures 3.15–3.23. These are medians of the draws of the posterior distribution in a fifty-months horizon. Dotted lines delimit 68% posterior probability regions of the responses. On average, a one-percent standard deviation innovation in capital requirements occurs with an increase in capital ratios ranging from 0.05% to 0.2%. Loans flow decrease within an interval of –0.2% to –0.4%, while lending rates increase about 1 to 5 basis points on average. However, the effect on capital ratios is persistent in all countries apart from France. The effect on loan flows lasts on average thirty-five months, while lending rates decay below zero after twenty months. On average, after the shock, industrial production reduces up to –0.1% and it recovers within the following thirty months, while the average reduction in CPI (–0.04%) persists in all the countries after the shock. The responses of CLIFS are much more heterogeneous. Few months after the shock the latter reduces significantly only in Austria, France, Greece, and Portugal. However, after ten months, the CLIFS starts to lower significantly in all countries about 0.5%. Monetary policy action allows to reduce the MRO since three months after the shock. Finally, the CR shock decreases significantly the financial stress in all countries with an average reduction up to –0.5%, but this effect is more pronounced as loan flows and industrial production recover.

The CR shock seems to have significant, although relatively small, macro effects. These findings are consistent with the existent literature reviewed before. The most significant difference is that, here the CR shock is an exogenous component of macroprudential capital measures and then it materializes with relative small changes of capital ratios. In fact, previous studies assess the effect of marginal increases of capital ratios or of macroprudential index, while, here the one-percent standard deviation innovation represents a simultaneous variation of the variables

[20]Since the announcement was made on 26th October 2011 I take announcement dated as November 2011.

involved in the identification scheme. Small deviations may reflect the fact that, when macroprudential capital measures are set, financial authorities allow banks to meet new requirement in a wide grace period.

3.4 State-dependent effects of capital requirement shocks estimated through local projections

In this section I investigate state-dependent effects of the capital requirement shock. The variables in object are real total credit (that is, loans from any source in the financial system), real bank credit (that is, loans from banks), bank lending rates on households and on NFCs, real GDP, GDP deflator, capital ratios and financial stress. Differently from the previous section, the analysis here builds upon the idea to find possible nonlinear impact of the shock under different economic regimes. In order to do that, I exploit country-specific structural shocks from the panel VAR and estimate local projections (Jordà [2005]) for the variables of interest.

Local projections are suitable for panel data analysis and allow to easily accommodate nonlinearities, though they suffer a lack of efficiency of the estimates at longer forecast horizons. This cost is also associated to the use of heteroskedastic and autocorrelated consistent (HAC) variance-covariance matrix. Here local projections estimation is consistent with the bayesian approach, that is I build credible sets by exploiting the draws coming from the panel VAR estimation. In principle, the non-linear effect of the shock should be estimated in a one-step non-linear framework –as instance, through a threshold VAR[21], as the identified structural shock of the previous section emerges from a linear model. In this preliminary exploration I allow state-dependent impulse responses by estimating the following equation:

$$Y_{i,t+h} = \alpha_i + \gamma_t + I_{i,t-1}\Big[\beta^{A,h}\Delta CR_{i,t} + \phi^{A,h} Z_{i,t} + \Gamma^{A,h}(L)X_{i,t-1}\Big] + ... \tag{3.2}$$
$$... + (1 - I_{i,t-1})\Big[\beta^{B,h}\Delta CR_{i,t} + \phi^{B,h} Z_{i,t} + \Gamma^{B,h}(L)X_{i,t-1}\Big] + u_{i,t+h}$$

where $I_{i,t-1}$ is a dummy indicating whether the economy is in state $\{A, B\}$ in the period before the shock occurs. The states are defined as expansionary and contractionary regimes. More specifically, I take the GDP cycle obtained with the HP-filter with a large smoothing parameter ($\lambda = 100,000$). Then I identify the regimes by using the Harding and Pagan [2002] algorithm with a minimum length of each phase of four quarters. An expansionary state is

[21] I am trying to estimate a TVAR with stochastic volatility, where the effect of a CR shock is explored in two financial-stress regimes. However, two limitations emerge: one is that the analysis passes from a panel to a single-country (EA) dimension and, second is that the structural shock is obtained through a recursive identification scheme. Currently I am trying to implement zero and sign restrictions in this non-linear framework. However, this kind of application is almost unexplored in the literature and preliminary results are in progress.

defined as the period between a trough and a peak while a contractionary is the state between a peak and a trough.

As in Auerbach and Gorodnichenko [2013], the dummy is taken at $t-1$ so to avoid simultaneity problems between the shock and the state of the economy.[22] The vector $Y_{i,t}$ contains variables to be projected for country i at time t, while α_i^h and γ_t^h are respectively country and time fixed effects. For each variable's projection we add respective contemporaneous, $Z_{i,t}$, and lagged, $X_{i,t-1}$ controls (where L is the lag operator). Controls include real credit, real GDP, harmonized CPI, lending rates, capital ratio and the CLIFS. At any horizon $h = 0, 1, ..., 20$ a regression is run. Four lags of both controls and dependent variables are included. The point estimates of $\beta^{A,h}$ and $\beta^{B,h}$ coefficients of equation (3.2) at each horizon h provide the state-dependent dynamic causal effect of the capital requirement shock, $\Delta CR_{i,t}$.

3.4.1 Local projection analysis to the capital requirement shock

In order to study the potential nonlinear effect of the CR shock I use the country-specific structural shocks coming from the identification of the CR shocks in the equation 3.1 to estimate local projections in equation 3.2. Local projections are reported in Figures 3.24–3.27. The shortcuts "Exp" and "Con" in the figures, indicate regimes of business cycle expansions and contractions respectively, while "DIFF" is the difference in the dynamic multipliers of passing from an expansionary to a contractionary regime.

One concern of using the CR shocks in Figures 3.6–3.14, is that those are medians coming from successful draws of the countries' posterior distributions. This would lead to biased confidence bands and point estimates for local projections especially at larger horizons. Therefore, local projections are built on structural shocks of single draws, in order to make the estimation more consistent to the bayesian approach employed for the panel VAR.[23]

In particular, I take structural shocks of the last 800 draws of the posterior distribution that represent the 10% of the iterations net to the burn-in sample. Therefore, by following this procedure, for each variable of interest 800 local projections are run. Moreover, in order to avoid autocorrelation of taking consecutive draws I adopt also a thinning approach as a robustness check. No significant differences are found by following the latter. The credible sets of Figures 3.24–3.27 are built so to represent 68% of the points estimates' distribution, thus I take the 16th and the 84th percentiles of their distribution.

[22] See also Bernardini and Peersman [2018] on this point.

[23] There could be some skepticism about the use of credible sets in a frequentist framework. In the spirit of Fry and Pagan [2011], I estimate local projections also with a median target method and HAC confidence bands as a robustness check. Results are consistent and are available upon request.

Do capital requirement shocks exacerbate credit procyclicality?

Figure 3.24 reports local projections to credit variables. The shock now represent a one-percentage increase in the ΔCR. The latter reduces total credit about 0.5% during expansions in the five quarters after the shock. In contractions the same reduction reaches 1% and it continues significantly at longer horizon. Similar responses are found for bank credit. However, the difference of the drop between the two regimes in much more significant for total credit. These results suggest that unexpected macroprudential capital measures turn to be more costly in terms of credit dynamics when the economy is in a bad shape. The impact of macroprudential CRs seems to exacerbate credit procyclicality within the two years they are announced. During contractions, these shocks may indeed trigger (bad) side-effects such as credit crunch or fire-sales that are less likely during expansions. This can happen, on the one hand, because financial institutions are forced to cut outstanding loans in order to meet higher capital ratios (which is, they reduce total assets) and, on the other hand, because they weight credit risk higher during contractions than during expansions, so that the supply of new loans shrinks.

To better understand which role CR shocks play on credit supply, Figure 3.25 plots local projection of lending rates to households and to NFCs after a CR shock. The difference in passing from a contractionary to an expansionary state of the business cycle in significantly positive in the first two years after the shock, then it turns to be negative. During expansions both lending rates to households and to NFCs do not respond significantly at the impact, and tend to slightly decrease in the quarters following the shock in the case of NFCs rates. While, during contractions, the shock positively increases lending rates about 10% for households and 5% for NFCs. This result suggests that, during contractions, the sudden drop in the outstanding (total and banking) credit following the CR shock arises from a cut of credit supply to the private sector, rather than a risk-reshape of banks' balance sheets.

The top panels of Figure 3.26 show local projections for the system-wide capital ratio in the two regimes. At the impact the shock equally increases capital ratio about 1%, that rises up to 2% within three quarters, and then it drops towards zero. However, in the contractionary state, the capital ratio significantly rises up again at longer horizon. Overall, these results suggest that the CR shock, which can be seen as a policy-shock related to the announcement of macroprudential capital measures, exacerbates credit procyclicality and then it can have an independent role in affecting the real economy.

The state-dependent impact of macroprudential capital requirements on the real economy

The bottom panels of Figure 3.26 show local projections for the GDP deflator in the two regimes. The CR shock seems to affect inflation negatively more during contractionary phases, though a significant difference is found only at longer horizon, between $h = 12$ and $h = 20$. In contractions, the drop accounts around 0.4% within fifteen quarters after the shock. The drop can be interpreted as tighter macroprudential regulation may contribute to worsen expectations about future inflation during contractions. This can be due to the fact that the lack of availability of the financial sector to lend money discourages the conditions for the recovery and thus the expectations of the private sector about the inflation.

Figure 3.27 plots local projections of real GDP and index of financial stress. These two are often used to gauge the effectiveness of macroprudential policy in terms of costs and benefits, respectively. I found that the dynamic multipliers of these two are strongly state-dependent. Surprisingly, a one-percentage CR shock during expansions does affect significantly and positively the real GDP, about 0.2% within five quarters. On the contrary, during contractions the shock reduces real GDP, about 0.4% within seven quarters. For a given CR shock, passing from an expansionary to a contractionary state implies a significant reduction of real GDP about 0.5% after one year from the announcement. While it is clear why the CR shocks should have an independent negative effect on real GDP during contractions, it is less straightforward to interpret the positive effect during expansions.

A possible explanation can be found in the response of financial stress index to the CR shock in the bottom panels of Figure 3.27. During expansions, the CR shock reduces financial stress about 8% and the drop is quite persistent over the entire estimated horizon. This reduction may trigger an independent positive effect on financial markets, as instance, through increasing asset prices, that transmits to real GDP. On the contrary, during contractions, the CR shock has a negative effect on financial stress just for few quarters, and then it turns to be positive or non-significant. However, passing from an expansionary to a contractionary state has a positive and persistent effect on financial stress that accounts a rise up to 12%. This suggests that the announcement of macroprudential capital measures have a significant and beneficial effect to control financial stability, but this effect can be even costly if measures are announced while the business cycle is down-shaped.

3.5 Conclusions

In this paper I investigate the macro economic impact of macroprudential capital measures in Euro Area countries. The empirical analysis builds upon the idea that countries' financial authorities use capital measures as a policy tool to improve the resilience of the banking system to financial shocks by setting higher levels of banking capital ratios. Though capital regulation comes mostly from the implementation of Basel II and Basel III prescriptions, I argue that, as in the European experience those measures have had sometimes an unexpected origin, capital measures can be seen as country-specific policy shocks. Then I assume the economy described in a panel VAR model, in order to study the impact of that capital requirement shock. I estimate the VAR with a Bayesian technique that takes into account cross-country differences between nine EA countries of the sample, so to obtain country-specific structural shocks.

In order to provide meaningful economic interpretation to the impulse responses I identify the structural shock by means of sign and zeroes restrictions. By following the economic theory and the empirical evidence I assume that the capital requirement shock increases the capital ratio of the banking system and it makes the equity a relatively costly source of funding for banks and then it increases the lending margins. Though these assumptions depart from the Modigliani and Miller [1958] framework, the empirical macro evidence presents quite solid results. The VAR includes also a narrative index that takes into account the announcement dates of capital measures in each country in the sample, so that the increase in capital ratio is assumed to emerge with a tightening macroprudential policy. Moreover, I allow the shock to have a negative impact on the flow of loans, so to embed the fact that banks may react to new requirements by both increasing equity, reducing risky assets or by shrinking their credit supply. Finally, I exclude that these restrictions can be endogenous reactions to financial or equity shocks, or to the activation of some monetary policy channel, or to real economy innovations.

The estimated structural shocks seem to match the most important capital measures announced at country level. This suggests that those announcements have had an unexpected nature that can be seen as an exogenous policy-induced source of variation. Impulse responses reveal that the shock has a significant negative impact on industrial production and price level. This result is in line with macro studies such as Eickmeier et al. [2018] and BCBS [2010b], although the sizes of the effects found here are relatively small. However, as noticed in Aiyar et al. [2014], small shifts in credit supply (and then on real variables) in response to capital requirement shocks are not surprising in macro studies, since aggregate series do not allow to distinguish between regulated and non-regulated banks or to see potential leakages via foreign branches.

In the second part, I investigate state-dependent responses to the capital requirement shock. I use the structural shocks estimated in the VAR to make local projections of different sources of credit, lending rates, real GDP and financial stress. I find that overall bank and total credit reduces more during business cycle's contractions. In other words, unexpected capital measures exacerbate credit procyclicality. This means that when economy is in a bad shape, banks (and also other credit institutions) are more willing to deleverage in order to meet new capital requirements. This is in line with the findings of Mésonnier and Monks [2014] and Gropp et al. [2018] about the EBA capital exercise. In respect to these studies, local projections here suggest that the decline in credit volumes are mostly supply driven since lending rates are shown to increase during contractions. Consequently, the potential threat of a credit crunch during an economic downturn would affect real variables more likely. This is consistent with the fact that during downturns the shock reduces both real GDP and inflation, while financial stress struggles to decrease. On the contrary, I found that during expansions announcements of macroprudential capital measures can be beneficial. Indeed, as the shock impacts financial stress reduces persistently, which possibly affects the real GDP in a positive way. However, as largely explained in Section 3.4, these results should be handled carefully since the non-linear impact of the CR shock should be explored through a one-step estimation.

However, the policy notice of these preliminary findings concerns the implementation of macroprudential capital measures. First, financial authorities should consider that capital-measure announcements have a *per se* impact on banks behavior, despite on whether or not the new requirement will be enforced. Second, policy makers should define an explicit transmission channel through capital measures impact the real economy and whether the functioning of this channel changes under different economic and financial scenarios. This also motivate the empirical research to further explore on the direction of regime-dependent capital requirements, possibly by investigating on a larger set of macro-financial variables and the interconnections of banking systems across countries.

Appendix

Data sources

Monthly level data: index of industrial production has been taken from Eurostat. The harmonized CPI index, the notional stock of loans, the country level index of financial stress, the total assets of MFIs, the capital and reserves of MFIs, the lending rates and the main refinancing operation rate, from the Statistical Data Warehouse of the ECB. *Quarterly level data*: total credit to households and NFCs have been taken from BIS. Nominal GDP from OECD. House and stock prices from mixed sources (BIS, National central banks, Eurostat, Bloomberg).

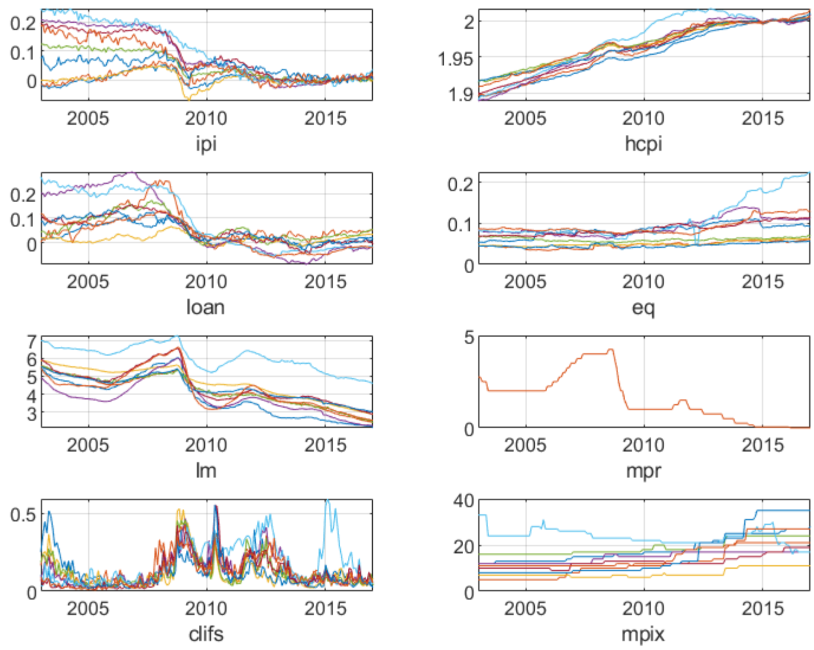

Figure 3.2: Time-series included in the estimation of the panel VAR in equation 3.1. The figure shows the industrial production index in real terms (ipi), harmonized CPI index (hcpi) and notional stock of loans in real terms (loan). These variables are taken in logs. Moreover I include the ratio equity-to-assets of MFIs (eq), lending rates of MFIs (lm), the country level index of financial stress (clifs) and the macroprudential index (mpix). These variables are taken in level.

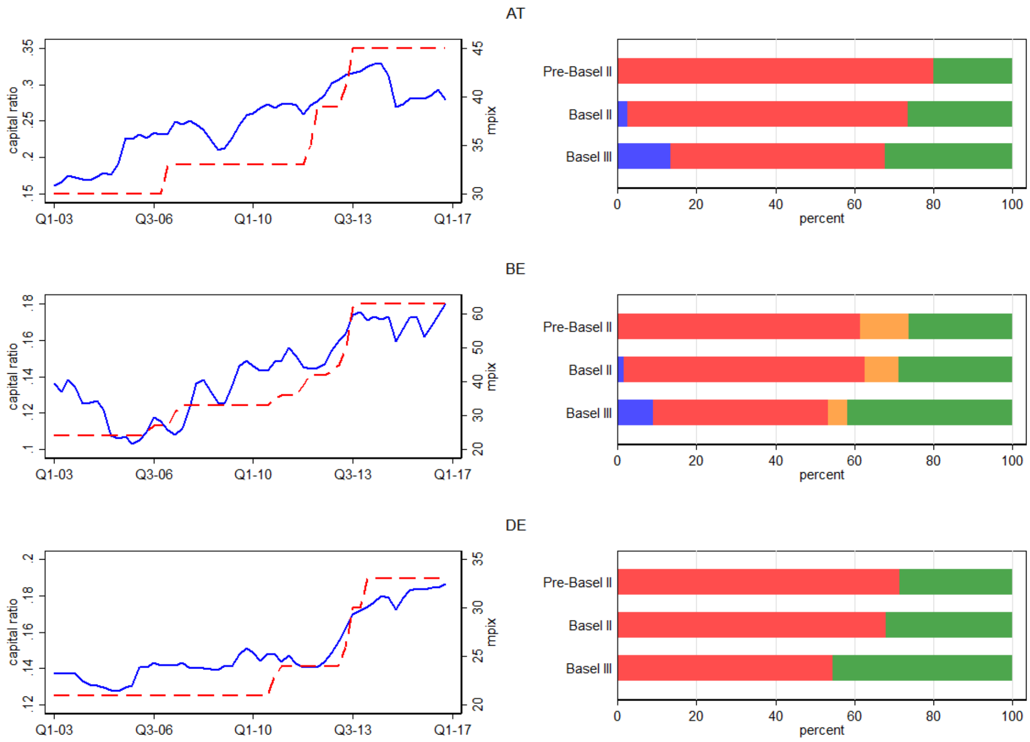

Figure 3.3: Left panels: MPIX and capital ratios. Notes: MPIX on the right axis and capital ratio (equity-to-total assets) on the left axis (blue solid line). Right panels: contribution of specific measures (percentage). The figures report minimum capital requirements (green), capital buffer (blue), limits on concentration and exposure (red), loan loss provisioning (gray), leverage ratio (orange).

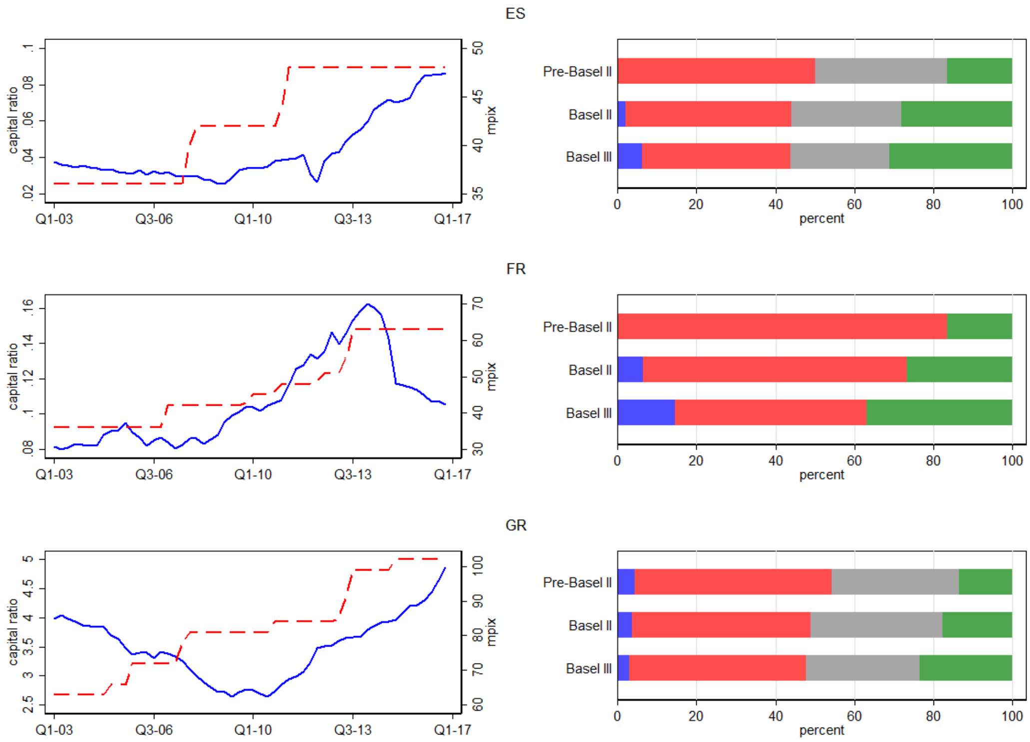
ES
capital ratio
mpix
Q1-03
Q3-06
Q1-10
Q3-13
Q1-17
Pre-Basel II
Basel II
Basel III
percent
FR
GR

Figure 3.4

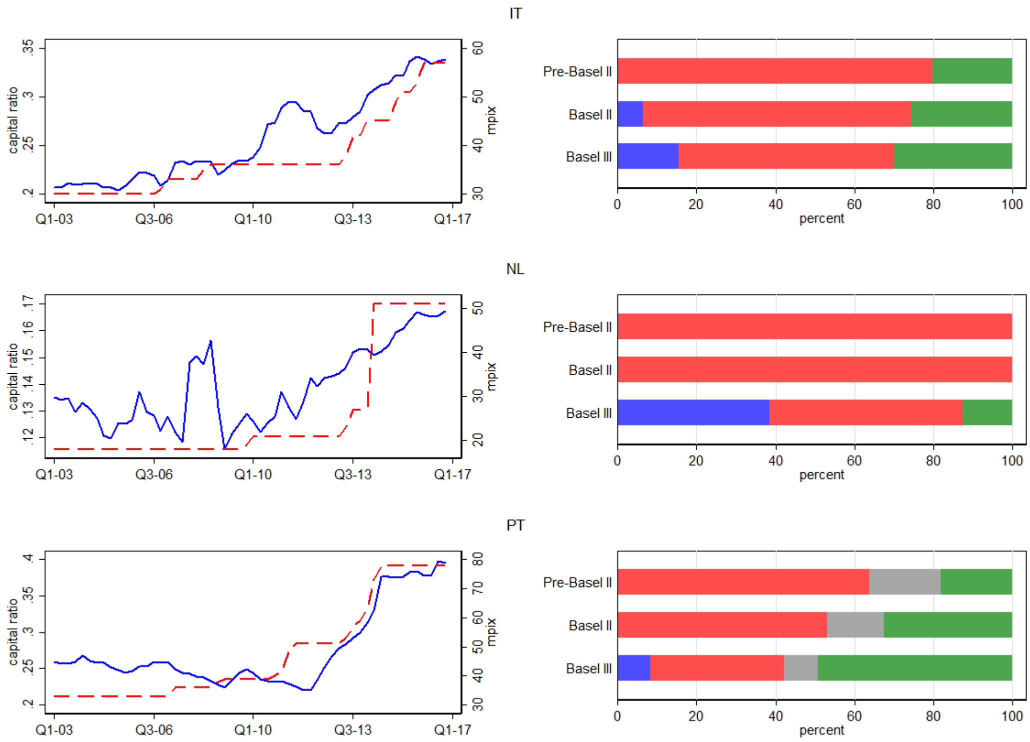

Figure 3.5

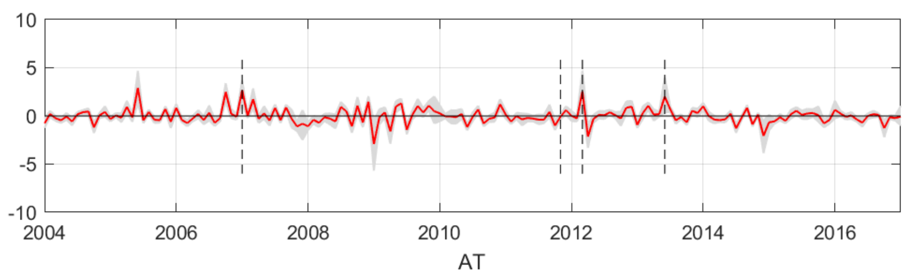

Figure 3.6: Main CR in Austria: 1) 2007m1, minimum CR, implementation CRD. 2) 2012m13, Capital buffer implementation. 3) 2013m6, minmum CR and capital buffers, CRD IV harmonization.

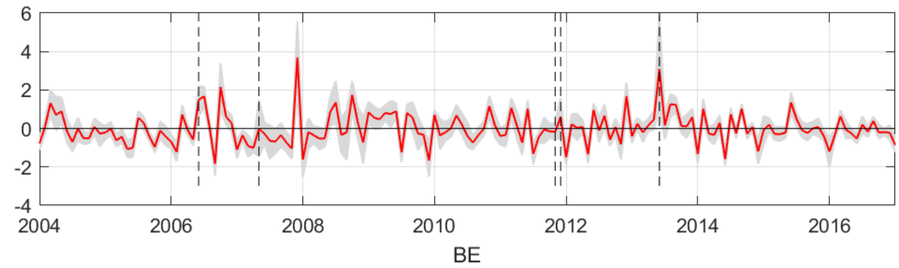

Figure 3.7: Main CR in Belgium: 1) 2006m6, minimum CR, announcement CRD. 2) 2007m5, Limit on large exposure and concentration, national law. 3) 2011m12, capital buffers, CRD harmonization. 4) 2013m6, minimum CR and capital buffers, national banking law.

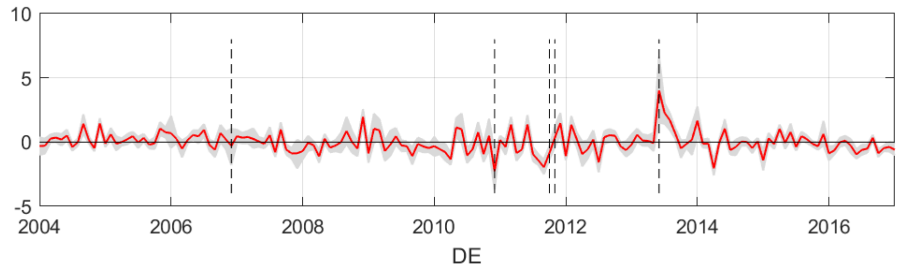

Figure 3.8: Main CR in Germany: 1) 2006m12, minimum CR, announcement CRD. 2) 2010m11, minimum CR, CRD harmonization. 3) 2011m10, EBA capital exercise. 4) 2013m6, minimum CR, CRR harmonization.

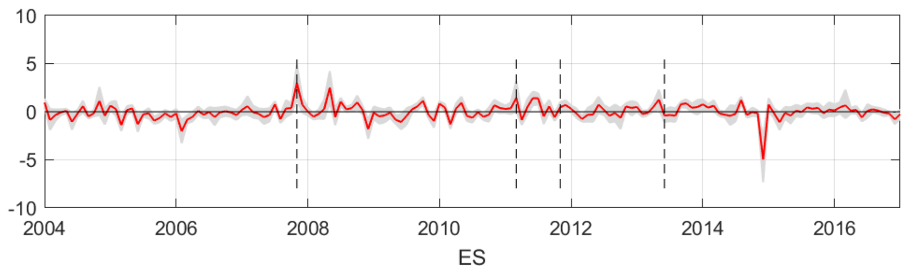

Figure 3.9: Main CR in Spain: 1) 2007m11, minimum CR, announcement CRD. 2) 2011m3, minimum CR and capital requirements, government ministry 3) 2013m6, minimum CR, CRR harmonization.

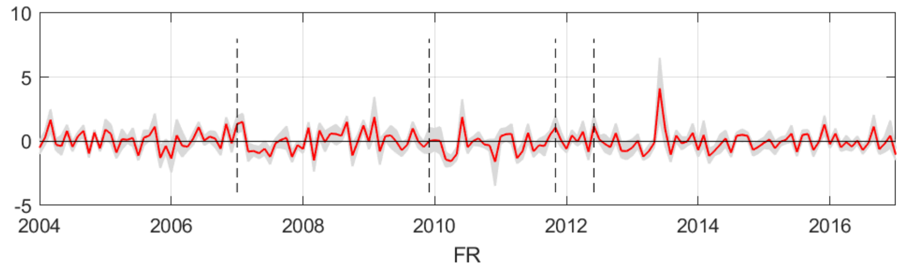

Figure 3.10: Main CR in France: 1) 2007m1, minimum CR, implementation CRD. 2) 2009m12, capital buffer, government ministry. 3) 2013m6, minimum CR, CRR harmonization.

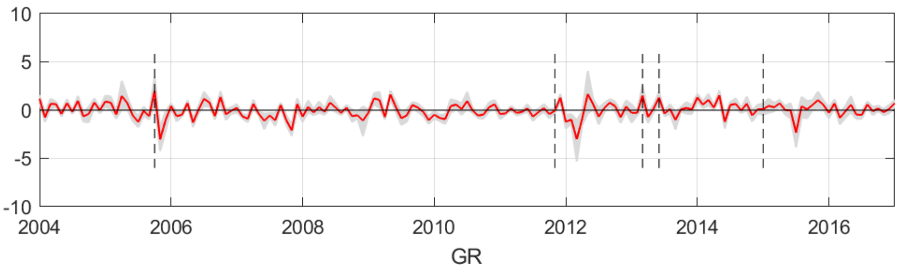

Figure 3.11: Main CR in Greece: 1) 2005m10, loan-loss provisioning, national banking law. 2) 2013m3, minimum CR, national banking law. 3) 2013m6, minimum CR, CRR harmonization. 4) 2015m1, loan-loss provisioning, Central Bank and EU institutions.

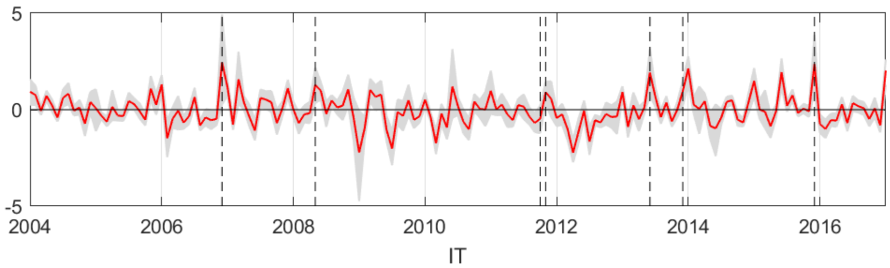

Figure 3.12: Main CR in Italy: 1) 2006m12, minimum CR, announcement CRD. 2) 2008m5, capital buffers, Bank of Italy. 3) 2013m6, minimum CR, CRR harmonization. 4) 2013m12, capital buffers, transposition CRD. 5) 2015m12, capital buffers, transposition CRD.

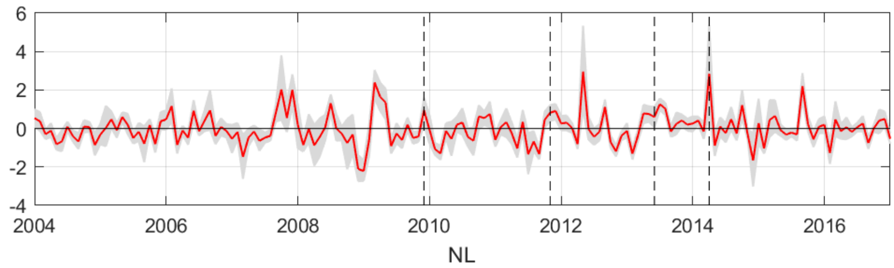

Figure 3.13: Main CR in the Netherlands: 1) 2009m12, limit on large exposure and concentration, transposition CRD. 2) 2013m6, minimum CR, CRR harmonization. 3) 2014m4, capital buffers, transposition CRD.

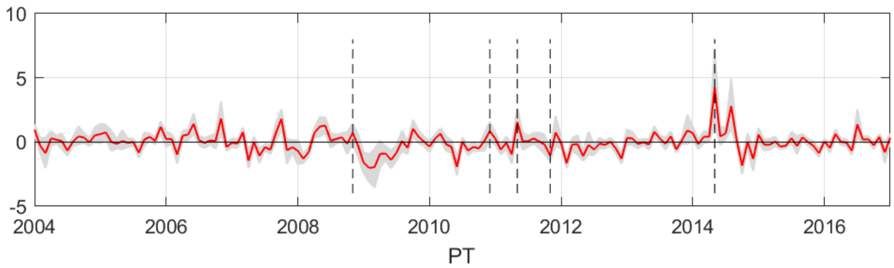

Figure 3.14: Main CR in Portugal: 1) 2008m11, minimum CR, implementation CRD. 2) 2010m12, limit on large exposure and concentration, Central Bank. 3) 2011m5, minimum CR, national regulation. 4) 2014m5, capital buffers, Central Bank and EU institutions.

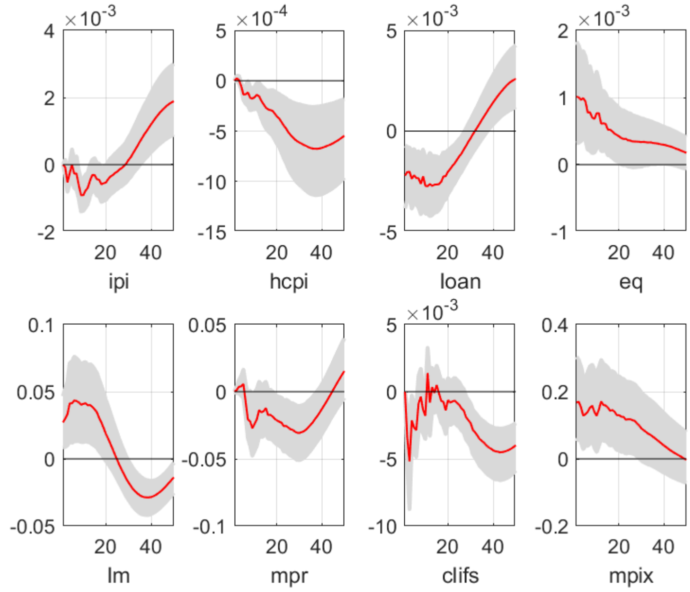

Figure 3.15: IRFs to CR shock in Austria

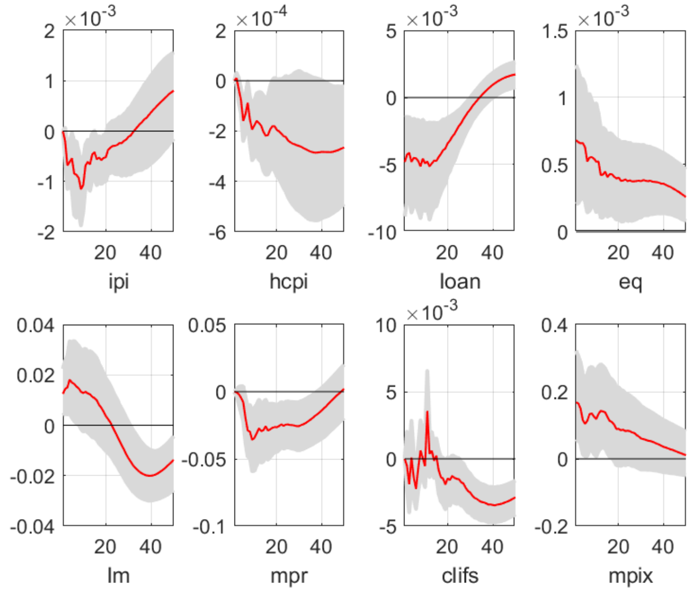

Figure 3.16: IRFs to CR shock in Belgium

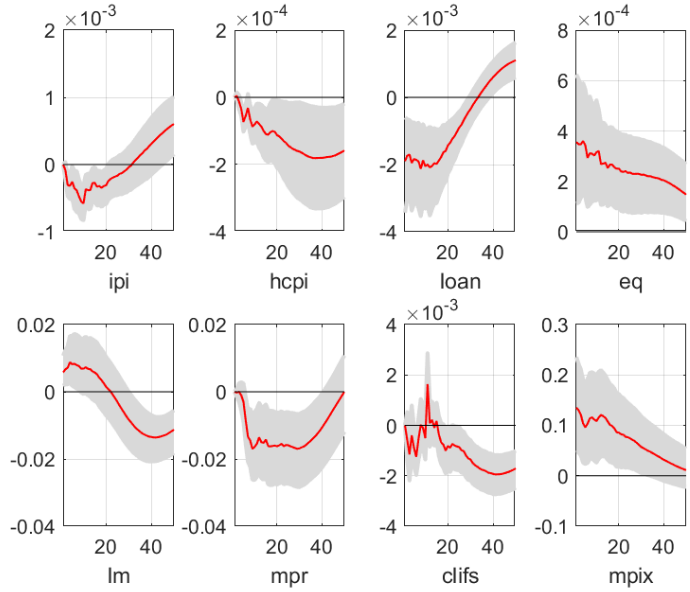

Figure 3.17: IRFs to CR shock in Germany

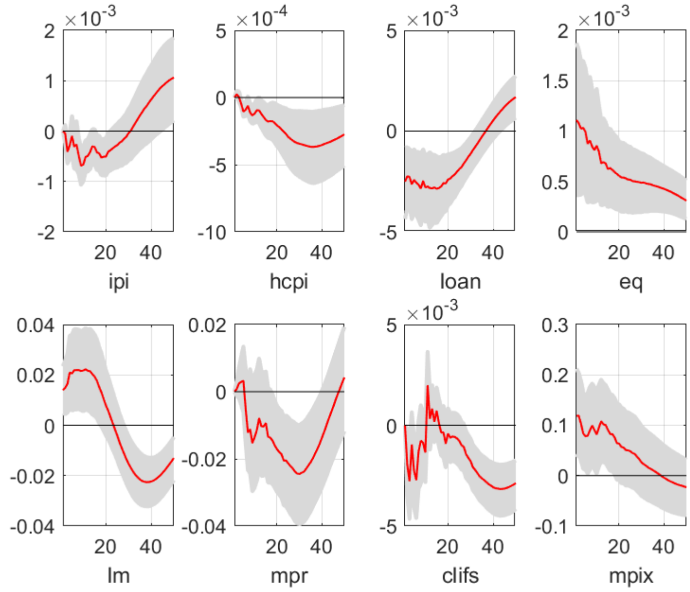

Figure 3.18: IRFs to CR shock in Spain

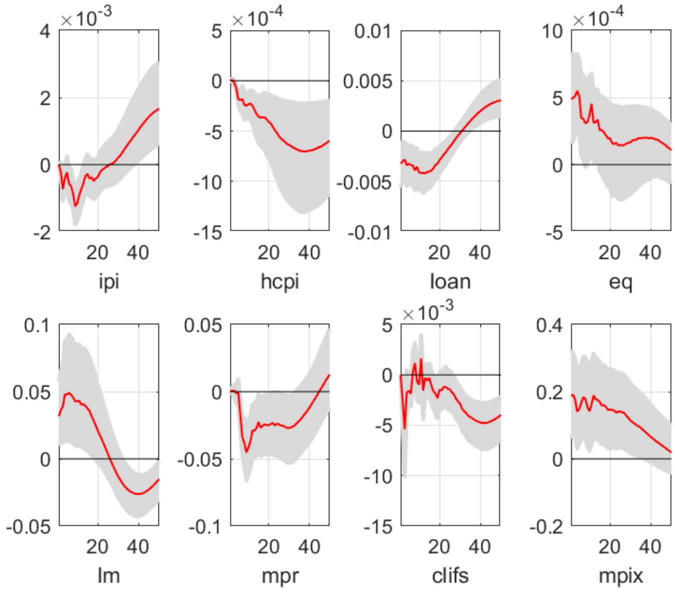

Figure 3.19: IRFs to CR shock in France

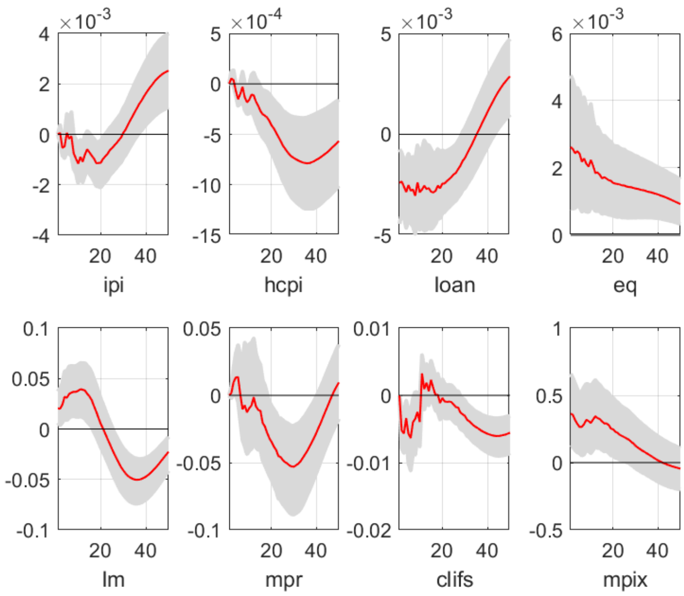

Figure 3.20: IRFs to CR shock in Greece

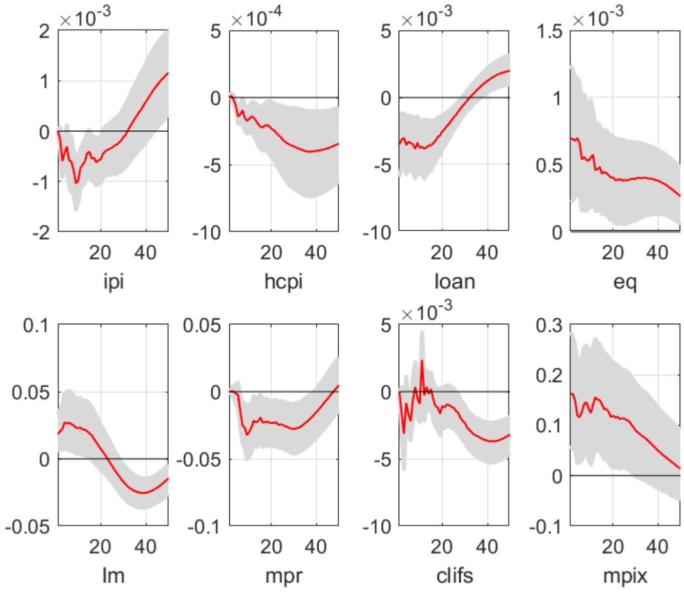

Figure 3.21: IRFs to CR shock in Italy

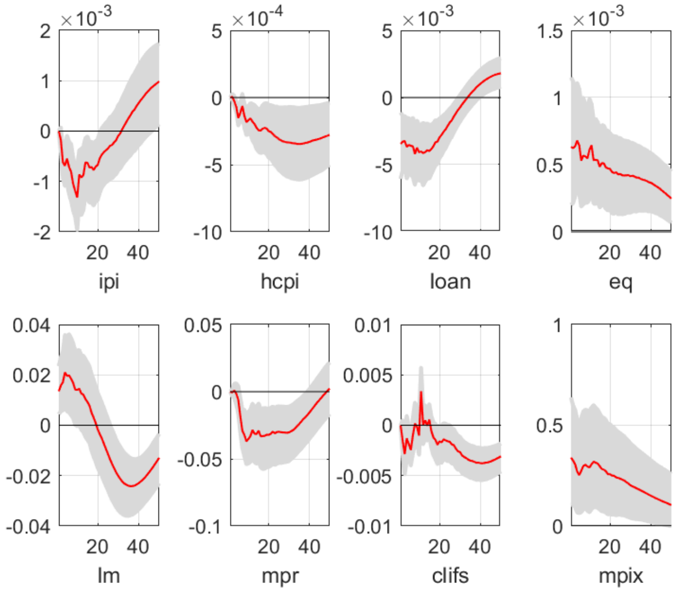

Figure 3.22: IRFs to CR shock in the Netherlands

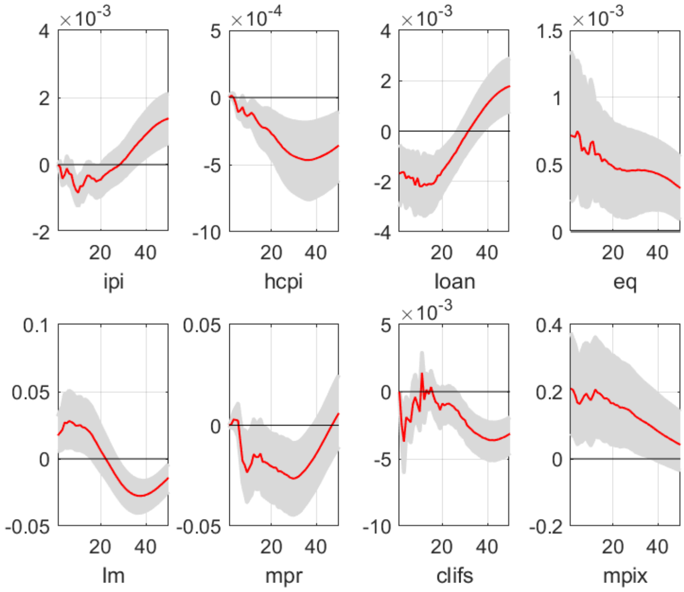

Figure 3.23: IRFs to CR shock in Portugal

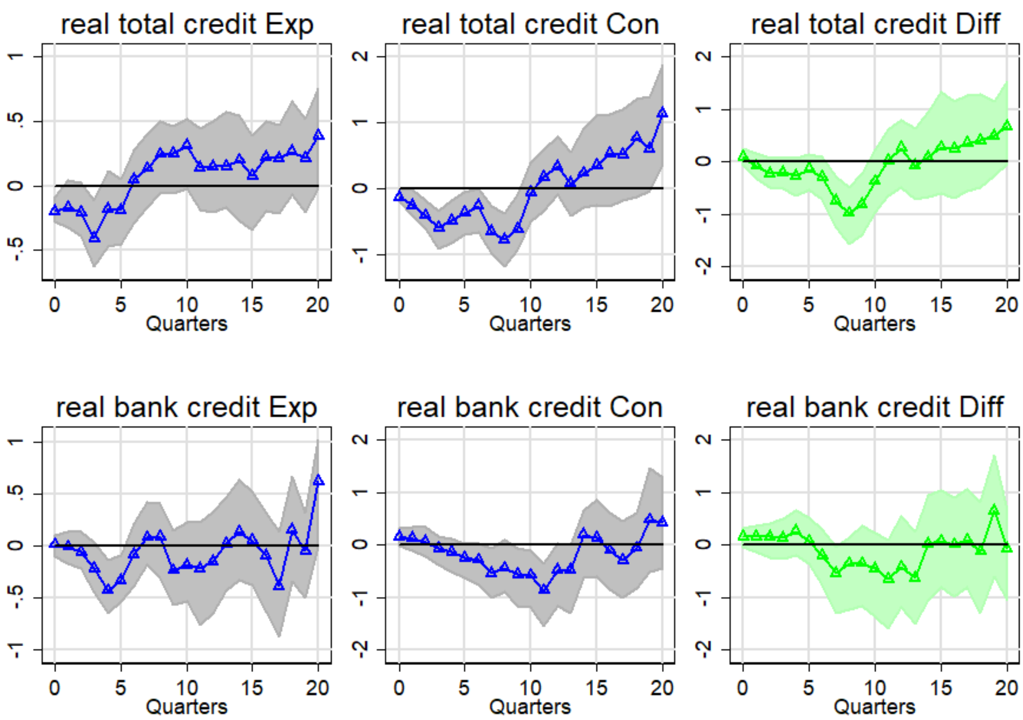

Figure 3.24: CR shock state-dependent local projections. *Note*: the figures show 68% credible set (16th and 84th percentile of the points estimate's distribution). "Exp" and "Con" are states of business cycle expansion and contraction, respectively. DIFF is the difference Con-Dif of the dynamic multipliers.

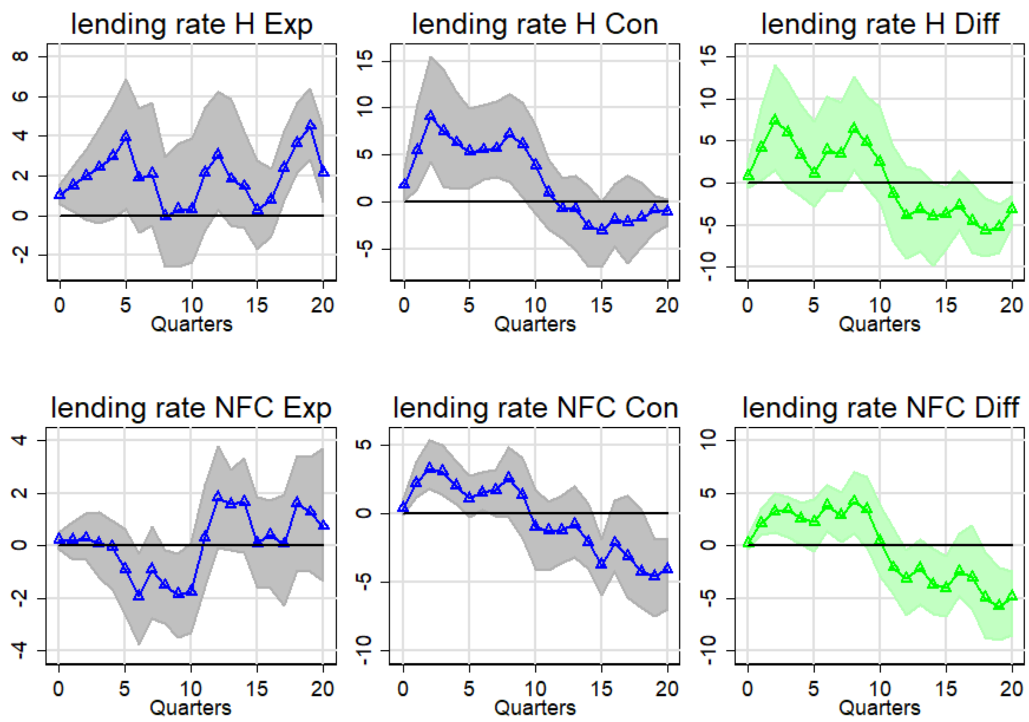

Figure 3.25: CR shock state-dependent local projections. *Note*: the figures show 68% credible set (16th and 84th percentile of the points estimate's distribution). "Exp" and "Con" are states of business cycle expansion and contraction, respectively. DIFF is the difference Con-Dif of the dynamic multipliers.

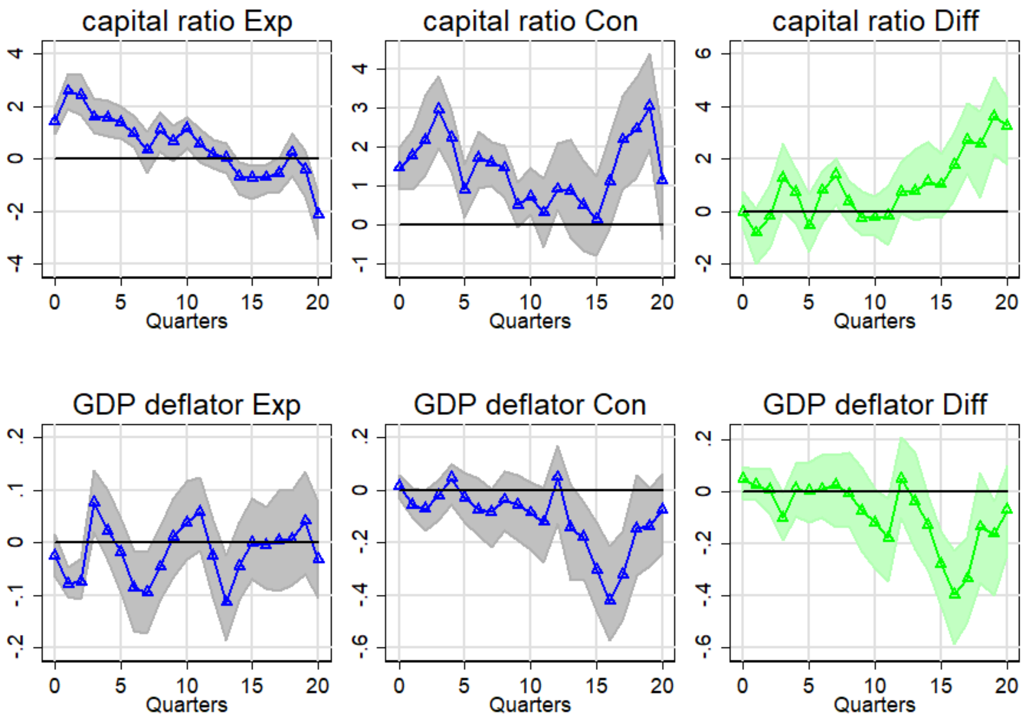

Figure 3.26: CR shock state-dependent local projections. *Note*: the figures show 68% credible set (16th and 84th percentile of the points estimate's distribution). "Exp" and "Con" are states of business cycle expansion and contraction, respectively. DIFF is the difference Con-Dif of the dynamic multipliers.

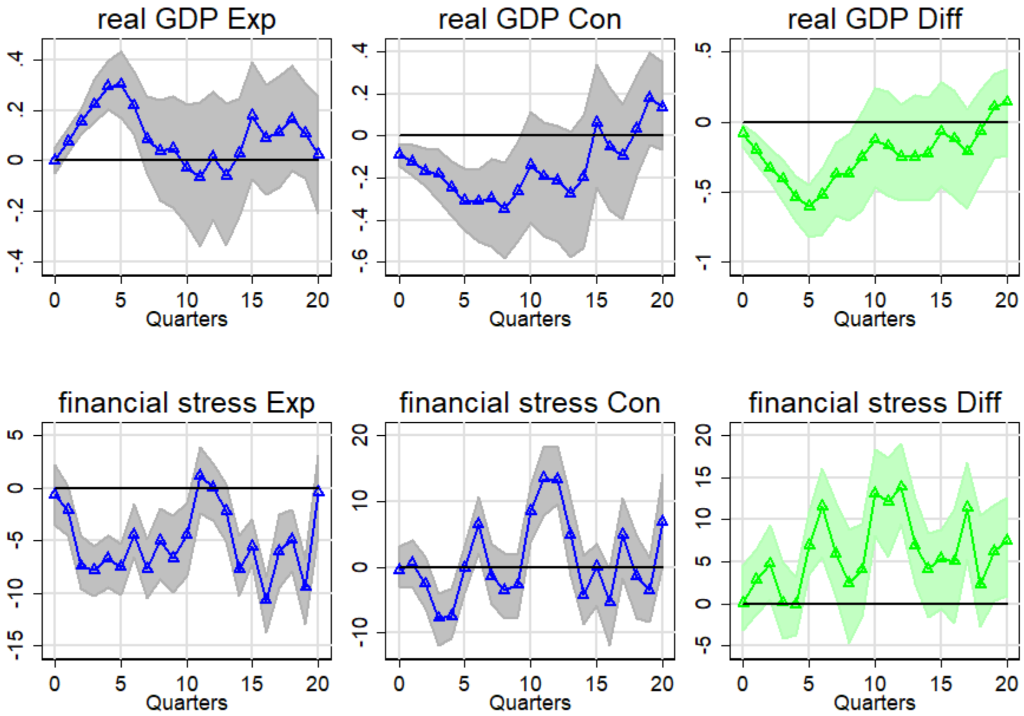

Figure 3.27: CR shock state-dependent local projections. *Note*: the figures show 68% credible set (16th and 84th percentile of the points estimate's distribution). "Exp" and "Con" are states of business cycle expansion and contraction, respectively. DIFF is the difference Con-Dif of the dynamic multipliers.

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