Essays in banking, credit and the macroeconomy

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“Realize deeply that the present moment is all you ever have.
Make the Now the primary focus of your life.”
Eckhart Tolle

Abstract

Over the last two decades, banks have become increasingly large and interdependent due to the ongoing process of globalization of international trade and finance, as well as the advent of a wide range of technological advances that have made financial services more easily accessible to the public. These developments in the banking sector translate into more credit availability in the financial system. Credit availability is essential for households and firms' financing and investment decisions with potential direct effects on economic growth. On this regard, scholars agree that while, on the one hand, a sustainable credit expansion can foster economic growth, on the other, such expansion can undermine financial stability if not properly handled. Thus, the magnitude and time dynamics of credit aggregates pose significant policy challenges for policy-makers. This thesis contributes to the ongoing debate on the nexus between banking and the real economy, in the attempt of leaping forward in the quest of causality between finance, stability and growth.

In Chapter Two, we investigate the link between shocks originating from the banking sector and aggregate leverage, as measured by the credit-to-GDP gap. Using a balanced panel of 15 advanced countries for the period 1989-2016, we build on the Granularity Hypothesis and investigate banking granular shocks, based on balance sheet data of large banks, as an indicator of banking distress. Using methods that account for potential endogeneity between the real and financial sectors, we find that banking shocks Granger-cause aggregate leverage risk. In particular, banking shocks tend to increase the level of leverage and cause departures of the credit-to-GDP ratio from its long-term trend. This result highlights the importance of closely scrutinising how the lending activities of large banks evolve, as the cohort of large banks is capable of moving upward/downward overall leverage of the entire financial systems.

In Chapter Three, we first uncover the time series properties of private credit in a panel factor model of 12 Eurozone and 8 non-Eurozone European countries and find evidence of credit convergence. We then focus on the first principal component of total credit, credit-to-GDP ratio, and credit-to-GDP gap series, and find the occurrence of long-run relationships between the latter and measures of ECB's unconventional monetary policy, such as total assets and the shadow interest rate. Such a relationship is robust even after accounting for multiple structural breaks in the data. Within a structural factor augmented VAR (SFAVAR) approach, shocks to the above unconventional monetary policy variables are found to be positively related to the common factor of total credit, which we take as evidence on the transmission mechanism of UMP through the credit channel.

In Chapter Four, we examine the factor structure of private and public debt for a cohort of 22 advanced economies over the period 2000-2019. We control for cross-sectional dependence in the panel data using a principal component approach, where we also disentangle the data into unobserved common factors and idiosyncratic components. Using methods that account for the long- and short-run dynamics and potential endogeneity, as well the presence of cross-sectional dependence, we shed light on the heterogeneous behaviour across credit types and countries. Empirical results show that common factors affect the causality in the credit-growth nexus.

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Declaration

I declare that this thesis is the result of my own original research under the guidance and supervision of Professor Giorgio Fazio and Dr Fabrizio Casalin. Both of my supervisors have provided comments, suggestions on drafts of all chapters of this thesis. I confirm that the work submitted is my own, except where work which has formed part of jointly-authored publications has been included, and where stated otherwise by reference or acknowledgement, the work presented is entirely my own. I further declare that this thesis has not been submitted, or is being concurrently submitted, in whole or in part, for any such degree, diploma or other professional qualification at Newcastle University or any other university or similar institution of learning.

Chapter Two and Chapter Three have been enriched with comments and suggestions received in conferences and discussions with participants, colleagues and peers in the profession.

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Chapter 1. Introduction

The outbreak of the global financial crisis of 2007-2008 has made more evident than ever the importance of banks at both the local and global levels. The recent advent of several innovations in the way individuals and institutions do finance has made the nexus between credit institutions and the real economy possibly even more convoluted. Such changes allow for the creation of large, sophisticated and highly interconnected banking institutions with a wide range of products and services to offer. These transformations in the banking industry, however, have not altered some fundamental features of banks, which makes them fragile and inherently unstable institutions. This aspect poses several potentially troublesome implications and concerns for the financial system, highlighting the need for an empirical renaissance of banking research in the context of financial stability. In this vein, academics and policymakers need to reassess the role of credit – and the bank lending channel – within the domain of the finance and economic growth literature. This relationship is one of the crucial issues in financial economics, and the understanding of its key elements is a matter of first-order that might lead to a better formulation of banking regulation and crisis management tools as effective instruments to ensure the stability of the financial systems.

Consequently – despite its importance – the relationship between real and financial sectors remains highly debated. Surveys on this literature routinely highlight the ongoing disagreement within the economics profession about the finance-growth nexus (Popov, 2018). On the one hand, several scholars argue that the contribution of the financial markets to growth has been pivotal (Schumpeter and Redvers, 1934). On the other hand, some scholars argue that if finance grows excessively, it might become a venomous seed for future economic recessions (Schularick and Taylor, 2012; Arcand et al., 2015; Mian and Sufi, 2015; Zhu et al., 2020). Hence "too much" finance may not be beneficial for the real economy (Cecchetti and Kharroubi, 2012). In this regard, credit expansion has two potential outcomes, it can either foster economic growth, or undermine financial stability if not properly handled.

The interest over the role of banks in the real economy, most notably, is discussed in the literature that integrates financial market imperfections in macroeconomic models where market participants are exposed to more or less risk than they might desire. Early literature recognises that a large part of the cyclical behaviour in real variables is significantly generated by financial frictions as a result of constraints on households and firms' borrowing ability (see, e.g., Bernanke and Gertler (1989); Kiyotaki and Moore (1997); Brunnermeier et al. (2012)). Importantly, banks, as financial intermediaries, are also modelled as part of financial frictions. For example, banks' balance sheet and leverage ratios exhibit constraints due to agency problems (Gertler and Kiyotaki, 2010). In this respect, even small shocks to the ability of banks to acquire assets would force them to deleverage and shrink their balance sheet, with known effects on banks' performance and hence on the real economy.

In this thesis, we examine three research topics and contribute to bridging the gap between banking and the macroeconomy by modelling the build-up and evolution of private credit and their role for real economic activity in a way that sheds light on the ongoing discussions by economists on the macroeconomic role of banking.

In Chapter Two, we investigate the endogenous propagation of banking shocks to the real economy by merging two important strands of the empirical literature on macro-financial linkages. In a first step, we build on the Granularity Hypothesis of aggregate fluctuations proposed by Gabaix (2011) and apply it to the banking industry. The intuition behind the granular view is that if banks' sizes are normality distributed, then shocks on the lending of such banks should cancel out in the aggregate. However, if their sizes are fat-tailed distributed or highly concentrated, i.e., a small number of large banks dominates the market, then shocks to these banks can lead to nontrivial aggregate fluctuations, and hence matter for macroeconomic aggregates. The granular hypothesis in banking sheds light on the importance of large banks in the economy, such as the dependence of the real economy on bank-level fluctuations that emerge from basic lending activities. There is extensive evidence that the size distribution of banks is highly asymmetric, so that aggregate shocks in bank lending might have a substantial impact on the real economy. In addition to this, shocks that originate from large banks are of great interest for regulators as they pose systemic and contagion risks to the economy during periods of financial turmoil and uncertainty.

To study granular shocks in banking, we first measure banking shocks based on lending figures obtained from the balance sheet of large banks and then average such measure across banks to work out an indicator for aggregate granular shocks at the country level. Some scholars have already applied Gabaix's concept of granularity to the banking sector (Blank et al., 2009; Buch and Neugebauer, 2011; Amiti and Weignstein, 2017; Bremus and Buch, 2017; Bremus et al., 2017; Bremus et al., 2018). However, these applications are limited to the effects of such shocks on output, house prices and aggregate firm-level investment. We take the analysis forward by bringing together the concept of granularity in banking with the literature on early warning indicators for financial crises. We do so by digging deeper on the relationship between the credit-to-GDP gap – a measure of risk and a proxy for regulators to impose countercyclical capital buffers as part of the macroprudential policy toolkit – and the previously defined banking granular shocks. Hence, we contribute to the literature by integrating the credit-to-gap in the empirical analysis and questioning the role of banking shocks in helping to predict financial crises. Additionally, we shed light on the usefulness of the gap as an indicator of financial vulnerabilities. While this indicator has received attention from academics and practitioners, some authors continue to argue on its ability to forecast financial crises, (see, e.g., Hamilton (2018); Drehmann and Yetman (2020)). Further, in this chapter, an increase in the credit-to-GDP gap is perceived as an undesirable outcome that poses risk to the entire financial system.

From an econometric point of view, we make use of a Panel Vector Autoregressive model (PVAR), embedded within a Generalized Method of Moments framework, to account for possible endogeneity and feedback effects. The latter can arise from the dynamic interaction between the two sides of the economy and among banking and macro variables. Previous authors addressing banking granular shocks avoid endogeneity concerns and use a single-equation framework in their analysis. They simply assume that, by construction, banking shocks based on Gabaix's concept are exogenous and independent from real output. However, we argue that our approach is more general, flexible and yet consistent with Gabaix's framework and economic theory. To the best of our knowledge, our work is the first to depart from the conventional view of the literature and thereby treat banking shocks as potentially endogenous. This assumption is indeed relevant because the banking system is vulnerable to macroeconomic shocks and subject to regulatory requirements, simultaneously or with lags, with feedback effects of banks instability on economic activity that are amplified during periods of extreme credit booms and busts (Baltas et al., 2017). Because all variables are treated as endogenous, feedback effects should not represent an issue in our estimation.

The contributions of this chapter lend support to the notion that banking shocks positively affect aggregate leverage by making the credit-to-GDP gap depart from its long-term trend. This result signals that shocks at the micro-level of large banks can capture events where the private sector borrows excessively at levels that are not consistent with the output capabilities of the economy. Hence, they exercise pressure on the financial system to enter a phase of a credit boom, leading eventually to a sudden correction, and a recession. Our results emphasize the importance of monitoring the supply of credit from large banks and signal the importance of using the banking shocks measure to flag instances of financial distress.

Because the mortgage market plays a significant role in the stability of the financial market, we indirectly account for the mortgage market by adding the real house prices into the analysis and find a bi-directional and causal relationship between banking granular shocks and house prices. Such a result is in line with the endogenous response between credit, the housing market and the macroeconomy that emerges from the wealth and collateral effects of households and investors.

An implication of the results of this chapter is that future research should model endogeneity between the banking system and the macroeconomy and put policies that impact the market concentration of banks at the forefront of the financial stability agenda. Indeed, worries about too-big-to-fail banking institutions carry significant implications for the macroeconomy and are now more important than ever (Dávila and Walther, 2020)

The fact that bank sizes and their granular shocks matter for macroeconomic aggregates poses further challenges for their role as a significant source of credit for households, corporates and the governments.[1] In particular, monetary macroeconomics have traditionally focused on the role of the bank lending channel in the monetary transmission mechanism and in augmenting the impact of monetary policy changes on the economy. For example, bank lending tends to contract (increase) when monetary policy becomes tighter (loose) (Bernanke and Blinder, 1992).

Despite the lowering of interest rates to the zero lower bound (ZLB) in the aftermath of the financial crisis, growth in major economies has been sluggish, and further policy changes in conventional policy rate are no longer an option. As a result, the course of action taken by central banks to conduct monetary policy has been transformed, and countries needed new instruments to stabilize the banking system and, more generally, monetary conditions and credit markets. Central banks have increasingly resorted to large assets purchase programmes, referred to as quantitative easing (QE), and financed by the issuance of central bank money electronically, with the objective to inject large monetary stimuli into the economy, and thereby continue to exercise monetary policy; however, this time in an unconventional fashion (Kapetanios et al., 2012).[2]

The implementation of unconventional monetary policy (UMP) has raised pertinent questions about its effectiveness and sustainability, most notably in terms of inflation targeting, output stabilization and overall macroeconomic effects. This question has been the focus of the recent literature, see, e.g., Joyce et al. (2012); Gambacorta et al. (2014); Boeckx et al. (2017); Boeckx et al. (2020); Feldkircher et al. (2020).

The European Central Bank's (ECB) UMP has attracted the attention of scholars to question the effectiveness of the monetary policy since the ongoing challenges ensuing from the outbreaks of the subprime and sovereign debt crises. During the last decade, monetary economists have called for extending the objectives of the ECB to include financial stability on top of inflation targeting, in which the ECB should also monitor and control bank credit (Grauwe, 2018). It is worth noting that the ECB continues to perform unconventional measures at present, given the unprecedented downturns caused by the COVID-19 pandemic. Such measures consist of the so-called the envelope for the pandemic emergency purchase program (PEPP) that was increased in June 2020 by €600bn,

[1] Early scholars have sought to explain the important roles of the banking system and their intermediation mechanism in the economy, for example, information production, liquidity transformation, consumption smoothing. Such remarkable contributions are summarized in Leland and Pyle (1977), Diamond and Dybvig (1983), Diamond (1984), Fama (1985), Boyd and Prescott (1986), Friedman (1995), Bernanke and Mihov (1998) and Kashyap and Stein (2000).

[2] QE was first conducted by the Bank of Japan starting in the late 1980s (Ugai, 2007). Only from the onset of the 2008 financial crisis other central banks in major economies started performing such unconventional monetary policy tools, this includes, among others, the Fed, BoE, ECB (Gambacorta et al., 2014).

to a total of €1,350bn and was extended to, at least, the end of June 2021. Despite these programs, benchmark interest rates have remained stuck at the ZLB. This phenomenon motivates the need for further analysis to uncover the macroeconomic effects of UMP, especially the effects on bank credit. In Chapter Three, we investigate the transmission mechanism of UMP through the credit channel despite the challenges imposed by the ZLB and the identification strategy of UMP shocks. This vital question has been addressed partially by a handful of scholars who focus on the Eurozone, for example, Altavilla et al. (2016); Boeckx et al. (2017); van Dijk and Dubovik (2018); Kenourgios and Ntaikou (2019); Boeckx et al. (2020).

A feature that makes our work different from existing studies is that we do not rely explicitly on the volume of private credit to observe its reaction to UMP shocks. Instead, we use factor analysis methods to extract the common factor of the national private credit series. This strategy is relevant for two reasons. First, it allows us to explicitly unravel the dynamics of private credit of the countries in our sample and investigate whether their cross-sectional dependence is dominated by a common factor structure. Previous works that use credit in a panel data framework treat the factor as a nuisance parameter rather than a key determinant to eliminate cross-sectional dependence (O'Connell, 1998; Sul, 2019). We assume that such a common factor carries important information about the evolution of credit and can be a proxy for the common UMP conducted by the ECB in the Euro area. Therefore, in a second step, we integrate the common factor in a structural VAR framework to study its response to UMP shocks identified using a combination of zero and sign restrictions. Our factor-augmented structural VAR (FASVAR) incorporates ECB's total assets as a proxy for UMP besides the traditional macroeconomic variables found in the literature on monetary policy. We also use the shadow rate as a replacement for total assets for robustness. This rate, unlike the policy rate, does not feature a zero-bound and it is, therefore, able to take negative values, hence capturing UMP. Albeit using quarterly data compared to monthly data used in the literature, our results are comparable and show that ECB's interventions using unconventional measures are capable of increasing output, and with lesser effects, prices, and reducing the levels of financial stress and interest rates. Most importantly, our results reveal that an expansionary UMP shock, identified using either total assets or the shadow rate, increases the common factor of total credit, which we take as evidence of the credit channel of UMP.

Since the ECB has been currently using unconventional measures to revive the confidence in financial markets and it is likely to continue in the future, banks remain a critical channel for the transmission of monetary policy, and our results offer a fresh perspective to understand the implications and reforms of central banks efforts to enhance the real economy. Unlike chapter two, in chapter three, a positive response of credit to UMP shocks is a desirable outcome by policymakers and can be seen as a boost in private lending to the real economy.

In Chapters Two and Three, we investigate the role played by the credit market and banking intermediation and argue that their size and soundness are priorities for financial stability and real economic activity. These ideas constitute the key responsibility of banks in channelling funds between borrowers and lenders. However, most clearly, they conceptualize the banking system aspects of monetary policy in the transmission mechanism, as first expounded by (Bernanke and Blinder, 1988). In this view, monetary interventions alter how banks behave and operate, and influence consumption, saving and investment decisions of households and corporates, who depend on banks for financing – assuming that other sources of funds are imperfect substitute to bank credit – (Kashyap and Stein, 1997).

Banks thus have been the engines of growth because they shape the way modern economies develop. In parallel, the written evidence shows that banking activities were not only present in modern economies, but also in the first and second centuries AD in Rome, and they were even found in the fifth century BC in Athens, Egypt and Palestine (Andreau, 1999). Nevertheless, a longstanding debate in the current literature pertains the direction of the relationship between bank credit and growth. The main reasons for such an unsettled argument are the issues of causality and endogeneity. Specifically, the empirical evidence in early studies demonstrates the correlation between finance and growth. Although such results are significant and robust, serious criticism of these findings has always been on the assumption as to whether banking intermediation – and the financial sector – is somewhat exogenously determined, and thus emerge independently from growth, or endogenously determined, and thus it is a natural reflection of the real sector (Cetorelli, 2015).[3] While addressing endogeneity is a legitimate step to solve the conundrum of the finance-growth nexus, the overall analysis is furtherly compounded by the presence of common factors that might affect both the financial and real sectors (Zingales, 2003).

Thereby, the presence of global common factors makes examining the credit and growth nexus more complex (Chudik et al., 2018). In Chapter Four, we study this relationship while examining the factor structure of aggregate credit measures. Previous scholars use the cross-sectional averages (CSA) method to treat cross-sectional dependence in panel data settings and account for the common factors (see, e.g., Chudik et al. (2017); Lombardi et al. (2017)). However, several scholars have highlighted how this method suffers from several shortcomings. Firstly, CSA is not capable of detecting any heterogeneity in the response of units to common factors. Secondly, if the factor number increases, then the accuracy of CSA decreases. An alternative and possibly more suitable approach

[3] For a comprehensive review and illustration on different econometrics methodologies and identification problems used to assess the nexus between finance and growth, see, e.g., Beck (2009).

would be the principal component (PC) method as long as the number of common factors in the panel data of interest is greater than one (Sul, 2019).

Thus, in Chapter Four, we differentiate our work from the previous literature in two ways. First, we disentangle the credit series of a panel of 22 countries into two components, global common factors, and idiosyncratic components using the PC approach. We also use three different types of credit, namely, household and corporate lending, as well as public debt, to observe if the relationship between growth and finance varies depending on the type of credit series. In a second step, we make use of the idiosyncratic components of credit and growth and study their relationship in the long- and short-run in panel Autoregression Distrusted Lag (ARDL) and panel Vector Autoregression (VAR) frameworks. This choice of empirical methods presents a holistic and more nuanced remedy for the endogeneity and cross-sectional dependence issues to ensure valid inference.

Our findings are twofold. First, we uncover the time series properties of the three types of credit. Global unobserved common factors are important for household credit and public debt, while corporate credit exhibits mostly idiosyncratic behaviour. Additionally, household credit and public debt are driven by three and two common factors respectively and cannot therefore be summarized by a single indicator. Hence the PC approach is more appropriate than the CSA method previously used in the literature. Second, we find that economic growth is a drag on credit variables in the long-run. The short-run results show that the negative effects go from growth to credit and not the other way around using the de-factored variables, i.e., the idiosyncratic data. However, only with the presence of common factors, credit variables have significant effects on growth. Given these findings, we conclude that the common factors found in the data are a consequence of the global banking system integration, and responsible for the propagation of shocks from the financial sector to the real economy.

At the time of writing this thesis, and to the best of our knowledge, we are the first to examine the common factors of private and public debt. While this chapter's main contribution is on credit and growth nexus, our results provide a good starting point for exploring the hypothesis that credit should, at least to some extent, be modelled as a global rather than local phenomenon. In this vein, we believe that our results present a platform on which future studies can build on the role of the common factors in transmitting monetary policy shocks to the real economy and eventually affect the global sustainability of credit aggregates.

Finally, Chapter Five concludes this thesis by summarizing the contribution of each chapter, the main results and policy implications. It also discusses the research limitations and possible avenues for future research.

Chapter 2. Bank-specific shocks and aggregate leverage: Empirical evidence from a panel of developed countries

2.1 Introduction

The pivotal role of the banking system in the 2008 financial crisis has led to a resurgence of interest in the role of the banking channel in smoothing or exacerbating financial and real shocks. From the theoretical standpoint, several studies have incorporated the behaviour of banks in standard Dynamic Stochastic General Equilibrium (DSGE) and agent-based models to describe the endogenous propagation of shocks between financial and credit markets and the rest of the economy (see, e.g., Greenwood and Jovanovic (1990); Gerali et al. (2010); Laeven et al. (2015)). Empirical studies have extensively focused on gauging the link between credit shocks and the real economy, triggering intense debates on the influential role of credit in driving global activity during recessions (Helbling et al., 2011). Many scholars agree that stock market bubbles are accompanied by credit market booms (Miao and Wang, 2018) and that the main source of interaction between financial and real variables is financial markets' imperfections. Since firms' balance sheets and households' creditworthiness are both likely to be procyclical, they are core determinants and amplifiers of macroeconomic activity. Variations in the constraints that limit the ability of firms to borrow are described as financial shocks (Jermann and Quadrini, 2012). Such financial shocks – originating from asset prices, stock markets, and corporate bond spreads – have their effects on production and spending, and are believed to convey important signals regarding risks to the economic outlook (Gilchrist and Zakrajšek, 2012).

However, scholars have devoted less attention to the role that banking shocks play for the overall risk in the economy. Inarguably, the presence of large banks makes government interventions and costly bailouts more likely, deserving close attention from scholars (Dávila and Walther, 2020). This issue is crucial for policymakers, particularly when such shocks originate from large banks, posing systemic and contagion risks to the economy. In this chapter, we fill this gap in the literature and investigate the link between shocks originating from the banking system and aggregate leverage, which is essential for financial stability and regulatory discussions.

Our analysis builds on the Granular Shocks Hypothesis introduced by Gabaix (2011) in the context of the relationship between large firms and aggregate output, where the hypothesis posits that idiosyncratic shocks to large firms have the potential to generate nontrivial aggregate shocks that affect GDP growth. Such an impact can be sizeable when firms are highly concentrated within an economy, and their size follows a power-law distribution. Similar hypotheses have been formulated in the banking literature, where the argument is that if the banking system is highly concentrated –

i.e., few large banks own and produce a large share of loans in the market– the shocks generated by these banks do not average out over time, and they may have an impact on the real economy.

Moreover, according to Gabaix (2011) small firms/banks would have no systemic implications on the macroeconomy in a highly concentrated banking industry. In the light of this, and to be consistent with the granularity hypothesis and the literature that addresses this hypothesis in banking, we exclude small banks in our sample and focus only on large banks.

In this regard, Buch and Neugebauer (2011) find a positive link between banking granular shocks constructed out of the total loans aggregate and the real economy. Bremus and Buch (2017) look at the relationship between banking granular shocks and financial openness and show that banking shocks tend to be stronger in financially closed economies. Recently, a boost to the existing literature has come from Bremus et al. (2018), who provide both theoretical foundations and empirical evidence that banks' size follows a Pareto distribution, especially when there are a few large banks that dominate the market, so that their size matters for aggregate outcomes. Similarly, Galaasen et al. (2020) provide another example of a Pareto distribution that occurs in banks' loans data. This result is significant, as it is one of the main assumptions of Gabaix's model.

In this chapter, we uncover the link between banking granular shocks and aggregate leverage – as measured by the credit-to-GDP gap. More specifically, we follow Gabaix's approach and analyze whether shocks to large banks – measured in terms of their lending and size – have any effect on the credit-to-GDP gap.[4] The latter is considered in the literature as an important leading indicator of financial crises as well as a measure of aggregate leverage (see, among the others, Giese et al. (2014); Jokivuolle et al. (2015)). Our focus is on 15 developed economies and main international banking centres. In these countries, the interplay between finance and the real economy has been particularly relevant, with economic downturns affecting the soundness of financial institutions, and vice versa, as witnessed in the Global Financial Crisis. For these economies, we gather data between 1989 and 2016, a period interspersed with episodes of financial distress and economic slowdowns.

To the best of our knowledge, this is the first time that the credit-to-GDP gap is considered in the empirical literature of banking shocks. Moreover, from the methodological standpoint, while previous studies mostly use single equation frameworks, here we exploit a Panel Vector Autoregressive (hereafter PVAR) approach that, coupled with a long time span of data, allows to better model the time dynamics and interactions among the observed variables, accounting for

[4] The unequal distribution of banking firms in terms of size motivates the empirical analysis and the strategy in calculating the shocks variable. See, e.g., Bremus et al. (2018).

possible endogeneity.[5] As discussed in the existing literature, accounting for the dynamic interaction and feedback effects between banking and macro-aggregates can be particularly important when banks face cyclical macroeconomic conditions as well as simultaneous and correlated regulatory changes (Kanngiesser et al., 2017).

Our analysis presents a contribution to the banking literature on the granular hypothesis. We find that shocks originating from large banks have positive effects on aggregate leverage.[6] The empirical results suggest that shocks originating from large banks increase the credit-to-GDP gap by as much as 4.5 percentage points over a time horizon of two years. We also find that such dynamics are unidirectional, with banking shocks affecting the leverage but not vice versa, and asymmetric in terms of length and magnitude, as positive shocks boost the gap while negative shocks dampen it. These results are of relevance for policymakers and regulators for several reasons.

First, they emphasize the importance of monitoring the supply of credit from large banks, as these can lead to increased levels of leverage that can generate financial imbalance and crises. Second, they show that the credit-to-GDP gap conveys useful information about the dynamics of lending – especially from large banks – giving support to its use as an early warning indicator. Finally, Granger-causality tests show that banking shocks can anticipate the occurrence of peaks and troughs in the gap. As such, they might be able to flag instances of financial distress in a timelier way than the gap itself. The use of banking shocks in this direction could become particularly important in the phenomenon of the zero lower bound and in the presence of unconventional monetary policies that may distort the ability of the term structure to predict the fluctuations of real and financial aggregates.

The remainder of this chapter is organised as follows. Section 2.2 discusses the literature on banking shocks and the real economy. Section 2.3 describes the dataset. Section 2.4 presents the empirical methods, and Section 2.5 discusses the empirical results. Finally, Section 2.6 concludes.

2.2 Literature review

This chapter builds on the recent strand of research on the "Granularity Hypothesis", first formulated by Gabaix (2011), in which idiosyncratic shocks to individual large firms do not average out in the aggregate. In this seminal paper, the author investigates the behaviour of large firms in a

[5] As explained in Section 2.3.1, unlike previous authors, we do not compute banking granular shocks as residuals obtained from regressions that filter out the effects of GDP and its time lags. Instead, we follow the original approach proposed by Gabaix (2011) which does not remove such effects. Then, we use PVAR methods to account for any feedback effect among the variables under scrutiny. In this respect, we believe that our approach is more general than alternatives used in the literature.

[6] We define leverage as the private sector (i.e., non-financial corporations and household) debt outstanding in relation to GDP at the country level, which is common in the macro-finance literature. A detailed explanation on how to measure aggregate leverage is given in Section 2.3.2.

theoretical context with model calibration and tests the above hypothesis empirically using US annual data from 1951 to 2008. He finds that the idiosyncratic fluctuations, calculated using balance sheet ratios for productivity and size of the 100 largest firms, explain about one-third of the variation in output growth.[7] He then concludes that idiosyncratic shocks are an important part of business cycle fluctuations and that a higher degree of firm concentration makes the relationship between firm shocks and macroeconomic fluctuations stronger.

Some scholars have applied Gabaix's concept of granularity to the banking sector (Blank et al., 2009; Buch and Neugebauer, 2011; Amiti and Weignstein, 2017; Bremus and Buch, 2017; Bremus et al., 2017; Bremus et al., 2018). While these applications validate the importance of looking at granularity, their focus has been on the effects of such shocks on output, house prices, and aggregate firm-level investment.

Blank et al. (2009), for example, explore whether shocks originating from large banks affect the probability of distress of small banks, and thus the stability of the banking system. In calculating banking granular shocks, they argue that bank loans and deposits are increasingly biased measures of banks' activities because of the growing importance of investment banking and the so-called universal banking. Consequently, they use banks' total operating income as a proxy for banks' size and use the cost-to-income ratio as a measure of the origins of shocks. Using annual data from 1991 to 2005 for the 10 largest banks in Germany, they present two main findings. First, size matters in banking, i.e., German banks follow an uneven size distribution. Second, the soundness of the whole banking system is affected by adverse shocks to large financial institutions. As a result, shocks originating from large banks increase the probability of distress for small and medium-size banks.

Buch and Neugebauer (2011) generalize the previous finding by applying the concept of banking granularity to a larger sample of 35 European countries for the pre-crisis years from 1996 to 2006. In order to identify the largest banks, they choose only those banks that generate at least 5% of the total operating income of the industry in each country. They argue that a 5% threshold ensures that large and systemically important banks are included. Also, they choose net loans as a measure of productivity for the largest banks. Their findings can be summarized as follows. First, idiosyncratic shocks in the loan growth of large banks have a statistically and economically significant impact on the rate of economic activity, explaining about 16% of the cyclical variation of GDP growth. Second, they find strong evidence of a positive link between shocks from loan growth to real GDP in Eastern European countries compared to Western European countries. They claim that the lower degree of financial development in Eastern Europe and the difficulties in switching to alternative financial sources due to severe information asymmetry can explain such dichotomy in the results.

[7] Such cohort of firms excludes however firms in the oil, energy and financial sectors.

In the case of Japan, Amiti and Weignstein (2017) study the effects of banking granularity on investment. Their work incorporates three major distinguishing features. First, they exploit the heterogeneity in sources of firms' financing to aid the identification of time-varying banking shocks hitting firms. Second, their approach to the estimation of banking shocks accounts for the impact of new lending relationships between banks and firms. Third, they estimate the shocks directly from the loan data and do not rely on the use of instruments in their shock's identification strategy, because such instruments may be correlated with firm-borrowing and bank-supply shocks. By developing a new methodology on a unique dataset from 1990 to 2010, they separate bank-supply shocks from firm-borrowing shocks. Using Weighted Least Squares, they show that idiosyncratic granular bank supply shocks explain 30-40% of aggregate loans and investment fluctuations.

In another study, Bremus and Buch (2017) focus on the relationship between granularity in banking and economic growth, while accounting for an economy's financial openness and market concentration. They use a panel of 79 countries from 1996 to 2009 and calculate banking granular shocks from the banks' assets and credit volumes. They find that financial openness affects the strength of granular shocks: the different availability of alternative credit options means that these shocks produce smaller (larger) effects on macro fluctuations in more (less) financially open countries.

Integrating the housing market with banking granularity, Bremus et al. (2017) study the relationship between mortgage supply shocks at the bank level and regional house prices in the US from 1990 to 2014. They point out that there is a positive and statistically significant link between idiosyncratic mortgage shocks and house price growth and that the stronger concentration is in the mortgage market, the more micro-level shocks spread across the housing market.

In a similar vein, Bremus et al. (2018) model granularity in a theoretical context, considering banks as heterogeneous in terms of their cost of intermediation while competing to provide homogenous loans. They test the model empirically by employing panel regressions on annual data from 1996 to 2009 for 83 countries. Using total loans to calculate banking shocks, they find support for the hypothesis that bank size follows a power-law distribution. Their study concludes that banking granular shocks are positively and significantly associated with the growth rate of domestic credit and real GDP. While our work focuses on banking granular shocks, it differs from theirs in three ways. First, from the methodological standpoint, whereas they rely on single-equation methods (panel fixed-effects), we exploit a multivariate panel equation setting (PVAR). Second, while their sample includes a broader cross-section of countries but a shorter period of 14 years, we investigate a smaller set of developed countries but for a more extended period of 28 years. Third, while they test the effects of the shocks on the growth rate of credit, we test for their role on the credit-to-GDP gap that, as mentioned before, is considered a measure of leverage risk.

In summary, motivated by the above applications, our study aims to shed light on the granularity hypothesis in banking by considering its role on a measure of leverage, namely the credit-to-GDP gap, often considered as a leading indicator of impending financial crises and used by policymakers as a component of the macroprudential toolkit to enhance banking system resilience and mitigate systemic risk through bank capital regulations. Specifically, we test the hypothesis that banking granular shocks accelerate the economy's financial leverage. In contrast to previous studies, we contribute to the current debate by investigating the ability of the gap to convey information about the banking industry and by using PVAR methods. Unlike conventional single-equation methods which are common in previous studies, our PVAR settings account for possible endogeneity among the variables under scrutiny.

2.3 Data

We gather balance sheet annual data for the largest banks operating in 15 developed economies for the period 1989-2016. We then retrieve the time series of macroeconomic variables, such as real GDP, interest rates and consumer prices, over the same period.

First, we use *Datastream* to identify the largest banks operating in each country and then calculate a measure of shocks' granularity.[8] Similarly to Buch and Neugebauer (2011) and Bremus et al. (2018), we select for each country all commercial and universal banks that generate an average of 5% of net operating income of the industry in each of the selected countries during the sample period. In some cases, countries are too small and have a very concentrated banking system, so setting the threshold at 5% would select only one bank. In this case, we drop such countries from our data set and we only include countries with at least three banks in the sample.[9] We also exclude large banks whose data are available only for shorter time spans or are missing, and replace them with banks of similar size from the same country. By applying such criteria, we are able to gather a balanced panel, which is advantageous especially in terms of efficiency gains when using PVAR methods. Table 2.1 reports the countries and the number of banks considered in the empirical analysis, as well as the percentage of banks from the total sample in each country considered for the computation of the banking shocks variable.[10]

[8] Compared to alternatives, *Datastream* allows us to construct a dataset with a sufficiently large cross-section of countries and a time period that spans more than 25 years. Since data for Japanese banks are available only from the year 2000, we have decided to drop this country from our dataset.

[9] This restricts the cohort of countries under scrutiny to 15.

[10] We do not rule out the importance of shocks to banks that went bust, however, data on such banks are not available to us, and therefore it is not feasible to include them into the analysis.

Table 2.1. Total number of banks used in the analysis and banking market concentration

Country	Number of banks	% of the Total	Market concentration
Austria	4	6.452	55.39
Belgium	3	4.839	63.98
Canada	6	9.677	61.05
Denmark	4	6.452	86.60
France	5	8.065	57.67
Germany	3	4.839	66.94
Greece	4	6.452	77.04
Ireland	3	4.839	66.44
Italy	5	8.065	59.40
Portugal	3	4.839	80.93
Spain	4	6.452	62.12
Sweden	3	4.839	92.07
Switzerland	4	6.452	64.09
United Kingdom	5	8.065	51.12
United States	6	9.677	35.12
Total	62	100	

Notes: This table reports for each country, the number of large banks used to calculate the banking shocks variable, their percentage over the whole sample of banks (commercial and universal banks) and banking market concentration. Concentration is calculated using the assets of the largest banks within a country divided by the total assets in the banking system. Calculations are based on balance sheet data for the year 2016 (source: *Datastream*).

Even though the total number of banks varies widely among countries, the last column of Table 2.1 shows that all considered countries have a relatively high degree of concentration. On the one hand, the US has the lowest concentration of 35.12%, which is expected for a more market-oriented economy. On the other hand, Sweden has the highest concentration of 92.07%, supposedly due to considerable economies of scale and substantial barriers to entry in the banking system. Moreover, the substantial level of concentration (i.e., >35%, with an average of about 55-60%) suggests that large banks play a pivotal role in the countries under analysis. It is, therefore, quite possible that shocks emanating from such large banks might have an impact on the macroeconomic conditions of such countries, and possibility on the credit-to-GDP gap.

2.3.1 Computing banking granular shocks

We start our analysis by identifying the variables that can be used to calculate the banking granular shocks (BGS) variable. In line with Gabaix (2011), one input must be a measure of a bank's output and the second a measure of a bank's size. We, therefore, choose total operating income, including interest and non-interest income, as a proxy for the size. This variable will also help us identify and select the largest banking firms in each country. The rationale behind this analogy is that larger banks are expected to generate more profits than smaller banks and that the market share (i.e., bank concentration) is positively related to profits (Berger et al., 1993). We then choose total loans – a broad measure including consumer, real estate, commercial and industrial loans – to account for bank productivity. Although their traditional lending services have declined, loan contracts remain a significant element of a bank's balance sheet as a measure of its output (Allen and Santomero, 2001), as well as a key indicator for the credit channel of monetary policy (Kashyap and Stein, 2000). Also, using loans to work out our measures of granular shocks is consistent with previous studies such as Blank et al. (2009); Blank et al. (2009); Buch and Neugebauer (2011); Bremus et al. (2018).

The following three steps describe the procedure we follow to compute shocks of large banks in each country. In the first step, we calculate the annual growth rate of output of bank *i* in country *j* by taking the natural logarithm of its total loans:

$$\mathrm{g_{ij,t}} = \ln(\mathrm{loans})_{\mathrm{ij,t}} - \ln(\mathrm{loans})_{\mathrm{ij,t-1}}, \tag{2.1}$$

In the second step, we calculate the average growth rate of total loans of the largest *L* banks in country *j*:

$$\bar{\mathrm{g}}_{\mathrm{j,t}} = \frac{1}{\mathrm{L}} \sum_{\mathrm{i=1}}^{\mathrm{L}} \mathrm{g_{ij,t}}, \tag{2.2}$$

Finally, we obtain a measure of the banking granular shocks by summing up the weighted differences between the bank *i* growth rate and the mean growth of largest L banks, where the weights are calculated as the ratio between the total operating income for each bank *i* ($\mathrm{S_{ij,t}}$) and the total operating income of all largest banks in the country ($\mathrm{S_{j,t}}$).[11]

$$\mathrm{BGS_{j,t}} = \sum_{\mathrm{i=1}}^{\mathrm{L}} \frac{\mathrm{S_{ij,t}}}{\mathrm{S_{j,t}}} \left(\mathrm{g_{ij,t}} - \bar{\mathrm{g}}_{\mathrm{j,t}}\right). \tag{2.3}$$

According to *Datastream*, if two banks merge in a specific year then they will be treated as one bank from that year until the end of the observed period. Therefore, to account for possible outliers due to merger and acquisitions activities among banks in our sample, we follow Buch and Neugebauer (2011) and winsorize the values of banking shocks that fall outside the range [-0.5, +0.5]. This procedure affects only 3% of our observations and does not have significant effects on the final BGS measure.

[11] Because some countries in our sample have fewer banks compared to others, we have tried to calculate BGS in Equation (2.3) both including and excluding bank *i* from the average growth rate of banks in country *j*. Since the two BGS figures feature a correlation of 99% or above for the full cohort of countries considered, we report here only the results based on the former method of calculation.

Figure 2.1 displays the banking shocks obtained for each country. Noticeably, only few banking shocks take values outside the above band, mostly during the 07/08 crisis.[12]

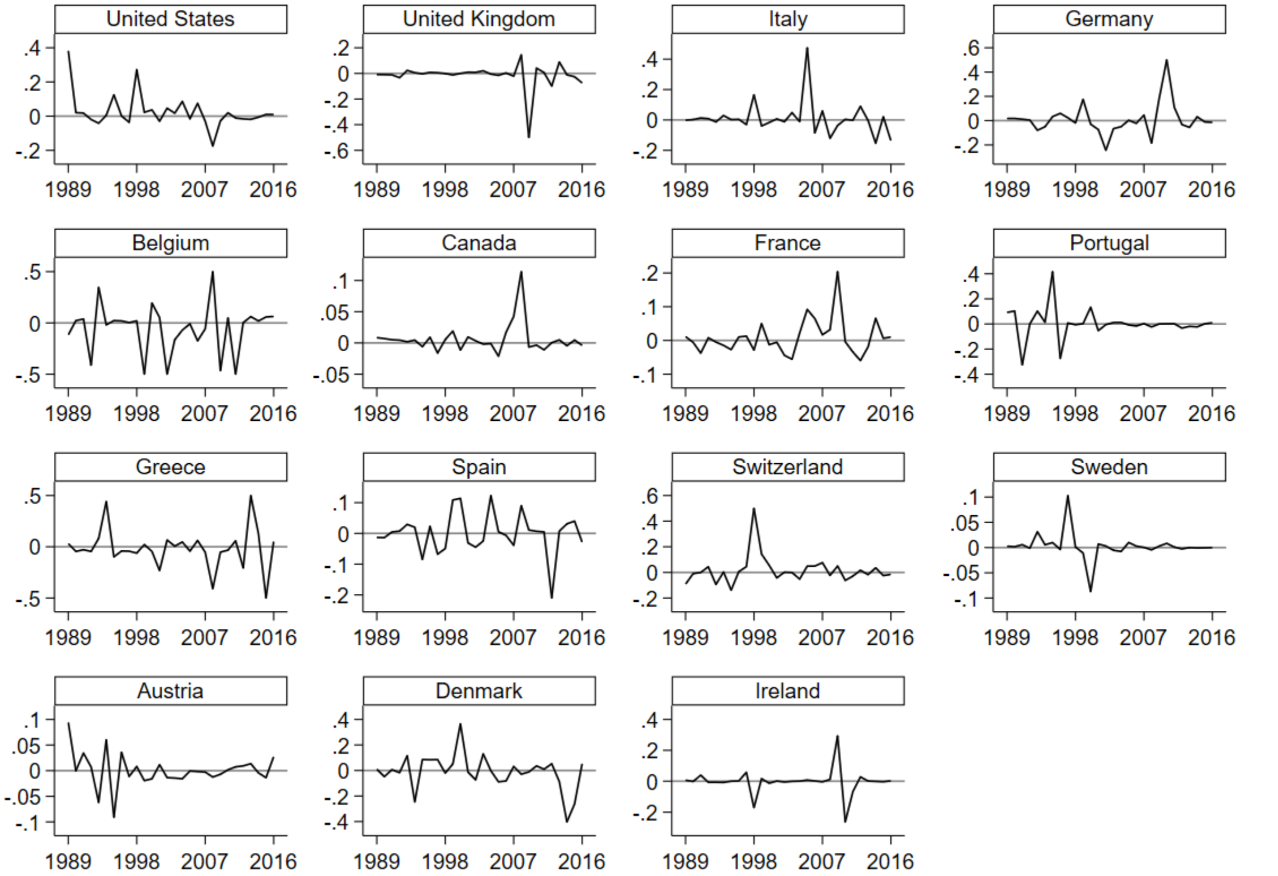

Figure 2.1. Banking granular shocks for 15 countries during the period 1989-2016 (N=15, T=28). These figures display the evolution of banking granular shocks calculated following Gabaix (2011) as set out in Equation (2.3).

Despite its application to the banking industry, the BGS measure is subject to potential weaknesses. First, one large bank with a positive shock can cancel out another negative shock of another large bank if the values of both shocks are equivalent in size and if they happen at the same year. In this case, the measure indicates a low value of BGS, and may not reflect an increase in lending as expected. Second, some scholars may argue that banks generate income through a large volume of non-lending activities, as a result, some banks in the sample can have a large net profit income but marginal lending activities. Third, if we have banking sectors like Germany and Italy that are based on large number of small and medium-sized financial institutions then the BGS measure may not fully capture the dynamics of large banking shocks.

[12] Unlike Buch and Neugebauer (2011) we do not calculate BGS as residuals of a regression of the bank loan growth on average country loan growth and current and lagged values of GDP growth. We instead use the standard BGS indicator, as in Gabaix (2011), which does not remove such macroeconomic effects.

2.3.2 Computing credit-to-GDP gap

We gather the data on the credit-to-GDP ratio from the Bank for International Settlements database, which also specifies the credit-to-GDP gap as the difference between the credit-to-GDP ratio and its long-run trend.

$$\mathrm{GAP}_{j,t} = \frac{\mathrm{credit}_{j,t}}{\mathrm{output}_{j,t}} - \mathrm{trend}_{j,t}. \tag{2.4}$$

The credit figure is the total credit to the private non-financial sector, capturing total borrowing from all domestic and foreign sources. The trend component to generate the gap in Equation (2.4) is derived using the Hodrick and Prescott (1997) (HP) filter. Many scholars stress the importance of the credit-to-GDP gap as an Early Warning Indicator for banking crises. According to the BIS, a gap value higher than 2.5% indicates that the system is borrowing at levels that are not justified by the output producing abilities of the economy, hence a negative impact on the economy.

Drehmann and Yetman (2018) argue that the credit-to-GDP gap outperforms other gap measures across many forecast horizons as the best predictor of crises. Other authors use the credit-to-GDP gap to predict periods of excessive leverage and banking crisis (see, e.g., Jokivuolle et al. (2015); Teimouri and Dutta (2016); Alessi and Detken (2018)).

Since our banking data are at annual frequency, our credit-to-GDP gap is calculated by first taking the annual average of the quarterly ratio. We then measure its long-term trend using an HP filter with an appropriate smoothing parameter and finally compute the difference between the ratio and its trend.[13] Figure 2.2 displays the series of the credit-to-GDP gap for each country.

[13] Hodrick and Prescott (1997) use a smoothing parameter of 1600 in calculating the filter. However, since we use annual observations, we set the smoothing parameter to 6.4 as suggested by Ravn and Uhlig (2002).

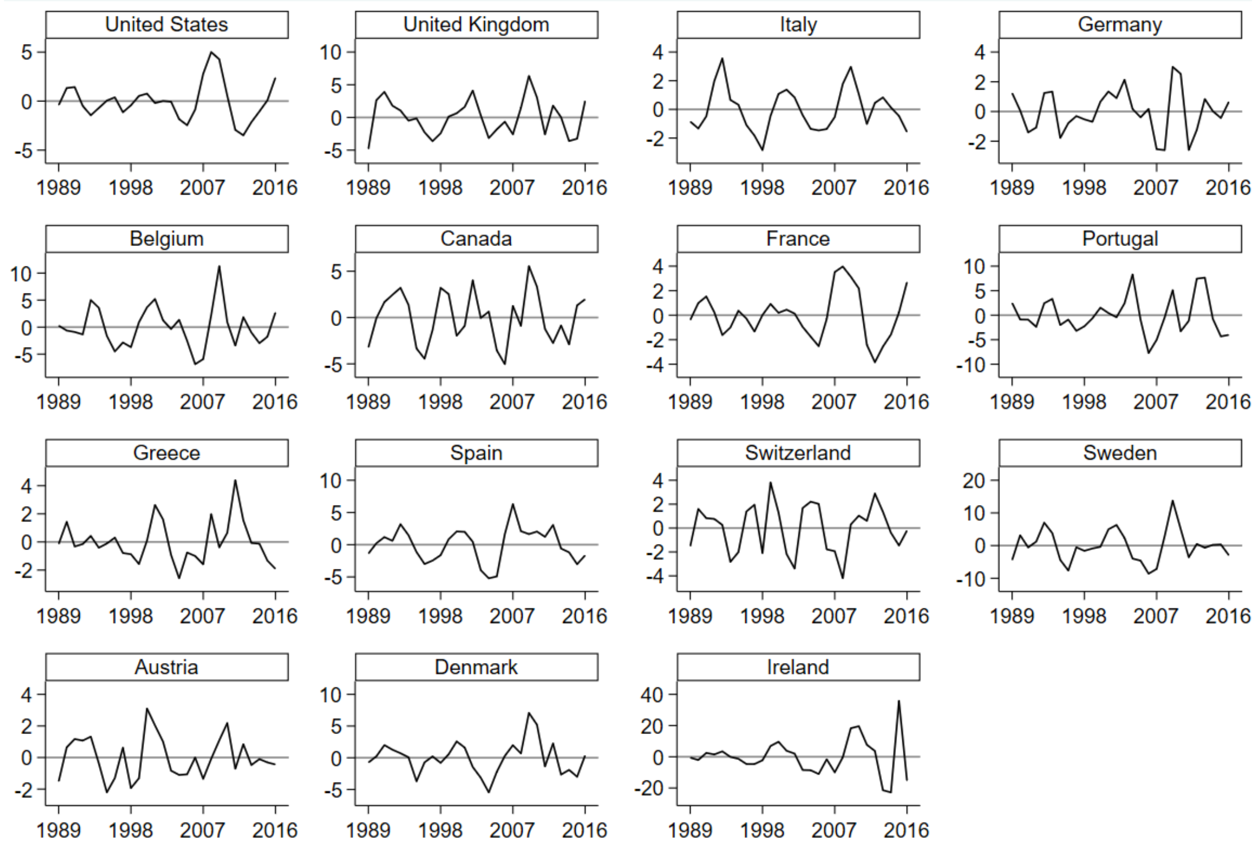

Figure 2.2. Credit-to-GDP gap for 15 countries during the 1989-2016 period (N=15, T=28). These figures display the credit-to-GDP gap calculated as the difference between credit-to GDP ratio and its long-term trend as set out in Equation (2.4), with the trend being calculated using the HP filter.

2.3.3 Macroeconomic control variables

Many other factors can affect the relationship between banking shocks and leverage. The most notable are the business cycle, inflation, and monetary policy. In line with the literature, we control for the cycle by considering the growth rate of real GDP (see, e.g., Albertazzi and Gambacorta (2009)). We compute the inflation rate as the annual percentage change in the Consumer Price Index. In order to account for the monetary policy stance, we include the interest rate spread, calculated by taking the difference between yields of five-year government bonds and three-month bills.[14] Table 2.2 provides descriptive statistics for the variables under scrutiny.

[14] Our source for macroeconomic control variables is the *Global Financial Database*.

Table 2.2. Summary statistics

Variable	Mean	Std. Dev.	Minimum	Maximum	Obs.
Credit-to-GDP gap	0.000	3.992	-22.80	35.91	420
Banking shocks	0.000	0.117	-0.500	0.500	420
GDP growth	0.020	0.031	-0.241	0.262	420
Inflation rate	0.025	0.025	-0.050	0.228	420
Spread	0.013	0.021	-0.055	0.285	420

Notes: Sample period 1989-2016 for 15 countries (N=15, T=28). Credit-to-GDP gap is the difference between credit-to-GDP ratio and its long-term trend as specified in Equation (2.4), where the trend is calculated using the HP filter. GDP growth (real) is the year-on-year growth rate of GDP deflated using current prices. The inflation rate is the annual percentage change in the consumer price index. Interest rate spread is the difference between five-year government bonds and three-month bills yields.

2.4 Empirical methodology

2.4.1 Panel Vector Autoregression

To investigate whether shocks generated by large banks affect credit-to-GDP gap, we use a Panel Vector Autoregression (PVAR) methodology estimated using Generalized Methods of Moments (GMM) framework. In particular, our approach follows that of Abrigo and Love (2016), who introduce a PVAR estimation based on the early work of Sims (1980). In a VAR setting, all variables are treated as endogenous and interdependent, although in some cases exogenous variables might be included. This approach can be particularly important, as the banking system is vulnerable to macroeconomic fluctuations, simultaneously or with lags, with feedback effects of banks instability on economic activity that are amplified during periods of extreme credit booms and busts (Baltas et al., 2017). Because all variables are treated as endogenous, feedback effects are not a problem in our estimation. Such feedback effects can arise from the dynamic interaction between the two sides of the economy and among banking and macro variables. For example, inflation might distort the allocation of bank loans, as bank managers behave "conservatively" when inflation is high (Caglayan and Xu, 2016). Consequently, the yield spread, a proxy for monetary policy stance, is known to affect output and the availability of credit (Tussing, 1966; Sofianos et al., 1990). In this regard, a number of studies have focused on the impact of monetary policy on banks' balance sheets (Kashyap and Stein, 2000) and, more recently, on the response of the credit supply of large banks to monetary policy shocks (see, e.g., Barraza et al. (2019)). These studies support the hypothesis that the macroeconomic variables, as in our PVAR model, could affect the ability of banks to generate profits, their overall performance and the way they deal with shocks, and hence the banks' stability and lending policy, and justify the choice of our methodology.

Furthermore, modelling the dynamics of banking shocks, and financial and macroeconomic variables into a PVAR allows us to look at the Impulse Response Functions (IRFs) of different types of shocks, observing the response of the credit-to-GDP gap after simulating innovations to the banking granular shocks. We apply orthogonalized IRFs because the actual variance-covariance matrix of the errors is unlikely to be diagonal. A careful identification procedure for the PVAR is needed to isolate shocks to each of the variables. We choose a causal ordering of the variables and follow the standard procedure of Cholesky decomposition. It is relatively standard in the monetary transmission and macro-finance literature to adopt an ordering where real variables are placed before financial variables, i.e., output and prices before interest rates (see, e.g., Christiano et al. (1998) and Assenmacher-Wesche and Gerlach (2008)).

The inclusion of the credit-to-GDP gap and banking shocks variables, however, is new to the literature and warrants further assumptions. Goodhart and Hofmann (2008) place credit as last in the VAR they estimate under the assumption that monetary variables respond immediately to a real shock. On the contrary, Leroy and Lucotte (2019) place credit before interest rates and after real output as the bank interest rate pass-through is sluggish in the short term, hence the lack of immediate response from credit to a shock in interest rates. In our case, we use the deviations of credit relative to output and not the absolute term of credit as done by previous authors.

In our specification, we assume current shocks to the interest rate spread to affect the credit-to-GDP gap and banking shocks with a lag, in line with the notion that the channels through which monetary policy operates exhibit a lag before influencing the cyclical fluctuations in economic activity, as proposed by Friedman (1961). The interest rate spread, therefore, is ordered at the bottom of our PVAR setting and after inflation rate and output. We also place the credit-to-GDP gap after banking shocks and output for a similar reason. Indeed, according to the Basel Committee guide on Banking Supervision when the gap reaches two points or above, policymakers are advised to take buffer decisions, which allow banks to adjust their countercyclical capital buffer accordingly. Hence, the banking sector responds with a lag to regulatory changes. Real GDP growth is placed at the front-end of the PVAR before the banking shocks and credit-to-GDP gap variables, reflecting that the banking system responds immediately to a shock in output and, if there is a feedback effect, this is likely to happen with a lag.[15] The resulting order of a five variable PVAR model is, therefore: real GDP growth, banking shocks, credit-to-GDP gap, inflation rate, interest rate spread. We also aim to study the direction of transmission and causality between our variables using Granger (1969) causality tests.

[15] Following the standard approach in the literature, the assumption here is to follow a causal ordering of the variables. For example, the variables that come earlier in the ordering affect the subsequent variables contemporaneously as well as with a lag, while the variables that come later affect the previous variables only with a lag.

Following Love and Zicchino (2006), we can specify a first-order PVAR model as follows:[16]

$$Z_{it} = \Gamma_0 + \Gamma_1 Z_{it-1} + \varepsilon_{it}, \tag{2.5}$$

where, Z_{it} is a ($k \times 1$) vector of stationary variables of each of the i countries, i = 1, 2, 3, … 15. The subscript t denotes the time observations. Γ_0 is a vector of constants, Γ_1 is a matrix of parameters corresponding to the coefficients attached to Z_{it-1}, the vector of lagged endogenous variables. The disturbance ε_{it} is a vector of residuals, which encompasses the country-specific variance, σ_i^2.

Equation (2.5) imposes the restriction that the underlying structure is the same for each cross-sectional unit. However, this constraint is likely to be violated in practice, and the identification would be affected by unobserved heterogeneity. In order to account for this issue, it is possible to introduce fixed effects, f_i:

$$Z_{it} = \Gamma_0 + \Gamma_1 Z_{it-1} + f_i + \varepsilon_{it}. \tag{2.6}$$

However, introducing fixed effects would create biased coefficients, especially when the mean-difference procedure is used to estimate the model since the fixed effects are correlated with the regressors when including lags of the dependent variables. To avoid this problem, we use forward mean-differencing, also known as the Helmert procedure (Arellano and Bover, 1995). This procedure removes only the forward mean, i.e., the mean of all the future observations available for each country-year, and preserves the orthogonality between the transformed variables and the lagged regressors so that the application of GMM becomes valid when using lagged regressors as instruments to estimate the coefficients.

2.5 Results

2.5.1 Pre-testing for stationarity

Before presenting our estimation results, we determine the time series properties of the variables under scrutiny. We first test for the presence of unit roots by using a battery of standard panel unit root (PUR) tests. Specifically, we make use of the statistics proposed by Choi (2001), Im et al. (2003) and Levin et al. (2002). We then test for the presence of unit root by using the panel LM test proposed by Im et al. (2005) which allows for shifts in the levels of the series. Empirical results, presented in Table 2.3, show that the null of unit root is rejected at the 1% level for all the series of our panel. Therefore, in the remainder of the analysis, we consider the series in levels.[17]

[16] A lag length of one was selected based on the minimization of the Akaike Information Criterion (AIC). This lag order is also supported by the Bayesian Information Criterion (BIC) and Quasi Information Criterion (QIC).

[17] We then consider one series at time and compute Ng and Perron (2001) univariate unit root test to corroborate the findings of the PUR tests. Similarly, in this case, empirical results consistently reject the null of unit root for all the series. These results are presented in Table 2.7-Table 2.11 in Appendix A.

Table 2.3. Panel unit root tests

Variable	Fisher type	Im-Pesaran-Shin	Levin-Lin-Chu	Im-Lee-Tieslau
Credit-to-GDP gap	-10.74***	-9.844***	-10.13***	-22.87***
Banking shocks	-9.847***	-8.910***	-6.997***	-35.53***
GDP growth	-7.858***	-7.079***	-4.379***	-30.34***
Inflation rate	-7.197***	-6.434***	-6.698***	-20.82***
Spread	-3.303***	-3.142***	-4.208***	-26.70***

Notes: Sample period 1989-2016 for 15 countries (*N*=15, *T*=28). Im-Lee-Tieslau test allows for one shift in levels. The reported values are the t-statistic for each test. Lag length is based on the minimum of the AIC. */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels.

2.5.2 Impulse response functions

Having checked for stationarity, we proceed by estimating the above mentioned PVAR specification for the above set of variables across the 15 countries. Our interest is to study the response of the credit-to-GDP gap series following innovations in the banking granular shocks variable. Figure 2.3 illustrates the IRFs obtained from the PVAR estimation.[18] We find that a one-standard-deviation shock to banking granular shocks triggers a positive and statistically significant response of the gap of about 4.5 percentage points after one year. This result is significant for three reasons. Firstly, it shows that the credit-to-GDP gap can convey information on the build-up of systemic vulnerabilities that may arise from banks' lending. This finding is expected as banks tend to increase their intermediation activities through rapid credit growth and by taking on risks (Drehmann et al., 2011). Secondly, positive shocks originating from large banks may trigger a credit boom – as detected by high values of the credit-to-GDP gap – and may tend to amplify the business cycle. Such an impact lasts as long as four years, with a cumulative effect raised to 9.4%. Thirdly, we provide empirical insight into the impact of banking shocks on a leading indicator of financial crises. To the best of our knowledge, this is the first time that this result is highlighted in the literature.

Additionally, the response of the gap following a shock to real output growth is positive and significant up to two years. This finding supports the idea that the expansion of credit is procyclical and that banks may behave in a way that collectively undermines the stability of the financial system during the expansionary phases of the cycle (Brunnermeier et al., 2009). This result is in line with the literature that documents the positive link between the credit cycle and the economy.[19] Furthermore, the response of the gap to a one-standard-deviation shock in the interest rate spread is negative and statistically significant, which can be interpreted as implying that expectations of future

[18] All eigenvalues of the dynamic matrix in the PVAR system are within the unit circle.
[19] For a detailed review on this topic see Borio (2014).

growth, or a looser monetary stance, are associated with a reduction in the gap, and hence the risk in the economy. We then find that a positive shock to inflation triggers a negative and statistically significant response of the credit-to-GDP gap. This result is in line with a number of previous studies. For instance, Boyd et al. (2001) show that an inflationary cycle would adversely affect the allocation of credit, as it can intensify informational asymmetries leading to less intermediary activity and deterioration in borrowers' ability to meet payment obligations. Caglayan and Xu (2016) argue that bank credit tends to decrease when inflation hits higher levels. Our results provide empirical support for this argument and highlight the importance of price stability for the supply of credit. We then report in Figure 2.6 in Appendix A, the response of the other macro variables to an impulse in the banking shocks variable. Initially, output responds positively by up to 0.15% to a positive banking shock, which then turns insignificant for a time horizon beyond two years. This positive response of output to banking shocks is consistent with the results of Buch and Neugebauer (2011). Furthermore, it can be seen that the interest rate spread responds negatively to a positive shock to the banking shocks variable, which is in line with the literature on monetary policy where regulators decrease interest rates in response to banking crises (Taylor, 2009). Lastly, inflation responds negatively to a shock in the banking shocks variable, but this is not significant during the observed period.

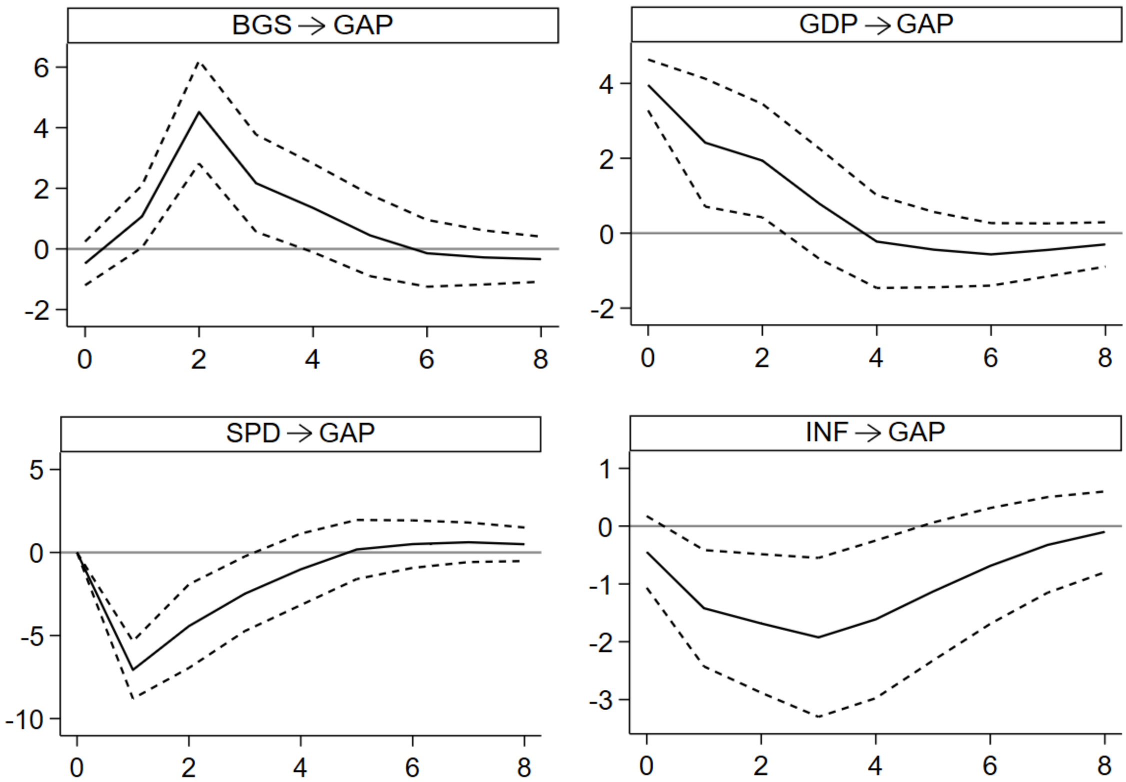

Figure 2.3. Credit-to-GDP gap IRFs (solid lines) following a one-standard-deviation shock in the banking shocks, real output, interest rate spread, and inflation rate variables. The dashed lines denote the upper and lower bounds of the 95% confidence intervals. IRFs obtained from PVAR model estimated on the panel data of 15 countries over the period 1989-2016 *(N*=15, *T*=28).

Following the baseline estimation, we then re-estimate our PVAR specification for the same set of variables while separating banking granular shocks based on their sign, i.e., positive and negative ones. In particular, we introduce an interaction term between banking shocks and an indicator variable for positive and negative shocks, similar to Buch and Neugebauer (2011). By doing so, we should be able to document whether the credit-to-GDP gap responds differently to positive and negative banking shocks.[20] The left panel of Figure 2.4 below reports the response of the credit-to-GDP gap to positive banking shocks. As expected, positive shocks lead to a positive response of the gap. The right panel of the same figure shows that the gap responds negatively to a negative banking shocks impulse. The two diagrams display some degree of asymmetry in terms of the length and magnitude of the responses.

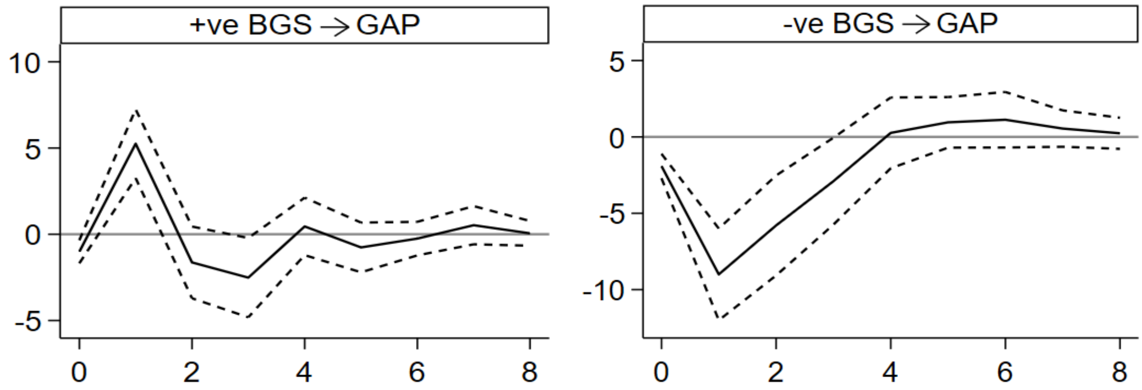

Figure 2.4. Credit-to-GDP gap IRFs (solid lines) following a one-standard-deviation shock in positive (left panel) and negative (right panel) banking granular shocks. The dashed lines denote the upper and lower bounds of the 95% confidence intervals. IRFs obtained from PVAR model estimated on the panel data of 15 countries over the period 1989-2016 (N=15, T=28).

2.5.3 Granger-causality

We then proceed to test for the direction of causality among our variables. Table 2.4 displays the results of the Granger-causality tests obtained from the PVAR estimation.[21] As anticipated by the IRFs previously set out, we find that banking shocks Granger-cause the credit-to-GDP gap. However, such a relationship is not bi-directional, so that the credit-to-GDP gap does not Granger-cause banking shocks. Furthermore, all macroeconomic variables in our model Granger-cause the gap, in particular real GDP growth, supporting our previous evidence obtained from the impulse

[20] We find that the number of positive shocks is substantially greater than that of negative shocks, as the latter are mainly concentrated in the years surrounding the Subprime crisis.

[21] A possible alternative would be to test for Granger-causality in a frequency domain in the spirit of Breitung and Candelon (2006) in a panel OLS context, rather than the PVAR setting adopted in this chapter. Following the approach suggested by Croux and Reusens (2013), our results confirm that banking shocks significantly Granger-cause the gap at both low and high frequencies. However, even if favorable, the results of this approach should be taken with caution given that, as pointed by Croux and Reusens (2013), the method is not robust when the time dimension is small, as it is in our case. These results are available in Appendix A.

responses. This result is also in line with the recent literature on the procyclicality of credit, which documents how credit is amplified and becomes more attractive to borrowers during the expansionary phases of the cycle (Leroy and Lucotte, 2019). We also find that Granger-causality results highlight the presence of feedback effects between some of the variables under scrutiny, most importantly, between GDP growth and banking shocks, and between inflation and credit-to-GDP gap. Such feedback effects are accounted for by our PVAR setting.[22]

Table 2.4. Granger-causality results

Null hypothesis	χ^2	p-value
Banking shock does not Granger-cause credit-to-GDP gap	19.74***	0.000
GDP growth does not Granger-cause credit-to-GDP gap	11.09***	0.000
Inflation rate does not Granger-cause credit-to-GDP gap	17.86***	0.000
Interest rate spread does not Granger-cause credit-to-GDP gap	63.95***	0.000
Credit-to-GDP gap does not Granger-cause banking shock	0.314	0.575

Notes: Sample period 1989-2016 for 15 countries (N=15, T=28). Lag length = 1, which is selected based on the minimum of AIC. Granger-causality tests are based on a likelihood ratio statistic that follows a χ^2 distribution with one degree of freedom. */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels.

2.5.4 Variance decomposition analysis

In Table 2.5, we report the results of the variance decompositions analysis, which highlights the importance of banking shocks and the other macroeconomic variables in explaining the credit-to-GDP gap. Specifically, approximately between 13% and 15% of the forecast error variance of the credit-to-GDP gap, over a time horizon from three to nine years, can be explained by banking shocks. Unsurprisingly, there is some degree of variation in the ability of each variable to forecast the credit-to-GDP gap; variations in the interest rate spread account for the highest percentage and can explain up to 43% of the variation in the gap. This finding is likely a reflection of the importance that expectations of future growth or monetary policy stance, as embedded in the spread, have on leverage. This result is in line with previous studies on the information content of the term structure and its predictive power in relation to the real cycle and financial conditions (see, e.g., Estrella and Hardouvelis (1991); Gertler and Lown (1999)).

[22] Refer to Table 2.6 in Appendix A for comprehensive results of Granger-causality results.

Table 2.5. Variance decomposition of the credit-to-GDP gap over different time horizons

Horizons	Banking Shocks	GDP	Inflation	Spread	GAP
3	13.40	15.53	3.101	42.77	25.17
6	15.40	14.10	6.812	41.44	22.23
9	15.31	14.24	7.042	41.38	22.01

Notes: Sample period 1989-2016 for 15 countries (N=15, T=28). Each time horizon (in years) shows the share of forecast error variance of the credit-to-GDP gap explained by banking shocks, GDP growth, inflation rate, interest rate spread, and credit-to-GDP gap itself. For each row figures add up to 100.

2.5.5 Robustness

We carry out an extensive sensitivity analysis of our baseline results by estimating alternative specifications of our PVAR model. We begin by testing whether a different ordering of the Cholesky decomposition has any effect on the estimation of our baseline specification. We do so by first placing the banking shocks variable after GDP growth and credit-to-GDP gap, and then by placing it before both of them. We also place the banking shocks and credit-to-GDP gap variables at the bottom end of the PVAR ordering after output, inflation and interest rate spread, assuming that financial variables respond immediately to shocks originating from the real economy (Christiano et al., 1998). For each of the three cases, we estimate the PVAR specification, obtain the IRFs and compute the Granger-causality tests. These results are not reported here since we do not observe substantial changes to the baseline results.

We then investigate whether our main results are driven by a specific year or period. We do so by estimating the PVAR model on a shorter dataset where we drop one year at the time. Empirical results suggest that the estimated coefficients of the PVAR model, as well as the related IRFs results, remain substantially unaffected. We carry out a similar task by dropping one country at the time. This exercise can be particularly important for two reasons. Firstly, our sample combines countries with different credit and banking systems, as well as levels of financial development. Secondly, as mentioned in the data section, there can be robustness implications when the small size of a country implies that very few banks are included in the calculation of the granularity shocks. Again, this analysis delivers results that are very similar to those of Figure 2.3.

We then check whether our results are sensitive to the Global Financial Crisis. We do this, first, by using a dummy for the second part of the sample from 2008 onwards. Again, this analysis returns results broadly similar to those in Figure 2.3. Second, we split the sample into pre-crisis (up to 2006) and post-crisis (from 2007) sub-samples. The IRFs of Figure 2.7 and Figure 2.8 in Appendix A confirm the baseline results of a positive and negative response of the gap to banking shocks and yield spread respectively, as previously seen in Figure 2.3, with some differences in the response of the other variables.[23]

We also acknowledge that, especially in the 2000s, the mortgage market had played an important role in aggregate financial stability. Unfortunately, we are not able to control for the sub-components of bank lending due to data limitations. However, we can indirectly account for the role of the mortgage market by including the growth of real house prices as an additional control variable.[24] We, therefore, estimate a six-variable PVAR model by including the growth of real house prices, and by placing such series as last in the Cholesky ordering to allow for lagged impacts originating from the remaining variables of the specification, including a dummy variable from 2008 onwards.[25] Figure 2.9 in Appendix A illustrates the responses of the gap to the other variables when house prices are included in our setting. The baseline result of a positive response of the gap to a shock in the banking shocks variable holds, again, with some differences in the responses to the other variables. In particular, we find a different response to real GDP and inflation rate shocks compared to Figure 2.3 with real GDP and inflation having a negative and positive response, respectively. The response to a shock in the spread has the same initial negative reaction, later followed by a positive one.

Figure 2.10 in Appendix A shows that house prices respond positively and significantly to a positive shock in banking shocks for up to two years, with a small negative correction taking place at year three. Interestingly, banking shocks also respond positively and significantly to a shock in house prices up to two years. This result signals the importance of banks in the transmission of shocks to the real economy. A positive banking shock, which indicates an increase in bank lending, raises house prices via housing wealth and collateral effects. In parallel, credit supply depends on house prices, as homes are commonly used as collateral for loans. This last result, and in particular the endogenous response between banking shocks and house prices, is in line with the literature on the interplay between the credit and housing markets, and the macroeconomy (see, e.g., Goodhart and Hofmann (2008); Favara and Imbs (2015)).

Finally, we perform a number of robustness checks by using slightly different specifications of the variables in use to calculate the BGS indicator. More specifically, we re-estimate our baseline

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[23] Some differences emerge in the response of real GDP and inflation, with the second being positive before the crisis (Figure 2.7) and the first being negative after the crisis (Figure 2.8). However, one should be wary in interpreting the results of the split samples since, especially for the second period, the sample size is rather small.

[24] Indeed, mortgage lending in relation to other loans supplied by large banks has increased substantially in the last decades. The literature highlights the importance of such type of lending for macroeconomic aggregates, and the risk that it poses to aggregate economic stability (Jordà et al., 2016).

[25] As before, we follow a similar order to Goodhart and Hofmann (2008) by placing the real variables first, followed by the financial variables (i.e., real GDP, inflation, spread, house prices), and by adding credit-to-GDP gap and banking shocks at the bottom end of the Cholesky ordering. Again, we also compute the IRFs with alternative orderings to check the robustness of the PVAR results with house prices. We confirm that this does not alter the findings.

PVAR by using modified series for bank loan growth and banking shocks. We do so by calculating the former without taking the logarithm, and the latter by setting negative values for operating income equal to zero. The rationale behind such robustness is that a negative operating income may provide a misleading value for the BGS indicator based on Eq. 2.3. This may happen when the BGS indicator is also associated with a negative loan growth for one bank at a certain point of time because the product of these two negative values becomes positive. Such a positive BGS value induces that such large bank has an increase in lending at that year, which is not the case.

We then use the growth rate of real GDP per capita instead of real GDP growth, and the Baxter and King (1999) band-pass filter to compute an alternative measure for the credit-to-GDP gap. In all these cases, the modified specifications have a minimal impact on the series in use and do not alter our findings.

2.6 Conclusions

In this chapter, we build on Gabaix's granularity hypothesis and investigate how banking granular shocks impact on the aggregate leverage of the economy, as measured by the credit-to-GDP gap. We construct a measure of banking shocks derived from the balance sheet data of large banks for 15 developed countries over the period 1989-2016 and study the link between the two while controlling for GDP growth, inflation and the interest rate spread in a PVAR setting that accounts for possible endogeneity among the variables of interest. Allowing for endogeneity can be important, as macroeconomic factors could affect the modus operandi of banks, their way of dealing with shocks, and their lending policy. While the role of banking granular shocks has been considered in recent studies, to the best of our knowledge, we are the first to uncover their impact on the credit-to-GDP gap, a measure of leverage risk often considered as an early warning indicator of crises.

Our empirical results show that large and positive banking shocks are associated with substantial increases in the levels of the credit-to-GDP gap. A sizeable deviation of the credit-to-GDP ratio from its long-term trend indicates that the private sector is borrowing at levels not consistent with the level of economic activity. In such a scenario, the banking system becomes vulnerable and exposed to substantial rates of loan defaults, potentially leading to an economic slowdown, banking disintermediation and crises.

Macroprudential policies such as borrower-based tools (i.e., loan-to-value and loan-to-income) besides lender-based tools (i.e., countercyclical capital buffer) are often believed to reduce the risk of default. These tools would eventually curb the magnitude of banking shocks that emerges from large banks and prepare the system to absorb losses should such banks fall into financial distress. Such positive link between credit-to-GDP gap and lending by large banks is important for regulators, as it conveys the idea that a high degree of concentration is the foundation whereby banking shocks do not cancel out and therefore matter for macroeconomic outcomes. Based on this evidence, policies that may increase market concentration should be considered carefully in the context of banking resilience. Similarly, an outlook to monitor banking shocks is not only wise, but a realistic strategy to reinforce the stability of the banking system.

Future work could expand our analysis in different directions. One possibility could be to examine the micro and macro determinants of banking granular shocks. Also, our analysis grants further inspection of the responses of the credit-to-GDP gap to shocks other than the banking granular shocks. Additionally, from the macroprudential standpoint, it would be important to study the role of banking granular shocks alongside other indicators considered in the early warning indicators literature, such as global liquidity and risk measures. Finally, it would also be interesting to examine the sub-components of the credit-to-GDP ratio and test the nexus between different types of credit and banking shocks. Research in these directions could complement the literature on banking and financial crises and help identify appropriate policy responses.

Appendix A

- **Granger-causality in a frequency domain.**

We perform Granger-causality in frequency domain test procedure to study how banking shocks affect the credit-to-GDP gap in the spirit of Breitung and Candelon (2006) in the multi-country settings developed by Croux and Reusens (2013) and using the code provided by Peter Reusens. More specifically, similarly to Croux and Reusens (2013), we apply Breitung and Candelon (2006) Granger-causality test to analyse the predictive power of banking shocks for the credit-to-GDP gap in a multi-country context using seemingly unrelated regression (SUR) equations estimated by feasible generalized least squares (FGLSs). Figure 2.5 below plots the incremental R^2 statistic for Granger-causality against the angular frequency domain ω in $(0, \pi)$**.** The angular annual frequency can be translated into a periodicity of T years using the formula $= \pi/_{2\omega}$. We consider the "slowly fluctuating components" to have a periodicity longer than one year, which corresponds to an angular frequency smaller or equal to 1.5. The "quickly fluctuating component" has periodicity smaller than one year, which corresponds to an angular frequency larger than 1.5 (Croux and Reusens, 2013). Figure 2.5, then, shows the strength of Granger-causality in the frequency domain at the 5% critical value. A higher incremental R^2 is associated with more predictive power at any given ω. These results show that the banking shocks variable significantly Granger-causes the credit-to-GDP gap at the 5% critical value for all frequencies, meaning that past values of banking shocks help forecast the gap at both low and high frequencies. We also find that Granger-causality is stronger at higher frequencies (i.e., in the short-run with a time horizon of one "periodic" year or less) where the incremental R^2 reaches a maximum of 24%. At lower frequencies, therefore for time horizons longer than one year, the incremental R^2 reaches a minimum of 11%. This result is in line with our PVAR Granger-causality test, where we find that banking granular shocks Granger-cause the gap in the short-run. That said, it is important to recall that two caveats might apply to the analysis in the frequency domain in this chapter: First, the suggested methodology is usually applied to series with fairly long-time dimension. On this point, Croux and Reusens (2013) apply Granger-causality in frequency domain to a quarterly panel data with 78 observations, and their simulation study shows that there are size distortions in small samples, i.e., with limited time observations the finite sample properties of the regression estimators depart from the asymptotic properties. This caveat would apply in our case, given that our sample has 28 time observations. Second, spectral analysis is based on the concept of Fourier transformation which has not yet been defined (to the best of our knowledge) in the context of panel VAR models – or at least in the macro-finance literature.

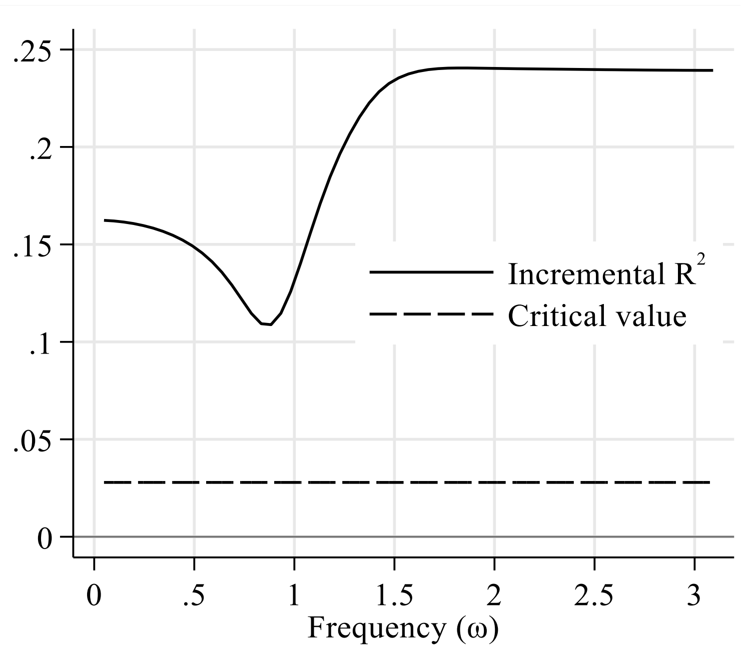

Figure 2.5. Panel Granger-causality test in frequency domain for the 15 countries over the period 1989-2016 (N=15, T=28). The incremental R^2 value is presented as a function of the frequency ω in (0, π). The dashed line represents the 5% critical value of the null hypothesis of no Granger causality at frequency ω.

Table 2.6. Granger-causality results (continued)

Null hypothesis	χ^2	p-value
GDP growth does not Granger-cause banking shock	8.628***	0.003
Inflation rate does not Granger-cause banking shock	12.85***	0.000
Interest rate spread does not Granger-cause banking shock	3.068***	0.000
Banking shock does not Granger-cause GDP growth	17.53***	0.000
Inflation rate does not Granger-cause GDP growth	13.65***	0.000
Credit-to-GDP gap does not Granger-cause GDP growth	1.790	0.181
Interest rate spread does not Granger-cause GDP growth	65.68***	0.000
Banking shock does not Granger-cause inflation rate	7.838***	0.005
GDP growth does not Granger-cause inflation rate	14.93***	0.000
Credit-to-GDP gap does not Granger-cause inflation rate	5.129**	0.024
Interest rate spread does not Granger-cause inflation rate	1.739	0.187
Banking shock does not Granger-cause interest rate spread	76.65***	0.000
GDP growth does not Granger-cause interest rate spread	0.059	0.808
Credit-to-GDP gap does not Granger-cause interest rate spread	2.353	0.125
Inflation rate does not Granger-cause interest rate spread	0..525	0.469

Notes: Sample period 1989-2016 for 15 countries (N=15, T=28). Lag length = 1 and is selected based on the minimum of AIC. Granger-causality test are based on a likelihood ratio statistic that follows a χ^2 distribution with one degree of freedom. */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels.

Table 2.7. Ng and Perron (2001) unit root statistics applied to Credit-to-GDP gap series

ID	Country	MZ_a^c	MZ_t^d	MSB^e	MPT^f
1	United States	-38.80***	-4.362***	0.112***	0.750***
2	United Kingdom	-19.14***	-3.031***	0.158***	1.501***
3	Italy	-33.59***	-4.078***	0.121***	0.788***
4	Germany	-44.47***	-4.715***	0.106***	0.553***
5	Belgium	-41.99***	-4.571***	0.109***	0.615***
6	Canada	-23.48***	-3.393***	0.144***	1.154***
7	France	-33.82***	-9.161***	0.054***	0.184***
8	Portugal	-62.80***	-5.574***	0.089***	0.459***
9	Greece	-79.26***	-6.267***	0.079***	0.367***
10	Spain	-26.88***	-3.660***	0.136***	0.931***
11	Switzerland	-23.42***	-3.422***	0.146***	1.048***
12	Sweden	-27.67***	-3.717***	0.134***	0.895***
13	Austria	-16.91***	-2.908***	0.172**	1.449***
14	Denmark	-13.25**	-2.572**	0.194**	1.857*
15	Ireland	-21.37***	-3.215***	0.150***	1.331***

Notes: Sample period 1989-2016. [c] Modified Philips-Perron with critical values of -13.80, -8.10 and -5.70 at 1%, 5% and 10% significance levels. [d] Modified Philips-Perron statistic with critical values of -2.58, 1.98 and -1.62 at 1%, 5% and 10%. [e] Modified Sargan–Barghava test with critical values of 0.17, 0.23 and 0.27 at 1%, 5% and 10%. [f] Modified Optimal Point statistic with critical values of 1.780, 3.17 and 4.45 at 1%, 5% and 10%. Tests computed using spectral GLS de-trended AR kernel based on Modified SIC. The above tests are applied under the null hypothesis of "series *X* has a unit root". */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels.

Table 2.8. Ng and Perron (2001) unit root statistics applied to banking shocks

ID	Country	MZ_a^c	MZ_t^d	MSB^e	MPT^f
1	United States	-12.94**	-2.509**	0.194**	2.027**
2	United Kingdom	-11.85**	-2.435**	0.205**	2.067**
3	Italy	-24.08***	-5.061***	0.094***	0.786***
4	Germany	-26.53***	-3.642***	0.137***	0.925***
5	Belgium	-12.68**	-2.518**	0.198**	1.932**
6	Canada	-10.85**	-2.307**	0.212**	2.346**
7	France	-13.43**	-2.583***	0.192**	1.856**
8	Portugal	-13.33**	-2.552**	0.191**	1.949**
9	Greece	-13.17**	-2.547**	0.193**	1.932**
10	Spain	-12.14**	-2.463**	0.203**	2.020**
11	Switzerland	-13.23**	-2.572**	0.194**	1.855**
12	Sweden	-13.43**	-2.592***	0.193**	1.825**
13	Austria	-11.12**	-2.249**	0.190**	3.847*
14	Denmark	-19.88***	-3.123***	0.157***	1.337**
15	Ireland	-13.01**	-4.060***	0.123***	0.750***

Notes: Sample period 1989-2016. [c] Modified Philips-Perron with critical values of -13.80, -8.10 and -5.70 at 1%, 5% and 10% significance levels. [d] Modified Philips-Perron statistic with critical values of -2.58,1.98 and -1.62 at 1%, 5% and 10%. [e] Modified Sargan–Barghava test with critical values of 0.174, 0.233 and 0.275 at 1%, 5% and 10%. [f] Modified Optimal Point statistic with critical values of 1.780, 3.17 and 4.45 at 1%, 5% and 10%. Tests computed using spectral GLS de-trended AR kernel based on Modified SIC. The above tests are applied under the null hypothesis of "series *X* has a unit root". */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels.

Table 2.9. Ng and Perron (2001) unit root statistics applied to real GDP (growth)

ID	Country	MZ_a^c	MZ_t^d	MSB^e	MPT^f
1	United States	-11.08**	-2.349**	0.212**	2.231**
2	United Kingdom	-10.66**	-2.307**	0.216**	2.306**
3	Italy	-11.20**	-2.363**	0.211**	2.203**
4	Germany	*7.139*	-2.003**	0.180**	5.552
5	Belgium	-12.52**	-2.494**	0.199**	1.987**
6	Canada	-11.94**	-2.443**	0.205**	2.053**
7	France	-9.915**	-2.194**	0.221**	2.596**
8	Portugal	-9.714**	-2.200**	0.227**	2.535**
9	Greece	-8.898**	-1.696*	0.288	4.217*
10	Spain	-9.380**	-1.921*	0.260*	3.321*
11	Switzerland	-11.05**	-2.331**	0.211**	2.293**
12	Sweden	-27.97***	-3.738***	0.134***	0.881*
13	Austria	-11.77**	-2.413**	0.205**	2.129**
14	Denmark	-12.63**	-2.513**	0.199**	1.940**
15	Ireland	-11.37**	-2.384**	0.210**	2.156**

Notes: Sample period 1989-2016. [c] Modified Philips-Perron with critical values of -13.80, -8.10 and -5.70 at 1%, 5% and 10% significance levels. [d] Modified Philips-Perron statistic with critical values of -2.58,1.98 and -1.62 at 1%, 5% and 10%. [e] Modified Sargan–Barghava test with critical values of 0.174, 0.233 and 0.275 at 1%, 5% and 10%. [f] Modified Optimal Point statistic with critical values of 1.780, 3.17 and 4.45 at 1%, 5% and 10%. Tests computed using spectral GLS de-trended AR kernel based on Modified SIC. The above tests are applied under the null hypothesis of "series *X* has a unit root". */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels.

Table 2.10. Ng and Perron (2001) unit root statistics applied to spread

ID	Country	MZ_a^c	MZ_t^d	MSB^e	MPT^f
1	United States	-9.739**	-2.194**	0.225**	2.563**
2	United Kingdom	-7.738*	-1.928*	0.249*	3.308*
3	Italy	-10.01**	-2.212**	0.221**	2.543**
4	Germany	-14.04***	-2.649***	0.189**	1.750***
5	Belgium	-9.797**	-2.206**	0.225**	2.530**
6	Canada	-8.233**	-1.939**	0.279	4.016*
7	France	-7.919*	-1.683*	0.284	4.251*
8	Portugal	-15.69***	-2.791***	0.178**	1.598***
9	Greece	-11.19**	-2.358**	0.211**	2.220**
10	Spain	-8.036*	-1.901*	0.284	4.132*
11	Switzerland	-6.080*	-1.719*	0.348	6.016
12	Sweden	-11.94***	-2.440**	0.204**	2.066**
13	Austria	-13.90***	-2.636***	0.190**	1.765***
14	Denmark	-15.24***	-2.752***	0.180**	1.643***
15	Ireland	-6.376*	-1.773**	0.345	4.732

Notes: Sample period 1989-2016. [c] Modified Philips-Perron with critical values of -13.80, -8.10 and -5.70 at 1%, 5% and 10% significance levels. [d] Modified Philips-Perron statistic with critical values of -2.58,1.98 and -1.62 at 1%, 5% and 10%. [e] Modified Sargan–Barghava test with critical values of 0.174, 0.233 and 0.275 at 1%, 5% and 10%. [f] Modified Optimal Point statistic with critical values of 1.780, 3.17 and 4.45 at 1%, 5% and 10%. Tests computed using spectral GLS de-trended AR kernel based on Modified SIC. The above tests are applied under the null hypothesis of "series *X* has a unit root". */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels.

Table 2.11. Ng and Perron (2001) unit root statistics applied to inflation rate

ID	Country	MZ_a^c	MZ_t^d	MSB^e	MPT^f
1	United States	-4.026	-1.372	0.341	6.128
2	United Kingdom	-6.364*	-1.730*	0.272*	4.023*
3	Italy	-3.235	-1.803*	0.356	8.480
4	Germany	-7.899*	-1.969*	0.249*	3.169**
5	Belgium	-10.62**	-2.295**	0.216**	2.345**
6	Canada	-4.292	-1.392	0.324	5.809
7	France	-5.126	-1.436	0.280	5.164
8	Portugal	-4.236	-1.614	0.502	9.936
9	Greece	-4.290	-1.635*	0.492	8.414
10	Spain	-5.431	-1.156	0.361	9.406
11	Switzerland	-5.794	-1.808*	0.382	8.398
12	Sweden	-6.084*	-1.723*	0.283	4.093*
13	Austria	-10.88**	-2.283**	0.210**	2.440**
14	Denmark	-5.611	-1.439	0.256*	4.990
15	Ireland	-10.03**	-2.166**	0.216**	2.722**

Notes: Sample period 1989-2016. [c] Modified Philips-Perron with critical values of -13.80, -8.10 and -5.70 at 1%, 5% and 10% significance levels. [d] Modified Philips-Perron statistic with critical values of -2.58,1.98 and -1.62 at 1%, 5% and 10%. [e] Modified Sargan–Barghava test with critical values of 0.17, 0.23 and 0.27 at 1%, 5% and 10%. [f] Modified Optimal Point statistic with critical values of 1.78, 3.17 and 4.45 at 1%, 5% and 10%. Tests computed using spectral GLS de-trended AR kernel based on Modified SIC. The above tests are applied under the null hypothesis of "series *X* has a unit root". */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels.

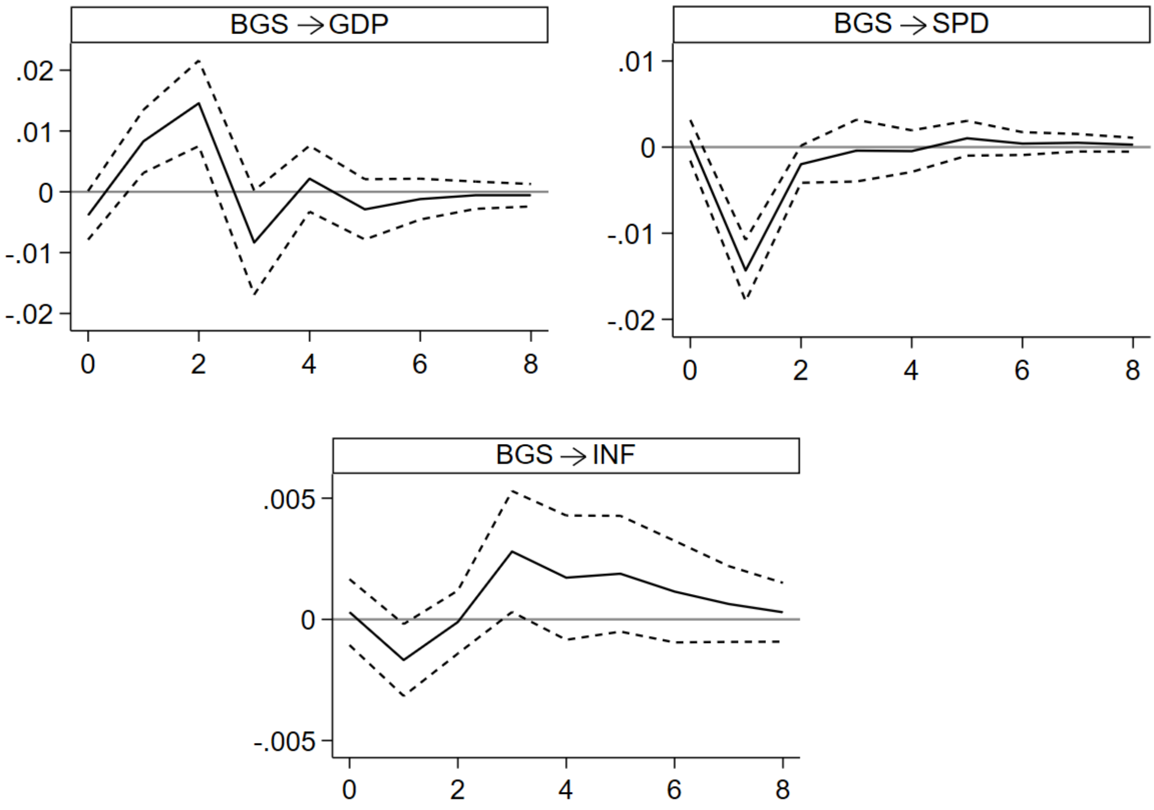

Figure 2.6. IRFs of real output, interest rate spread and inflation rate variables (solid lines) following a one-standard-deviation shock in the banking shocks variable. The dashed lines denote the upper and lower bounds of the 95% confidence intervals. IRFs obtained from PVAR model estimated on the panel data of 15 countries over the period 1989-2016 (*N*=15, *T*=28).

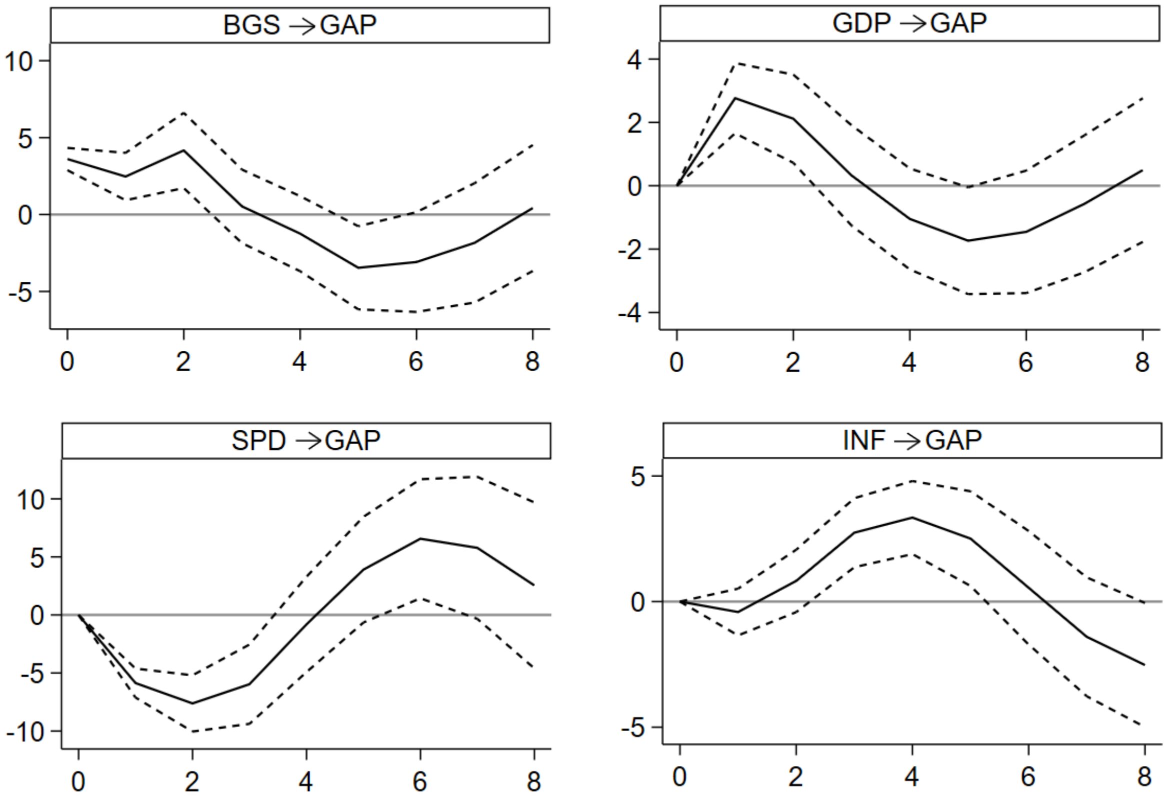

Figure 2.7. Credit-to-GDP gap IRFs (solid lines) following a one-standard-deviation shock in the banking shocks, real output, interest rate spread, and inflation rate variables for the pre-crisis period. The dashed lines denote the upper and lower bounds of the 95% confidence intervals. IRFs obtained from PVAR model estimated on the panel data of 15 countries over the period 1989-2006 (*N*=15, *T*=18).

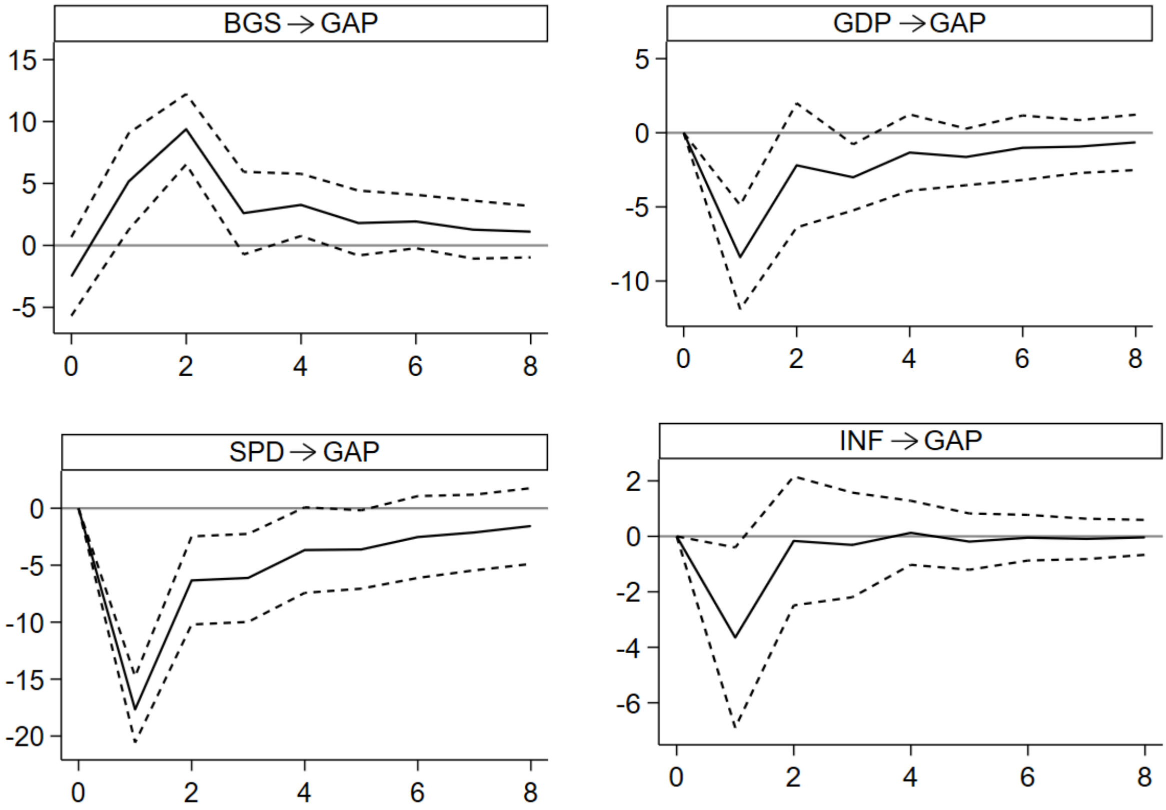

Figure 2.8. Credit-to-GDP gap IRFs (solid lines) following a one-standard-deviation shock in the banking shocks, real output, interest rate spread, and inflation rate variables for the post-crisis period. The dashed lines denote the upper and lower bounds of the 95% confidence intervals. IRFs obtained from PVAR model estimated on the panel data of 15 countries over the period 2007-2016 (N=15, T=10).

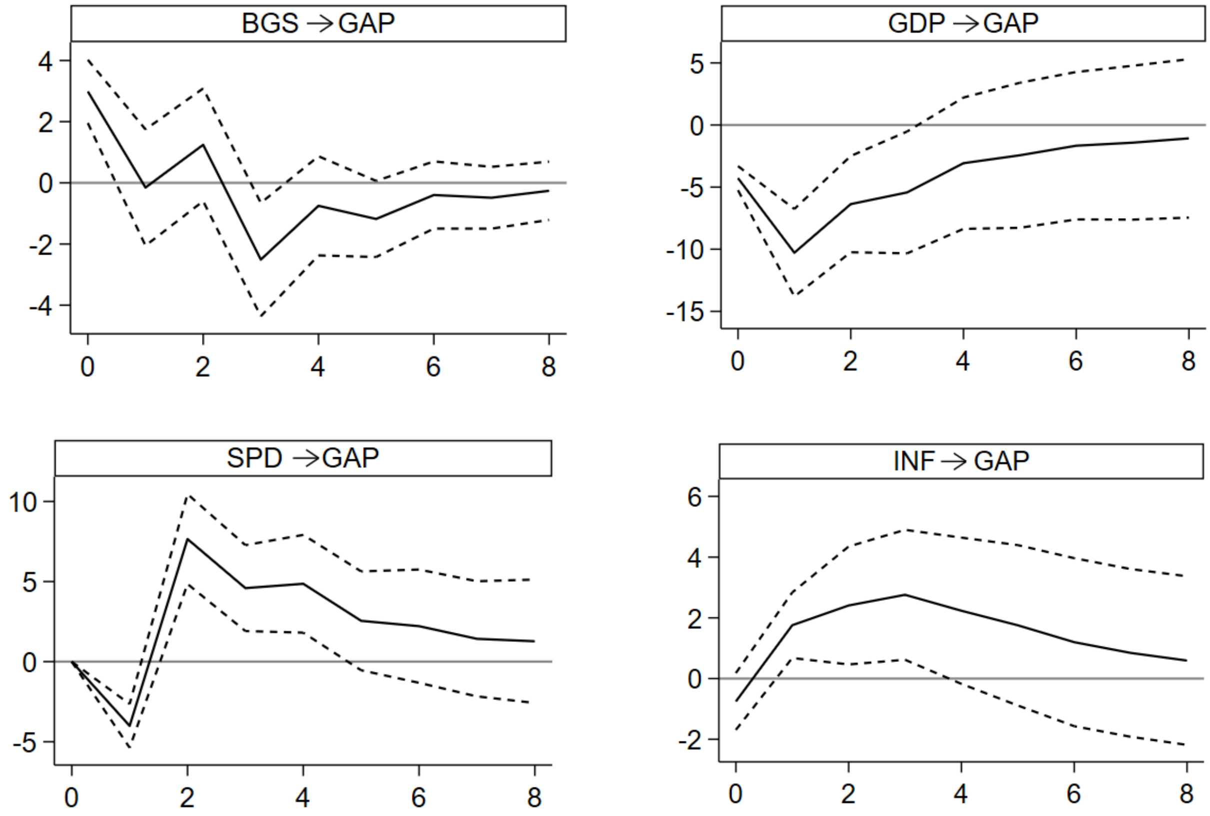

Figure 2.9. Credit-to-GDP gap IRFs (solid lines) following a one-standard-deviation shock in the banking shocks, real output, interest rate spread, and inflation rate variables. The dashed lines denote the upper and lower bounds of the 95% confidence intervals. IRFs obtained from the baseline PVAR after controlling for house prices and estimated on the panel data of 15 countries over the period 1989-2016 (N = 15, T = 28).

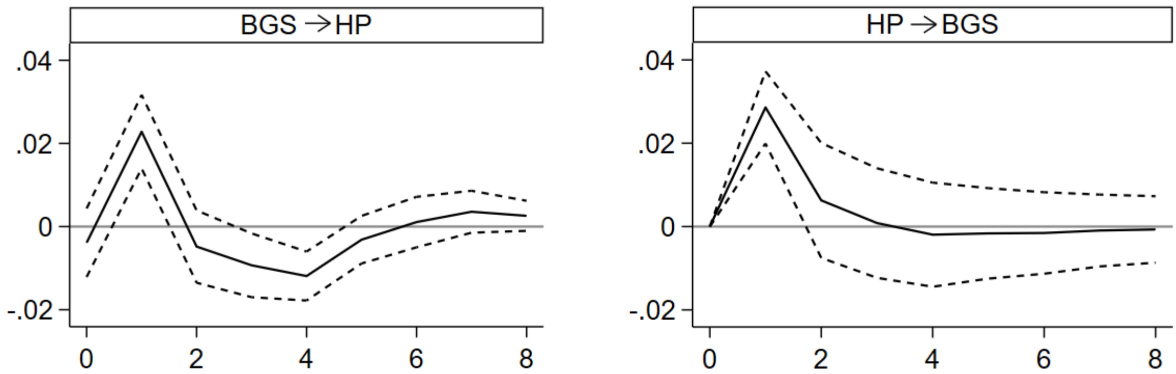

Figure 2.10. IRFs for banking shocks and house prices variables. The left panel displays the house prices response function (solid line) to a one-standard-deviation shock in banking shocks. The right panel displays banking shocks response function (solid line) to a one-standard-deviation shock in house prices. The dashed lines denote upper and lower bounds of the 95% confidence intervals. IRFs obtained from the PVAR model with six variables estimated on the panel data of 15 countries over the period 1989-2016 (N=15, T=28).

Chapter 3. The effect of ECB's unconventional monetary policy on credit

3.1 Introduction

Amid the financial crisis, the FED set the federal funds rate to near zero to stimulate growth (Wright, 2011). Similarly, official rates in major economies remained stuck at unprecedented low levels (Haldane, 2015). The zero lower bound (ZLB) is an issue because using conventional monetary tools is no longer an option for central banks to counterbalance economic slowdowns (Heise, 2016). As a remedy, central banks have shifted towards unconventional monetary policies (hereafter UMP) in the form of large-scale assets and other high-grade bonds purchase programs, also known as quantitative easing (QE).[26]

According to some authors, unconventional monetary policies are going to be the new normal in monetary policy. Before the global financial crisis, central banks used monetary policy to influence interest rates and achieve price stability (Chrystal et al., 2003). However, Borio and Disyatat (2010) argue that in response to the crisis, monetary policy will never be the same, and that balance sheet policies, which are decoupled from interest rate policies, are not anymore unconventional in their essence.

Since the outbreak of the 2008 Crisis, unconventional monetary policies have become the focus of much discussion and heated debate. According to van Dijk and Dubovik (2018) one goal of unconventional monetary policy is to achieve target inflation of 2% by positively stimulate the economy via investment and consumption and lowering interest rates for businesses and households. Further, central banks purchase long-term government bonds from private funds financed by the issuance of reserves that forces banks to create deposits. Such deposits do not attract private funds because they yield low return, and they end up in the hands of households to help them smooth consumption, hence increasing aggregate demand (Cui and Sterk, 2018). Therefore, the different policy goals for central banks to engage in QE are: stimulating the recovery of economic activity, prevention of a deflationary spiral, raising inflationary expectations, and spurring credit supply (Saraceno and Tamborini, 2020).

Several scholars have focused on the transmission channels of unconventional policies. Andrade et al. (2016), for example, show that asset purchases by the ECB reduce sovereign yields on long-term bonds and raise the share prices of banks. This finding is consistent with the portfolio rebalancing channel. They also find evidence of two other channels of transmission. The first is the

[26] Recent central banks interventions in the money market have one common feature, in that they inject additional base money into the economy, which is reflected into an equivalent expansion of the balance sheet of central banks, hence the term 'quantitative' (Saraceno and Tamborini, 2020).

capital relief channel, where higher prices of sovereign bonds benefit banks through an increase in the value of their bond holdings. The second is the signalling channel, where the policy "guides" market expectations of future long-term interest rates down and inflation expectations up. A complete overview of the various transmission channels through which unconventional monetary policy operates, is provided by Joyce et al. (2012); Barroso et al. (2016); Fratzscher et al. (2018).

While scholars have extensively investigated the nexus between unconventional monetary policies and macroeconomic performance, only a handful of studies has focused on the influence of such policies on aggregate lending. Some advocates argue that ECB's bond purchases aim to make cash available for Eurozone banks to increase lending. However, there seem to have been very little increase in such lending (Feldstein, 2016). A possible reason for such a negligible increase in lending is that the private sector throughout the same post-2008 period has been deleveraging (paying back) its' borrowing (Marcuzzo, 2017). In the instance where borrowers are absent, the liquidity provided by the ECB remains trapped within the financial system, and therefore, it does not reach out to the real economy (Koo, 2016).

Other scholars focus on the lending effects of QE. van Dijk and Dubovik (2018) study the effect of longer-term refinancing operations and asset purchase programs on the interest rates of corporate credit. Rodnyansky and Darmouni (2017) study the effects of QE on the lending behaviour of commercial banks, finding a heterogeneous response of commercial bank lending. Altavilla et al. (2016) perform an event study on daily data of bond yields to study the financial effects of the ECB's Outright Monetary Transaction (OMT) program and find a significant increase in real activity, retail credit, and prices in Italy and Spain. However, the strand of research on UMP and the provision of credit is still relatively limited, with a number of questions that remain unanswered. Despite these recent studies, there is still much to be learned about the QE experiment in the Eurozone (Saraceno and Tamborini, 2020).

Moreover, the fact that the ECB and other central banks continue to use UMP at the time of writing this chapter, and is likely to do so in the future, especially given the difficulties triggered by the pandemic and the damage it has done on growth prospects, makes this topic particularly worthy of investigation.[27]

Consequently, natural question in the empirical literature is whether the ECB's unconventional monetary policies have been effective so far in stimulating private credit. In this chapter, we

[27] In response to the COVID-19 pandemic, the ECB announced different measures to support the Eurozone. First, a €1,350 bn pandemic emergency purchase program (PEPP) which complements previous asset purchases programs and aims to increase lending in the Eurozone and lower the cost of borrowing. Second, easing borrowing standards for the collateral in form of insurance provided by banks when borrowing from ECB. Third, increase banks' lending capacity by being less strict about the amount of capital that banks are required to hold as a buffer for difficult times, and finally giving banks more flexibility on supervisors' deadlines and procedures (ECB, 2020).

contribute to such growing literature by investigating the nexus between policy measures and credit aggregates for a cohort of 12 Euro and 8 non-Euro, countries. The consideration of non-Euro countries alongside the Eurozone ones, allows us to test for the cross-border effects from the ECB to non-Euro countries. In the literature, these effects can transmit through an exchange rate channel and a broad financial channel, see, e.g., Feldkircher et al. (2020), Bluwstein and Canova (2016) and Horvath et al. (2016).

Our main objective is to assess the impact of the ECB's UMP on the volume of private credit. If UMP is successful in stimulating lending to the real economy, then we expect to observe a positive and significant response from the extracted common factor to UMP. This is crucial for policymakers to investigate whether the additional bank reserves, as a result of UMP, translated into further lending in the context of economic stimulus, inflation targeting, and financial stability (Kapetanios et al., 2012).

To investigate this issue, we consider three variables, namely, total private credit to non-financial sectors, the credit-to-GDP ratio, and the credit-to-GDP gap for the period from 1999Q1 to 2018Q1.[28] We study such aggregates together with ECB's policy variables, i.e., total assets and the shadow rate, using a panel factor model, cointegration methods for the long-run analysis, and structural VAR method embedded with the common factor of the data for the short-run analysis.

Through a preliminary analysis, we examine the time series properties of credit in our sample using Bai and Ng (2004) Panel Analysis of Non-stationarity in Idiosyncratic and Common components (PANIC) method. While the country-specific components of credit are stationary, we find that non-stationarity is due to pervasive common factors. We take this result as evidence of credit convergence which is needed for fostering common monetary policy, particularly in the case of the European Monetary Union (EMU) countries.

In a first step to answer the research question, we focus on the long-run because the common factors of credit and UMP policy measures have the same level of integration of $I(1)$. In this regard, we find the occurrence of long-run relationships using a battery of time series and panel cointegration approaches. We check the stability of these tests by using specific methods to account for multiple structural breaks and cross-sectional dependence in the panel data. Our main result on the long-run relationship between total credit and ECB's total assets in the Euro area is robust and survives multiple diagnostic tests.

[28] Total credit measures are vital to capture economic activity. If the level of debt is too high, economic agents become vulnerable to financial crisis. The credit-to-GDP ratio captures aggregate indebtedness relative to the size of the economy and it is useful when comparing countries with different output capabilities. The credit-to-GDP gap variable is often used as a proxy to set the countercyclical capital buffer for macroprudential policy and adding it to the analysis helps in informing coordination between monetary and macroprudential policies. See, e.g., Jordà et al. (2013); Cecchetti and Kharroubi (2019); Calem et al. (2020) on the role of private credit in the macroeconomy.

This result lends support to the hypothesis that a transmission mechanism occurs between UMPs and credit aggregates in the long-run. The rationale behind such transmission channel is that when yields are lowered in response to UMPs, borrowing constraints become relaxed, which ease credit availability for firms and households, hence, stimulating spending (Varghese and Zhang, 2018).

In a second step, and differently from past literature, we further our analysis and focus on the short-run by using a structural factor augmented VAR (SFAVAR) model, where we integrate the common factor of total credit, extracted using the PANIC method, into a VAR model. We identify unconventional monetary policy shocks using a mixture of sign and zero restrictions. We find evidence of the credit channel of UMP: a positive shock to UMP increases the common factor by 2% after four quarters. We take this as evidence of the transmission channel of UMP. Our results also show that UMP is important in supporting the macroeconomy by increasing output and prices, and decreasing interest rates.

Our findings in the long- and short-run between credit and policy measures can be perceived as a motivation for the application of UMP by the ECB. We, therefore, contribute to filling an important gap in the empirical literature that should help inform monetary policy discussions regarding the response of lending to ECB's policy measures.

The remainder of this chapter is organised as follows. Section 3.2 reviews the relevant literature. Section 3.3 introduces the data, and Section 3.4 examines the data, while Section 3.5 presents the empirical methodology and discusses the results. Finally, Section 3.6 concludes.

3.2 Literature review

The macroeconomic effect of unconventional monetary policy is a growing area of research. Given the many challenges faced by policymakers, such as inadequate demand growth, low business investment, and interest rates close to zero, banks remain a critical channel for the transmission of central bank's policies. Unconventional monetary policy programs by the Fed, the Bank of England, the European Central Bank, and the Bank of Japan, among others, aim to alleviate financial market distress and stimulate the real economy Fawley and Neely (2013).

The literature has identified two main channels through which central banks' asset purchases affect the economy: The signalling and the portfolio balance channels. The former is based on central banks' announcements of asset purchases programs. In doing so, central banks provide information and commitment about future monetary policy, in particular, signalling the reduction of future long-term rates (Bauer and Rudebusch, 2014). This channel works through the assumption that investors and market participants are rational and forward-looking, using policy announcements to make market-based decisions. In the latter channel, QE programs provide opportunities to institutional investors, namely insurance companies and pension funds, to buy other types of assets, remarkably, risky assets. In such a context, the investors mentioned above can rebalance their portfolios. Such reallocation aims to raise the level of funds available to corporates and the private sector (Joyce et al., 2012), and eventually boost aggregate demand, inflation, and real investment decisions (Butt et al., 2014; Thornton, 2014).

Furthermore, the theoretical foundation of the portfolio balance channel can be traced back to the studies on the macroeconomic effects of portfolio theory introduced by Tobin (1958); Tobin (1969). The starting point is that if money, bonds, stocks, and real assets were perfect substitutes, then they would yield the same return in an arbitrage-free market when investors swap between these assets. In this situation, a change in the portfolio position would not have any macro effect on interest rates or prices. However, investors consider a different class of assets based on how they perceive the level of risk associated with each type of instrument, affecting the demand on particular assets, and eventually, translating into changes in interest rates and prices of other assets. Therefore, the composition of assets purchased by central banks is important for the transmission channel of QE (Di Maggio et al., 2019).

A vast body of literature studies the effects of UMP on the real economy, mainly using structural VAR methods. In this regard, Gambacorta et al. (2014) assess the macroeconomic effects of unconventional monetary policy. They use monthly data of macro variables such as central bank assets, real GDP, consumer prices, stock market volatility, between January 2008 and June 2011 for eight advanced economies: Canada, Japan, Norway, Switzerland, Sweden, Euro area, UK, US. Based on a panel structural VAR, they find that an increase in the size of central banks' balance sheets positively affects economic activity and consumer prices, with such effects being similar to those achieved through conventional monetary policy operations. In the case of the ECB, few studies address the impact of UMP on economic conditions. Creel et al. (2016) focus on the effects of both conventional and unconventional ECB monetary policy on interest rates and lending volumes. Using monthly observations over the period from 2007 to 2014, they apply country-specific structural VAR models on four Eurozone economies: Germany, France, Italy, and Spain. They find that the transmission of the ECB rate to volumes has been weak and that unconventional policies have had uneven effects on interest rates. Bluwstein and Canova (2016) use a Bayesian mixed-frequency structural VAR to examine the international spillovers of ECB's unconventional monetary policy on nine European countries. They argue that the wealth, the risk, and the portfolio rebalancing channels (but not the credit channel) matter for the ECB's policy propagation across these countries.

Similarly, Horvath and Voslarova (2017) study the international spillovers of ECB's unconventional monetary policy on three central European countries, namely the Czech Republic, Hungary, and Poland. Estimating a panel VAR over the period 2008 to 2014, they find a positive response in output growth and inflation following expansionary UMP shocks. They also present vector decompositions and find that the ECB's unconventional policy explains more than 10% of economic activity, but only 2% of price fluctuations.

Other related papers use global VARs to study the international effects of UMP in the Euro area. For example, Hajek and Horvath (2018) examine the effects of both the ECB and the FED unconventional policies on the economic activity and prices of EU countries. Using a global VAR for the 2001 to 2016 period, they find positive qualitative effects with different magnitudes across countries. In a similar paper, Burriel and Galesi (2018) use a global VAR to show that Euro area members have benefited from ECB unconventional policy measures but with a substantial heterogeneity that peaked in correspondence with the sovereign debt crisis. They also argue that countries with more fragile banking systems benefit the least, especially in terms of output growth gains. Recently, Feldkircher et al. (2020) use Bayesian global VAR to analyze the effects of flattening the Euro area yield curve. Their finding indicates an easing of financing conditions which triggers an increase in private credit, coupled with positive effects of UMP on equity prices, output and consumer prices within the Euro area (core and periphery countries) as well as in non-Euro neighbouring countries, reflecting strong financial linkages.

Jäger and Grigoriadis (2017) investigate the nexus between ECB's UMP and the term structure of interest rates using pooled OLS estimations. They argue that asset purchase programs – including the Securities Markets Program (SMP) and Outright Monetary Transactions (OMT) – have significantly negative effects on the bond yield spreads of Euro area countries, with heterogeneous results across countries after controlling for crisis episodes. Babecká Kucharčuková et al. (2016) study the macroeconomic impact of conventional and unconventional ECB policies in the Euro area and its spillover to six non-Euro countries. They use a synthetic index of monetary conditions and a standard monetary VAR to show that prices reacted quickly to unconventional measures, whereas the response of output is delayed and weaker. They also document the importance of ECB policy for macroeconomic development in all other non-Euro European countries. Boeckx et al. (2017) use a structural VAR framework to estimate the effects of shocks to the balance sheet of the ECB in the Euro area. They find that an expansionary balance sheet shock stimulates bank lending to households and firms, reduces interest rates, and leads to a depreciation of the Euro, with a positive impact on the rate of economic activity and inflation. They also argue that the effects on output are smaller in countries where the banks are less capitalized.

Additionally, asset purchases are found to improve the banking sector's liquidity and reinforce the confidence of borrowers and lenders (Joyce et al., 2011; Joyce et al., 2015). Empirical results have shown that banks tend to accumulate additional reserves and deposits as a result of asset purchases programs, thus boosting their liquidity and lending capabilities to multiple sectors at reduced interest rates. This strand of literature attempts to quantify the impact of UMP via the so-called credit or bank lending channel. Addressing the Bank of England QE policy, Joyce and Spaltro (2014) demonstrate this concept by using quarterly data of banks' balance sheets over a 20-year period. They find a small but significant evidence where QE may increase bank lending. In the case of Japan, Bowman et al. (2015) examine the impact of the Bank of Japan's quantitative easing policy during the period 2001-2006. Using semiannual data for 137 large, medium, and small banks, they find evidence that QE operates through a credit channel, with an increase in banks' liquidity resulting in credit extension to borrowers. This finding is also in line with the liquidity channel of QE, in which central banks' assets purchases, increase the liquidity in the hands of investors (Hausken, 2013).

A recent study by Boeckx et al. (2020) examines the effectiveness and transmission channel of the Euro system's credit support policies in the wake of the banking and sovereign debt crisis. Using Jordà (2005) local projection methods for a panel of 131 Euro area banks during the period 2007-2015, they find that UMP has been effective in stimulating bank lending to households and firms. Specifically, an expansion in the balance sheet of ECB resulted in a fall in bank lending rates and a rise in the volume of lending. Using an event study method with daily and monthly data on money and capital market rates, Hofmann et al. (2020) investigate the overall effect of ECB's UMP on Euro area bank retail lending and deposits rates to households and non-financial corporates over the period 2007-2019. While their results show that ECB's measures varied considerably between countries, they find a significant decrease in retail lending and deposits rates in Germany, France, Spain. Such measures were most effective in Italy, where economic and financial stress was most pronounced, signalling the importance of the transmission channel of UMP in crisis-stricken countries.

Furthermore, van Dijk and Dubovik (2018) study the effects of UMP, namely targeted longer-term refinancing operations (TLTRO) and asset purchases programs (APP), on corporate credit. They find that UMP programs led to lower interest rates on new corporate credit and to flatter yield curves, and emphasize how the signalling channel may well have played a role in the transmission of the ECB's policies. García-Posada and Marchetti (2016) study the effect of UMPs on the supply of banks' credit in Spain. They find a positive and moderate-size effect on credit and also provide evidence that UMPs operates through the bank lending channel. Mamatzakis and Bermpei (2016) study the relationship between UMP and the profitability performance of the US commercial and savings banks by using panel dynamic threshold models. To account for UMP, they use the central bank's assets and excess reserves. They find that UMP harms the profitability of banks. Rodnyansky and Darmouni (2017) use a difference-in-difference identification strategy to study the effects of QE on US commercial bank lending while focusing on Mortgage-Backed securities (MBS) or MBS-to-assets ratio from banks' balance sheet. They find a strongly significant effect of both the First and Second Asset Purchases Programs on the lending of banks that feature large shares of MBS. In a similar paper, Chakraborty et al. (2020) control for unobserved aggregate economic conditions and changing in regulatory policy and consider the impact of QE by the Fed on bank lending and firm investment. Using panel fixed effect regressions on quarterly data for the period 2005 to 2013, they find that MBS assets purchases increase mortgage lending, however, they also find a reduction in commercial lending. Similar results on MBS purchases found in Di Maggio et al. (2019) and Dedola et al. (2020) which highlight a possible channel where QE works by improving credit availability and lowering interest rates for households.

Finally, the literature covers mainly the effects of ECB's unconventional monetary policy on output, prices, and interest rates, and focuses on data for particular countries. To the best of our knowledge, the evidence on private credit is still scarce. Therefore, in this study, we extend previous works and contribute to the existing empirical literature by including credit to non-financial sectors of both Euro and non-Euro zone countries to account for potential policy cross-border effects.

A key empirical question we are trying to answer in this chapter is whether UMP is successful in boosting bank lending while taking into account the factor structure of aggregate credit. We follow the vast body of literature that uses ECB's total assets to account for ECB's unconventional monetary policy, besides the shadow rate – that has been popular recently in measuring the policy stance at the zero lower bound (Conti, 2017) – and gauge the existence of long-run relationships, subject to multiple breaks, between credit and ECB unconventional monetary policy. We also introduce the credit-to-GDP gap as a measure of leverage risk and crises indicator. By doing so, we are able to gauge the effect of UMPs on the credit-to-GDP gap, and therefore integrate macroprudential policy in our analysis.

3.3 Variables description

To test the nexus between ECB's unconventional monetary policy and credit, we gather quarterly data from different sources over the period starting from 1999Q1 until 2018Q1. The data include a large sample of Euro and non-Eurozone countries such as Austria, Belgium, Germany, Finland, France, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal and Spain, Czech Republic, Denmark, United Kingdom, Hungary, Norway, Poland, Switzerland, and Sweden.[29]

[29] Data on other European countries are not included in the analysis as they are available only for a shorter time span.

3.3.1 Credit aggregates

Several scholars have highlighted how the total credit of an economy is an important driver of its business cycle (Jordà et al., 2013; Cecchetti and Kharroubi, 2019; Mihai, 2020). For instance, it is well-known that household credit is used primarily for consumption and housing purchases, and it can determine up and downswings in the demand for goods, services, and homes. From a policy standpoint, the level of private-sector borrowing is crucial for the monetary transmission mechanism and an important indicator of financial stability (Schularick and Taylor, 2012; Dembiermont et al., 2013; Comunale, 2020). In this chapter, credit is defined as the total private credit to non-financial corporations, households, and non-profit institutions serving households, hence an increase in private credit figures reflects a desirable outcome in response to policy measures. Such data include different types of loans (consumer, real estate, commercial and industrial) and debt securities (bonds and short-term papers) and are available from the Bank of International Settlement (BIS) database, "Credit to non-Financial Sector". We also use other measures such as credit-to-GDP ratio, and credit-to-GDP gap. The former is an indicator of how much the private sector is borrowing relative to the size of the economy, whereas the latter is defined as the difference between the credit-to-GDP ratio and its long-term trend and acts as a tool to set the countercyclical capital buffer of macroprudential policy.[30]

The following table provides summary statistics for our credit figures, followed by a graphical representation for each series in a panel graph.

[30] We add series on real GDP (source: *Datastream*) for each country in the empirical analysis to account for the macroeconomic performance.

Table 3.1. Summary statistics

	Total credit				Credit-to-GDP ratio				Credit-to-GDP gap			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Austria	2.655	0.149	2.369	2.816	2.136	0.027	2.056	2.170	-2.029	5.05	-11.20	9.40
Belgium	2.852	0.190	2.503	3.071	2.249	0.073	2.106	2.354	6.674	8.81	-10.90	23.00
Czech Republic	2.049	0.243	1.632	2.339	1.881	0.069	1.769	1.989	7.232	7.66	-2.80	19.70
Denmark	2.750	0.196	2.380	2.942	2.319	0.079	2.164	2.406	6.953	19.42	-31.90	34.50
Finland	2.499	0.190	2.147	2.700	2.176	0.076	2.048	2.290	4.013	10.99	-21.50	24.90
France	3.542	0.163	3.226	3.738	2.194	0.057	2.090	2.285	4.249	3.38	-5.60	11.30
Germany	3.550	0.081	3.367	3.667	2.070	0.032	2.024	2.118	-4.312	6.46	-13.70	8.20
Greece	2.317	0.267	1.775	2.616	1.967	0.158	1.626	2.127	9.903	13.46	-24.90	26.10
Hungary	1.970	0.292	1.338	2.280	1.956	0.129	1.685	2.140	5.732	19.72	-32.20	44.90
Ireland	2.645	0.319	1.995	2.984	2.340	0.167	2.044	2.600	19.070	41.21	-100.50	87.00
Italy	3.275	0.181	2.912	3.479	2.019	0.081	1.835	2.105	3.723	10.06	-17.90	17.30
Luxembourg	2.062	0.345	1.414	2.437	2.439	0.171	2.114	2.629	2.340	24.23	-61.90	46.10
Netherlands	3.239	0.162	2.924	3.410	2.394	0.050	2.313	2.468	0.409	7.26	-17.20	13.80
Norway	2.818	0.229	2.403	3.080	2.307	0.065	2.194	2.408	8.161	8.52	-7.10	29.70
Poland	2.316	0.309	1.730	2.683	1.774	0.128	1.544	1.936	1.819	4.56	-7.70	15.70
Portugal	2.554	0.180	2.163	2.759	2.269	0.071	2.076	2.365	7.523	26.99	-46.90	44.00
Spain	3.272	0.243	2.751	3.560	2.225	0.101	1.968	2.339	5.252	30.76	-50.80	42.10
Sweden	2.907	0.204	2.540	3.145	2.288	0.081	2.157	2.384	6.669	13.24	-13.00	40.80
Switzerland	2.999	0.182	2.696	3.230	2.314	0.035	2.270	2.383	0.301	9.14	-15.40	15.20
United Kingdom	3.602	0.129	3.315	3.771	2.227	0.046	2.106	2.291	-4.208	14.13	-31.00	12.60
	Policy variables											
Shadow rate	-0.254	2.950	-6.345	4.093								
Total assets	6.181	0.244	5.842	6.654								

Notes: Sample period 1999Q1-2018Q1. Statistics applied to each series at the log of levels for total credit and credit-to-GDP ratio variables. Total credit (in billions USD) is credit to the private non-financial sector, which include non-financial corporations, households and non-profit institutions. All series have a quarterly frequency, adjusted for breaks (change in data reporting methods) and capture the outstanding amount of credit at the end of the reference quarter. The gap is the difference between the credit-to-GDP ratio and its long-term trend calculated using HP filter. For shadow rate the sample period 2004Q3-2018Q1 (percentage points). Total assets are taken with the natural logarithm (in millions USD).

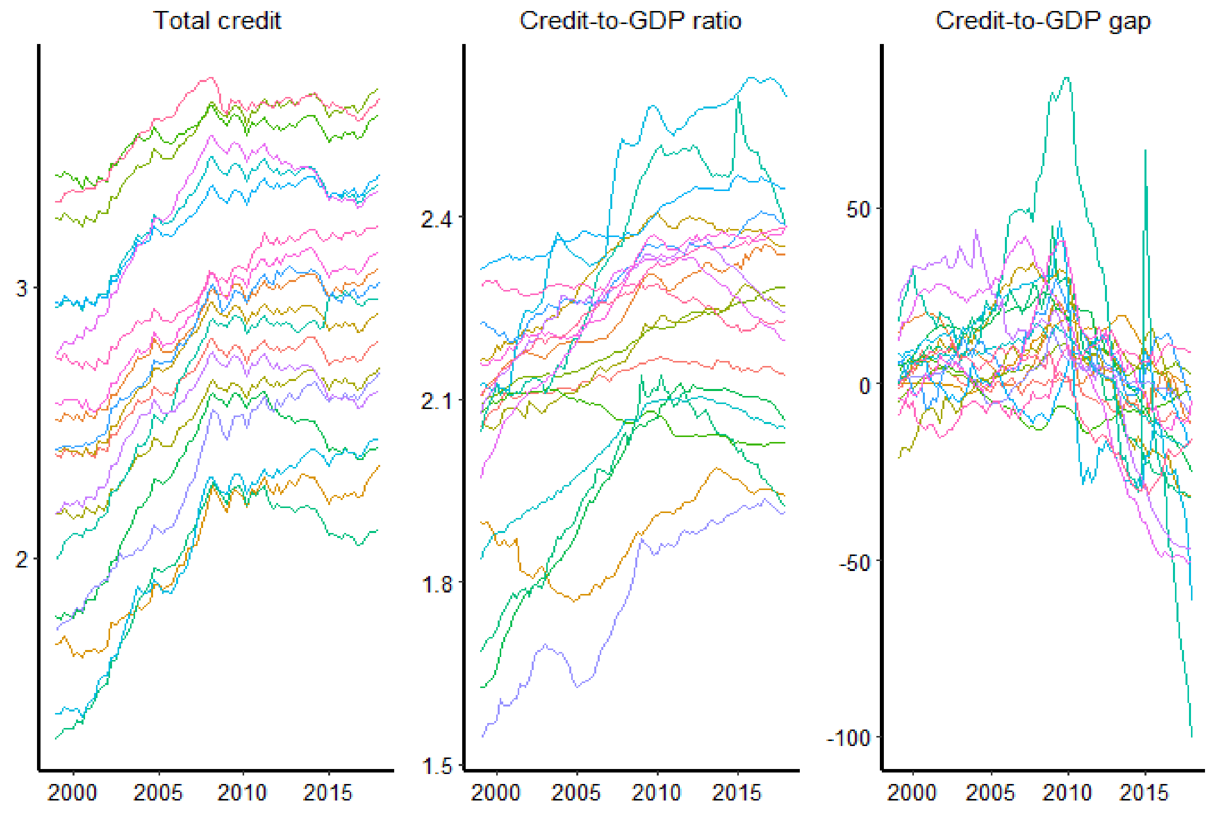

Figure 3.1. Total credit (in billions USD) and credit-to-GDP ratio are taken with natural logarithm. The gap is the difference between the credit-to-GDP ratio and its long-term trend using HP filter. Sample period 1999Q1-2018Q1 for the whole sample (*N*=20, *T*=77).

Total credit in Figure 3.1, shows a similar pattern for almost all of the countries in the observed period, it can be noticed that during the crises (2007-2008) total credit reached a peak, then it was followed by a trough. When GDP is combined with total credit in the credit-to-GDP ratio, the diagram shows a slightly less similar dynamic compared to total credit. For the Credit-to-GDP gap, similar patterns were found for a cohort of countries, whereas for some other such similarities tend to be weaker.

3.3.2 Policy variables

As a proxy for UMP, we use two measures. The first is ECB's total assets. The central bank balance sheet captures the amount of assets purchased as a result of UMP (Kapetanios et al., 2012; Dedola et al., 2020).

With nominal interest rate near the zero lower bound and the reduction in the effectiveness of interest rate channels, the size of central bank assets became an additional dimension of monetary policy conduct to maintain the transmission mechanism and allow for additional monetary stimulus to be undertaken. (Behrendt, 2013). UMPs affect the balance sheet of central banks mainly through an intervention in private and public debt markets through assets purchases, thus, the aim of such policies is to inject money into the economy by purchasing financial assets. When central banks pay for those operations with central bank money it is likely to boost the amount of money held by firms and households as well as the amount of central bank money held by banks. Besides banknotes, central bank money takes the form of reserves balances held by banks at the central bank. When the central bank purchase assets from the private sector, it pays for the assets via the seller's bank. It therefore credits the account of the seller with a deposit. Such scenario increases the monetary base and broad money and generates an expansion in the supply of central bank money, hence the total assets of central bank balance sheet. (Benford *et al.*, 2009).

Furthermore, several authors argue that the expansion in the central bank assets is a good proxy for UMP effectiveness by estimating exogenous innovations to central bank assets. For example, Gambacorta *et al.* (2014) argue that central bank balance sheets basically replaced the interest rates as the main policy instrument, as a result, short-term interest rate is no longer suitable for studying the effectiveness of monetary policy in the aftermath of the crisis. In parallel, the assets on central banks' balance sheet have grown in many economies to an unprecedented level reflecting unconventional measures to support low growth. Additionally, central bank assets take into account different UMP measures, for example, outright purchases, large-scale lending to banks, FX interventions, purchases of public and private securities, and refinancing operations. In the case of ECB, Boeckx *et al.* (2020) show that the Euro system have conducted assets purchases like covered bonds, assets-backed securities and government bonds, and these operations have expanded the balance sheet of the ECB. Therefore, central bank assets can thus be considered as a reasonable indicator of UMPs.

As an alternative to total assets, we use the shadow rate provided by Wu and Xia (2016) expressed with a time-varying lower bound as a nonlinear state-space model. The authors introduce a shadow rate term structure model (SRTSM) constructed by using three- and six-month-ahead and one-, two-, five, seven- and ten-year-ahead one-month forward rates for AAA-rated government bond yields in the Euro area. [31] Wu and Xia (2016) argue that the shadow rate has been more responsive than a historical version of the Taylor rule in response to unconventional policy measures. In particular, it has the desirable feature of being able to capture the behaviour of interest rates, and it is flexible enough to take negative values, unlike the conventional policy rate, and therefore, the zero lower bound and the unconventional measures are both addressed in the shadow rate (Conti, 2017; Zabala and Prats, 2020).

Consequently, an expansionary monetary policy shock is reflected in two aspects: i) an increase in total assets of the central bank, for example, a transaction to purchase assets from pension funds, ii) a decrease in the shadow rate, or both, which is expected to increase bank lending. Figure 3.2 displays the two policy variables. Total assets have increased from the year 2003 onward, whereas the shadow rate has decreased significantly and turned negative from 2007 onward.

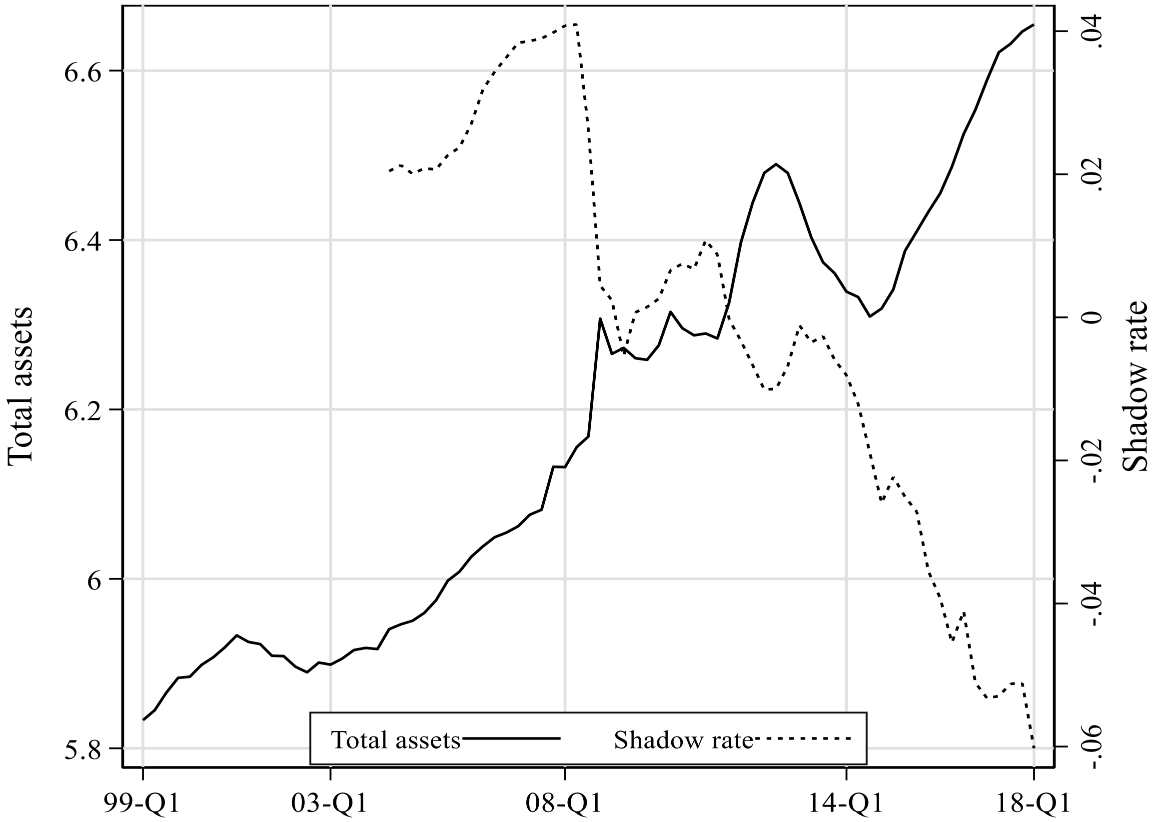

Figure 3.2. Total assets (left) sample period 1999Q1-2018Q1 taken with natural logarithm (in millions USD). Shadow rate (right) sample period 2004Q3-2018Q1 (percentage points).

[31] We collect data on ECB total assets from ECB database, and the shadow rate from the authors website available on https://sites.google.com/view/jingcynthiawu/shadow-rates.

3.4 Preliminary analysis

3.4.1 Testing for stationarity

In this section, we examine the time series properties of credit data using means of unit root tests to identify the order of integration of each series.

A precondition to perform the empirical analysis, and choose the suitable methods of analysis, is to check whether the series has a unit root in levels. This is important, because if two series present the same level of cointegration, then there could be a possibility that they also share a common trend in the long-run (Hendry and Juselius, 2001; Juselius, 2006). We test for the presence of unit roots by using multiple standard panel unit root tests. Specifically, we implement the tests introduced by Choi (2001), Im et al. (2003), Levin et al. (2002), and Hadri (2000).[32] We choose the optimal number of lags based on the minimum value of the Akaike Information Criterion (AIC). We start by testing for the presence of unit roots in the credit variables for each sample of countries in a panel context as shown in Table 3.2, followed by unit root tests on the principal component series for each cohort of countries shown in Table 3.3 and Table 3.4.[33]

Based on the results of all panel unit root tests performed on the original series, we fail to reject the null of unit root at standard significance levels for the credit variables in the full sample and two sub-samples under scrutiny. We check the robustness of these panel tests by applying standard unit root tests on the first principal component of the credit variables for each sample. More specifically, we apply ADF tests, DF-GLS, and modified versions of the Sargan and Bhargava (1983) and Phillips and Perron (1988) statistics which account for the presence of structural breaks to individual series of the first principal components (Dickey and Fuller, 1981; Ng and Perron, 2001).

In this vein, the importance of structural breaks in the implementation and interpretation of unit root testing is a concern often raised in the time series literature. Such trend was first introduced by (Perron, 1989) and (Reichlin and Rappoport, 1989) who suggest that the presence of breaks can influence the results of unit root testing. For example, the existence of a non-stationary process in one series may often be characterised by a single permanent break in the deterministic component of a stationary or trend-stationary process. In the application of macro-finance data, for example, private credit as in our case, the aspect of breaks becomes relevant due to the Global Financial Crisis and

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[32] Such tests derive the respective statistics under the same null of non-stationarity whereas the alternatives feature slightly different specifications.

[33] We apply principal component (PC) approach to reduce each panel of credit series into a small number of time series components that captures the maximum possible variables of the panel. In the subsequent analysis we use the first PC to represent each sample and credit type. In this case, we can use time series empirical tests. See Appendix B for more details on how to measure this component.

other unique events that could affect the level and trend of the series, and hence avoid providing biased results.

The tests in Table 3.3 fail to reject the null of unit root at the 1% significance levels for the first principal components of credit, credit-to-GDP ratio, and credit-to-GDP gap of three cohorts. In Table 3.4, the same tests are applied to the series in first differences, and soundly reject the null of stationary, with few exceptions for some subsamples. Based on the panel and time series unit root tests in levels and first difference, we find prevailing evidence of the presence of unit roots in all variables in levels, hence they all have the same level of integration, i.e., $I(1)$.

Table 3.2. Panel unit root tests applied to credit variables for the three samples

	Philips-Perron		Lm-Pesaran-Shin		Levin-Lin-Chu		Hadri-Lagrange multiplier	
Eurozone								
Variable	Levels	1st Diff	Levels	1st Diff	Levels	1st Diff	Levels	1st Diff
Total credit	5.193	-21.44***	5.094	-25.58***	1.501	-28.41***	127.6***	2.882
Credit-to-GDP ratio	2.359	-18.79***	3.854	-12.16***	3.366	-13.68***	109.6***	9.128
Credit-to-GDP gap	3.450	-18.75***	2.559	-14.85***	0.529	-16.73***	105.8***	0.093
non-Euro								
Variable	Levels	1st Diff	Levels	1st Diff	Levels	1st Diff	Levels	1st Diff
Total credit	5.014	-20.33***	4.511	-18.36***	0.623	-22.38***	122.6***	1.880
Credit-to-GDP ratio	5.414	-17.71***	2.236	-9.642***	0.062	-8.686***	106.6***	4.881
Credit-to-GDP gap	2.884	-16.39***	0.529	-12.83***	-1.506	13.27***	94.62***	5.890
Full cohort								
Variable	Levels	1st Diff	Levels	1st Diff	Levels	1st Diff	Levels	1st Diff
Total credit	7.217	-29.53***	6.791	-31.02***	1.591	-34.79***	177.2***	3.359
Credit-to-GDP ratio	5.608	-25.81***	4.303	-15.41***	1.972	-15.83***	153.2***	10.47
Credit-to-GDP gap	4.467	-24.93***	2.174	-19.57***	-0.704	-21.07***	144.2***	2.147

Notes: The reported values are test statistics for each unit root test. Lag length selection is based on the minimum of AIC. The statistics are calculated for the series in (log) levels and first differences and include a trend and an intercept specification. */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels. Sample period 1999Q1 to 2018Q1 (N = 12/8/20, T=77).

Table 3.3. Unit root test on the first component of credit variables (at levels) for the three samples

	ADF[a]	DF-GLS[b]	MZ_a[c]	MZ_t[d]	MSB[e]	MPT[f]
Eurozone						
Total credit	-0.896	-0.769	-1.476	-0.721	0.489	47.720
Credit-to-GDP ratio	2.648	-0.152	-5.694	-1.367	0.240	15.422
Credit-to-GDP gap	-0.895	-0.627	-3.173	-1.024	0.323	23.836
non-Euro						
	ADF[a]	DF-GLS[b]	MZ_a[c]	MZ_t[d]	MSB[e]	MPT[f]
Total credit	-0.669	-0.633	-1.179	-0.591	0.501	51.622
Credit-to-GDP ratio	-0.294	-0.620	-1.927	-0.725	0.376	32.298
Credit-to-GDP gap	-1.276	-1.023	-2.568	-0.985	0.384	30.310
Full cohort						
	ADF[a]	DF-GLS[b]	MZ_a[c]	MZ_t[d]	MSB[e]	MPT[f]
Total credit	-0.809	-0.712	6.791	-1.341	-0.666	0.497
Credit-to-GDP ratio	0.496	-0.554	-7.699	-1.700	0.221	12.454
Credit-to-GDP gap	-1.347	-0.963	-4.155	-1.274	0.307	20.267

Notes: Sample period 1999Q1 to 2018Q1 (N = 12/8/20, T=77). The reported values are test statistics for each unit root test. Lag length selection is based on the minimum of AIC. All tests equations are estimated in levels. All specifications include a trend and an intercept. [a]Augmented Dicky-Fuller test with critical values of -3.471 and -4.086 at 5% and 1% levels, respectively. [b]Dicky-Fuller GLS de-trended test with critical values of -3.113 and -3.678 at 5% and 1%. [c]Ng and Perron's (2001) Modified Philips-Perron test with critical values of -17.3 and -23.8 at 5% and 1%. [d]Modified Philips-Perron statistic with critical values of -2.91 and -3.42 at 5% and 1% levels. [e]Modified Sargan-Barghava test with critical values of 0.168 and 0.143 at 5% and 1% levels. [f]Modified Optimal Point statistic with critical values 5.48 and 4.03 of at 5% and 1% levels. All equations are estimated using spectral GLS-detrended AR. */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels.

Table 3.4. Unit root test on the first component of credit variables (at first difference) for the three samples

	ADF[a]	DF-GLS[b]	MZ_a[c]	MZ_t[d]	MSB[e]	MPT[f]
Eurozone						
Total credit	-8.610**	-8.324**	-37.42**	-4.323**	0.115**	2.448**
Credit-to-GDP ratio	-3.681*	-3.469*	-17.06*	-2.913*	0.170	5.380*
Credit-to-GDP gap	-4.162**	-3.834**	-16.87	-2.898	0.171	5.436*
non-Euro						
	ADF[a]	DF-GLS[b]	MZ_a[c]	MZ_t[d]	MSB[e]	MPT[f]
Total credit	-7.959**	-7.666**	-36.98**	-4.294**	0.116**	2.495**
Credit-to-GDP ratio	-4.998**	-5.032**	-28.54**	-3.768**	0.132**	3.246**
Credit-to-GDP gap	-5.170**	-5.196**	-29.59**	-3.817**	0.128**	3.250**
Full cohort						
	ADF[a]	DF-GLS[b]	MZ_a[c]	MZ_t[d]	MSB[e]	MPT[f]
Total credit	-8.372**	-8.078**	-37.32**	-4.316**	0.115**	2.461**
Credit-to-GDP ratio	-3.174	-3.141*	-15.03	-2.741	0.182	6.063
Credit-to-GDP gap	-3.368*	-3.632**	-18.67*	-3.052*	0.163*	4.898*

Notes: Sample period 1999Q1 to 2018Q1 (N = 12/8/20, T=77). The reported values are test statistics for each unit root test. Lag length selection is based on the minimum of AIC. All tests equations are estimated in levels. All specifications include a trend and an intercept. [a]Augmented Dicky-Fuller test with critical values of -3.471 and -4.086 at 5% and 1% levels, respectively. [b]Dicky-Fuller GLS de-trended test with critical values of -3.113 and -3.678 at 5% and 1%. [c]Ng and Perron's (2001) Modified Philips-Perron test with critical values of -17.3 and -23.8 at 5% and 1%. [d]Modified Philips-Perron statistic with critical values of -2.91 and -3.42 at 5% and 1% levels. [e]Modified Sargan-Barghava test with critical values of 0.168 and 0.143 at 5% and 1% levels. [f]Modified Optimal Point statistic with critical values 5.48 and 4.03 of at 5% and 1% levels. All equations are estimated using spectral GLS-detrended AR. */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels.

Furthermore, according to Baltagi (2008), employing panel data models induces some additional benefits in terms of efficiency in the identification and measurements of economic issues by rendering the time series observations for each group together. In this case, the panel data tests are able to gain statistical power to improve the poor power of their time series counterparts (Mátyás and Sevestre, 2013). However, one caveat of the first-generation panel unit root tests, i.e., Choi (2001), Im et al. (2003), Levin et al. (2002), and Hadri (2000), is that the panel data introduce a substantial amount of unobserved heterogeneity induced from stacking cross-sectional units together. In this regard, Breitung and Pesaran (2008) argue that it is inappropriate to assume that cross-sectional units are independent, a common assumption for the heretofore used panel unit root tests.

Therefore, with a high degree of integration between economies, especially in the EU, the second-generation of panel unit root tests aims to overcome this shortcoming by relaxing the assumption of dependence. In the following sections, we test for cross-sectional dependence followed by a second-generation panel unit root test, which we also use to shed the light on credit convergence in the EU. Such convergence, as discussed in the next section, is required for common monetary policy to achieve its mandate.

3.4.2 Cross-sectional dependence

Given the interconnectedness of national economies, especially within the same geographical area (e.g., through history, culture, trade and investment), it is important to test for cross-sectional dependence. Indeed, the impact of observable and unobservable components across different units in the panel is important for a reliable empirical analysis (Eberhardt and Teal, 2011). If cross-sectional dependence is present in panel data, then methods have to be employed that allow for dependence. In the context of this chapter, credit dependence can mirror the behaviour of credit concerning the soundness of the financial system, regulatory requirements and monetary policy which are the responsibilities of the ECB in the Eurozone. For example, banks from different countries could behave similarly and extend their lending when they know that they can borrow unlimited funds from the ECB at a fixed interest rate, i.e., fixed-rate full allotment. In this scenario, observations on bank lending across countries tend to be cross-correlated (Afonso and Rault, 2010). To this end, we consider the CD-test of Pesaran (2015) as a diagnostic tool to check for cross-sectional dependence of the data in a panel context.

The CD-test aims to detect the possible existence of cross-correlation, if any, in the innovations of each series under scrutiny: total credit, credit-to-GDP ratio, and credit-to-GDP gap. In general, such correlation may arise from common shocks (with heterogeneous impact across countries) or spillover effects among countries or regions, possibly as a result of increasing international integration (Moscone and Tosetti, 2009). In Table 3.5, we present the results of the CD-test on each credit variable by sub-sample and then for the full set of countries, along with the degree of correlation among the panel of series.

Table 3.5. Cross-sectional dependence test

	Eurozone			non-Euro			Full cohort		
Variable	CD test	$\overline{\hat{\rho}_{ij}}$	$\left\lvert\overline{\hat{\rho}_{ij}}\right\rvert$	CD test	$\overline{\hat{\rho}_{ij}}$	$\left\lvert\overline{\hat{\rho}_{ij}}\right\rvert$	CD test	$\overline{\hat{\rho}_{ij}}$	$\left\lvert\overline{\hat{\rho}_{ij}}\right\rvert$
ΔTC	61.19***	0.86	0.86	34.53***	0.75	0.75	96.84***	0.81	0.81
ΔRatio	15.03***	0.21	0.21	4.927***	0.11	0.16	19.36***	0.16	0.19
ΔGap	11.39***	0.17	0.19	6.533***	0.14	0.17	17.82***	0.15	0.17

Notes: This table presents the results of CD test of Pesaran (2015) under the assumption of covariance stationary. Sample period 1999Q1-2018Q1 for Eurozone, non-Euro, and whole sample countries (N=12/8/20, T=77). $\overline{\hat{\rho}_{ij}}$ denotes the average pairwise residual correlation coefficient between the (i,j) units once the original series are filtered using AR(1) specifications. $\left\lvert\overline{\hat{\rho}_{ij}}\right\rvert$ denotes the absolute value pairwise correlation. */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels.

Empirical results show that the null of weak cross-sectional dependence is soundly rejected for all three credit measures irrespective of the sample, implying that the data exhibit a strong dependence across countries. Moreover, the results show that the largest degree of correlation, $\left\lvert\overline{\hat{\rho}_{ij}}\right\rvert$ = 86% is evident for total credit for the Eurozone countries. While the result also indicates a rejection of the null hypothesis for the ratio and the gap, we notice that the degree of correlation becomes lower for both in comparison to total credit. Such differences in the degree of correlation can be evident from stacking all countries credit as presented in Figure 3.1.

The pervasive nature of high correlation and cross-sectional dependence warrants further investigation of the possible presence of common unobserved components that may affect each cross-section of credit measures, and it provides the rationale for the application of Panel Analysis of Nonstationary in Idiosyncratic and Common components (PANIC) approach due to Bai and Ng (2004). The advantage of using the PANIC method as a second-generation panel unit root test is twofold. First, it allows testing for credit convergence, and second, it allows establishing the source of the non-stationarity in the data while taking cross-sectional dependence into consideration (O'Connell, 1998; Maddala and Wu, 1999; Banerjee et al., 2005).

3.4.3 Credit convergence

Credit convergence is needed for monetary policy to be effective, particularly in the case of the EMU countries.[34] For example, in response to sovereign debt crises, the ECB aims to support the financial markets and reduce differences in financing conditions faced by households and corporates across different Euro countries. However, despite the union's monetary integration and policy initiatives including reforms of the economic governance, there could be potential divergent repercussions due to the remaining dissimilarity of EU economies (Chmelar, 2013). Therefore, we start by investigating the properties of credit convergence in our sample.

In PANIC analysis, a factor model is applied to derive the common and idiosyncratic components of the panel, and then determine the number of trends driving the common factors. In this step, we can further detect whether the non-stationarity in the series is pervasive, variable-specific, or both, where evidence of stationarity of the idiosyncratic component can be taken as an indication of a harmonized mechanism in credit between countries, and hence credit convergence (Bai and Ng, 2004; Westerlund and Basher, 2008; Byrne et al., 2012). Accordingly, the PANIC method is based on the heterogeneity assumption, hence there is no common autoregressive (AR) process in the series, and the panels are assumed heterogeneous. Following Bai and Ng (2004) we model non-stationarity in a panel times series of credit variables (Y_{it}) and decompose such series into

[34] Credit convergence refers to a situation where structural differences (overtime) narrow or be eliminated among a group of countries, hence harmonization patterns become evident in terms of private credit provisioning. Such structural difference arises from a variety of reasons, for example, economic, psychological and interest rate related conditions, and differences in loan limits, maturities and installments among a group of countries.

two unobserved components: a common factor and idiosyncratic components. We define this relationship algebraically:

$$Y_{it} = c_i + \lambda_i F_t + \varepsilon_{it}. \tag{3.1}$$

where the subscript i refers to each country in our sample, c_i is a fixed effect, λ_i is an $r \times 1$ vector of factor loadings, F_t in an $r \times 1$ vector of common factors, and ε_{it} is the series of idiosyncratic error terms. The factor is extracted by first differencing the data in levels, and then their series in levels is re-covered by re-cumulating the estimated values obtained for series in first differences back to levels.

Before we proceed to investigate the convergence in credit series, we employ information criteria based on penalty functions to obtain the appropriate number of common factors present in the panel of credit variables. We allow for a maximum of four factors and choose the Bayesian Information Criteria (BIC) to find the optimal number of common factors. Bai and Ng (2002) point out that BIC (IC_3 in the table below) is the most suitable criterion among others, and it has desirable properties when cross-sectional dependence is present in the panel. Additionally, BIC outperforms other criteria in selecting the number of factors when the minimum (N, T) is (≤ 20) (Moon and Perron, 2007; García-Cintado et al., 2015).

For the sake of comparison, we also provide the number of common factors based on other information criteria. Further, PANIC results are based on ADF tests under the null hypothesis of non-stationarity.[35] For the idiosyncratic component, a Fisher-type panel unit root test is applied. Table 3.6 reports the unit root tests for the common factors and the idiosyncratic components. Such tests are applied to the set of countries in the Eurozone, non-Euro, and finally to the full set of countries in the sample.

[35] The maximum number of lags for individual ADF regressions is set at $p = 4(\text{Time}/100)^{0.25}$ rounded to the nearest whole number as suggested by Bai and Ng (2004).

Table 3.6. PANIC evidence on credit variables

Variable	Factors	Idiosyncratic	IC_1	IC_2	IC_3
Eurozone					
Total credit	-1.054, -1.217, -1.208, -1.280	6.805*	4	4	1
	[0.880, 0.050, 0.020, 0.019]				
Credit-to-GDP ratio	-0.725, -1.064, -2.944*, -1.614	2.936*	1	1	0
	[0.295, 0.120. 0.098, 0.088]				
Credit-to-GDP gap	-1.027, -1.731, -2.997*, -0.824]	2.778*	1	1	0
	[0.254, 0.148, 0.102, 0.096]				
non-Euro					
Total credit	-0.706, -2.317, -2.946*, -2.135	1.830*	4	4	1
	[0.782, 0.064, 0.041, 0.035]				
Credit-to-GDP ratio	-0.840, -2.128, -2.117, -2.548	1.572	4	1	0
	[0.257, 0.168, 0.146, 0.122]				
Credit-to-GDP gap	-1.726, -2.449, -2.585, -1.520	2.589*	4	1	0
	[0.271, 0.156, 0.135, 0.129]				
Full cohort					
Total credit	-0.910, -1.421, -1.526, -2.482	4.693*	4	4	1
	[0.822, 0.037, 0.031, 0.023]				
Credit-to-GDP ratio	0.096, -1.965, -1.734, -2.028	4.450*	1	1	0
	[0.236, 0.095, 0.080, 0.072]				
Credit-to-GDP gap	-1.321, -1.492, -1.457, -1.799	4.555*	1	1	0
	[0.208, 0.097, 0.081, 0.073]				

Notes: This table presents the results of unit root tests on the factors and panel unit root tests on the idiosyncratic components using Bai and Ng (2004) PANIC method. This applies univariate unit root tests to the factors and panel unit root tests to idiosyncratic component. Sample period 1999Q1 to 2018Q1 for the three cohorts of countries (N=12/8/20, T=77). All variables are de-meaned and standardized. IC_1, IC_2, and IC_3 are the number of common factors recommended by Bai and Ng (2002) information criteria. * indicates rejection of the null hypothesis of non-stationarity at 5% significance level. Large negative tests statistics reject the unit root null hypothesis for the common factor (less than −2.89). Large positive test statistics reject a unit root null for the idiosyncratic component (greater than 1.64) Eigenvalues in square brackets [.].

Results show that the common factors, at least the first and second, for most of the series are non-stationary, while the idiosyncratic components of each credit series are stationary. Not surprisingly empirical estimates for both the Euro and non-Euro samples show similar patterns for the idiosyncratic and factor terms; therefore, convergence is also present when applying the factor model to the larger cohort of both Euro and non-Euro countries. For example, the null hypothesis of a unit root in total credit for the full set of countries cannot be rejected for the first common factor with a t-statistic of 0.910. However, a pooled ADF test on the idiosyncratic component rejects the null of a unit root with a t-statistic of 4.693.

Based on these results, we conclude that the common shocks are pervasive across the cohort of countries under scrutiny and they are the source of non-stationarity in the credit series. Moreover, we notice that the variance explained by the first common factor of total credit is considerably larger compared to the second, third and fourth factors, for example, up to 88%, 78.2% and 82.2% for the

Euro, non-Euro and the full cohort respectively. Such variation suggests that the first common factor does a good job at summarizing the variation in the evolution of total credit. In contrast, for the credit-to-GDP ratio and the gap, the variance explained by the first component clusters between only 23.6% and 20.8% for the full sample.

Figure 3.3 is a graphical representation for all four factors of total credit for the whole sample extracted using the PANIC approach. Such plots provide us with some indication of the factors that affect total credit in Europe. We notice that the first and third common factors remarkably share similar dynamics up until 2010, while both continue to rise afterwards, the increase in the third factor is larger than in the first one, and each shows a divergent pattern from the second half of 2014 until the end of the sample. Similarly, the second and fourth common factors seem to be tied together and move closely with similar patterns. Further, while the first and third factors feature a remarkable drop during the 2007/08 crisis, the second and fourth factors feature an increasing pattern, then reach a peak at the beginning of the crisis and show a decreasing pattern afterwards. Figure 3.4 shows the first common factors extracted from the credit-to-GDP ratio and the gap. Both factors are similar in direction and magnitude. This result shows that the ratio of credit relatives to output is more or less affected by the same factors that influence the gap.

In summary, the results reveal that source of non-stationarity of the credit series is due to the common factors. This finding implies that there could be common global or EU specific shocks, i.e., common monetary policies from ECB that can generate persistent effects on credit across the different economies under scrutiny. Thus, in the next section, we investigate the hypothesis that the ECB's unconventional policies are a driver of credit figures by focusing on the first PC of each type of credit.

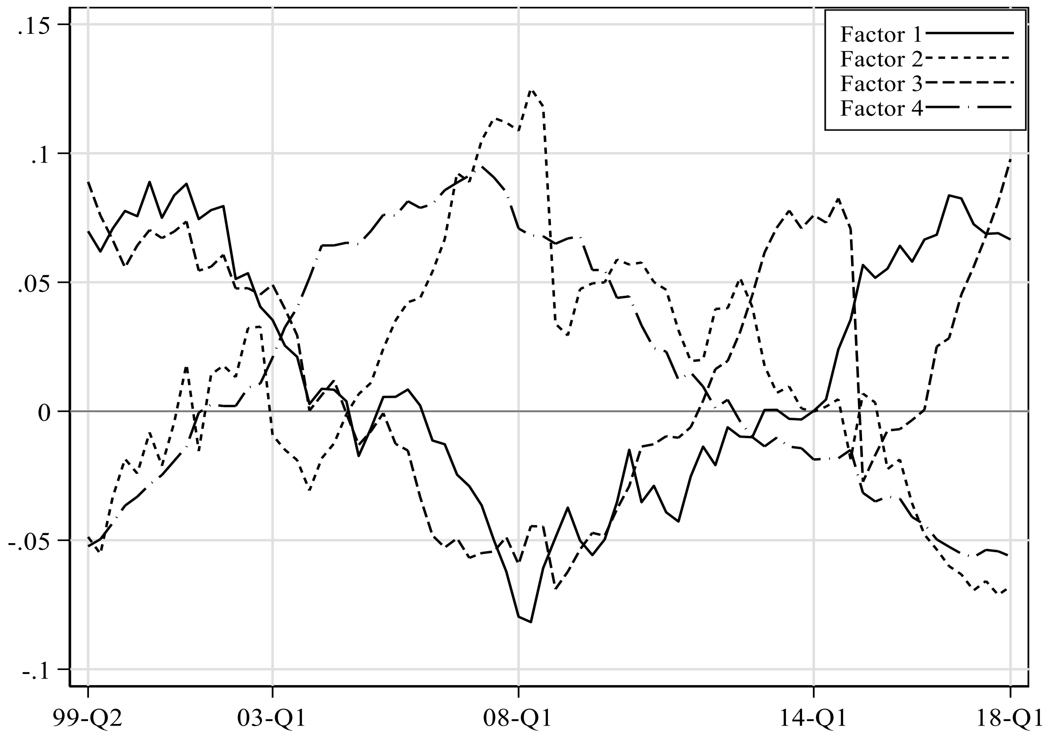

Figure 3.3. Common factors of total credit extracted from PANIC methodology of Bai and Ng (2004). Sample period 1999Q1-2018Q1 for 20 countries *(N*=20, *T*=77).

Figure 3.4. The first common factor of credit-to-GDP ratio (left) and credit-to-GDP gap (right) extracted from PANIC methodology of Bai and Ng (2004). Sample period 1999Q1-2018Q1 for 20 countries (*N*=20, *T*=77).

3.5 Methodology and empirical analysis

In light of the above findings, we notice substantial evidence of credit convergence across our sample, and more importantly, credit seems to be driven by common factors. In this section, we take the analysis forward by bringing together policy measures, namely, ECB's total assets and the shadow rate, and the three measures of credit, total credit, credit-to-GDP ratio, and credit-to-GDP gap. We carry out this analysis on the usual set of countries partitioned into Euro and non-Euro countries.

3.5.1 Time series and panel cointegration

After confirming that the PC of credit and all variables have the same level of integration as seen in Section 3.4.1, we proceed and perform cointegration tests using Johansen (1988) Trace statistic to examine the existence of any long-run relationship between the first component of credit and policy variables. This approach accommodates for the fact that economic variables are not jointly covariance-stationary in the short-run but may show a long-run association. In particular, we are interested in testing if the UMP variable comoves with the common factor of credit within a dynamic specification framework with a specific lag length. Johansen (1988) relies on the relationship between the rank of a matrix and its characteristic roots using maximum likelihood estimation.

We specify the following VAR of order *p* as the following:

$$\Delta Z_t = \prod Z_{t-1} + \sum_{i=1}^{p-1} \prod_i \Delta Z_{t-i} + \varepsilon_t. \tag{3.2}$$

$$\text{where} \qquad \prod = \sum_{i=1}^{p} A_i - I, \quad \text{and} \qquad \prod_i = -\sum_{j=i+1}^{p} A_j.$$

where Z_t is a *k*-vector of non-stationary *I*(1) variables, and ε_t is a vector of disturbances. The rank of the matrix $\prod$ is equal to the number of independent cointegrating vectors *r*. If the variables are not cointegrated then the rank of $\prod = 0$, and hence, Equation (3.2) becomes the usual VAR model in first differences. The parameter $\prod_i$ defines the short-run adjustment to changes in the variables. The error correction parameters contained in A_i measure adjustment towards the long-run equilibrium. Johansen's method is to estimate the matrix $\prod$ from an unrestricted VAR and test whether the restrictions implied by the reduced rank of $\prod$ are rejected or not. In practice, we can obtain the estimates of $\prod$ and the number of characteristic roots that are insignificantly different from unity using the Trace statistic as follows:

$$\gamma_{trace}(r) = -\mathrm{T}\sum_{i=r+1}^{n} ln(1-\hat{\gamma}_i). \tag{3.3}$$

where T is the number of observations, and $\hat{\gamma}$ is the estimated value of the characteristic roots from the estimated matrix $\prod$ (also called eigenvalues). If the Trace test statistic is larger than the critical value, then the null hypothesis of r cointegrating vectors is rejected against the alternative that there are r +1 vectors (Enders, 2015).[36]

One issue with Johansen (1988) approach is the assumption that the model parameters are unchanged over the estimation period, i.e., it presumes that the cointegrating vector is time-invariant under the alternative hypothesis. This assumption is likely to be violated due to the presence of structural breaks in the data sample, for example, the Global Financial Crisis. Therefore, we apply the time series cointegration test proposed by Gregory and Hansen (1996) to investigate whether allowing for a structural break in the model specification would alter our cointegration findings. Their residual-based tests can be seen as an extension of the ADF, Z_a, and Z_t tests for cointegration and allow for a regime shift in either the intercept alone or the entire vectors of coefficients, without prior information with respect to the timing of the regime shift. A standard model of cointegration with no structural change can take the following form:

$$Z_t = \alpha + \beta X_t + \varepsilon_t, \tag{3.4}$$

Where Z_t is the credit variable and X_t a vector of the UMP policy variable and real GDP, both variables are $I(1)$, and observed over periods t=1,…n. ε_t is the residuals and assumed to be $I(0)$. If there is a structural change, then it would be reflected in changes in the intercept α and/or changes to the slope β. To model the structural change, we follow Gregory and Hansen (1996) and define the dummy variable $\varphi_{t\tau}$ as the following:

$$\varphi_{t\tau} = \begin{cases} 0\ if\ t \leq [n\,\tau], \\ 1\ if\ t\ > [n\,\tau]. \end{cases}$$

where the unknown parameter $\tau \in (0,1)$ denotes the relative timing of the change point, and [ ] denotes the integer part. Gregory and Hansen (1996) discuss different forms of structural breaks, for example, level shift, regime shift and with or without a trend. In this chapter, we will focus on the case where the shift occurs in the level with a time trend because the variables exhibit a trend in their evolution over time. With further reparameterization, we define the cointegration model with a break as follows:

$$Z_t = \alpha_1 + \alpha_2\varphi_{t\tau} + \delta t + \beta X_t + \varepsilon_t. \tag{3.5}$$

[36] The critical values of the Trace test are obtained using the Monte Carlo approach.

where α_1 represents the intercept before the shift, α_2 represents the change at the time of the shift, and δt is a time trend. The cointegration relationship is estimated by ordinary least squared (OLS), and a unit root test is applied to the residuals.

However, there may be no information about the exact number of structural breaks in the data. In this case, if the true number of breaks is higher than one, then Gregory and Hansen (1996) approach, which considers only a single break, becomes misspecified and performs poorly. In response to this caveat, Maki (2012) develops a more suitable approach by combining Bai and Perron (1998) test for structural breaks and Kapetanios (2005) unit root test. The residual-based test assumes that the unknown number of breaks in the cointegrating vector is smaller than or equal to the maximum number of breaks k allowed and performs better than previous tests when the cointegrating relationship has multiple breaks or persistent Markov switching regimes. Therefore, we build on the standard model of cointegration in Equation (3.4) and adopt Maki's approach to test for cointegration with multiple breaks between the policy variables and credit, and consider the following two scenarios: Equation (3.6) allows for structural breaks of β in addition to α with a trend, and Equation (3.7) constitutes of structural breaks of levels, trends, and regressors.

$$Z_t = \alpha + \sum_{i=1}^{k} \alpha_i D_{i,t} + \delta t + \beta X_t + \sum_{i=1}^{k} \beta_i X_t D_{i,t} + \varepsilon_t, \tag{3.6}$$

$$Z_t = \alpha + \sum_{i=1}^{k} \alpha_i D_{i,t} + \delta t + \sum_{i=1}^{k} \delta_i t D_{i,t} + \beta X_t + \sum_{i=1}^{k} \beta_i X_t D_{i,t} + \varepsilon_t. \tag{3.7}$$

where $D_{i,t}$ takes a value of 1 if $t > T_{Bi}$ and zero otherwise, i=1,…,k, k is the maximum number of breaks allowed and T_{Bi} denotes the time of the break. The null hypothesis of Maki's is that of no cointegration, and the alternative hypothesis is the presence of cointegration with i breaks and $i \leq k$.

To further support the accuracy and reliability of our empirical results and to gain statistical power through the pooling of additional information across units, hence improving the low power of univariate tests, we consider a panel approach (Campbell and Perron, 1991; Westerlund and Edgerton, 2008). In particular, we apply three standard panel cointegration tests developed by Kao (1999), Pedroni (1999); Pedroni (2004) and Westerlund (2005), on the original data (without the principal component) to check the robustness of their time series counterparts.[37] In its most general form, we consider the following regression equation:

$$Z_{it} = \alpha_i + \delta_i t + \beta_i X_{it} + \varepsilon_{it}. \tag{3.8}$$

where Z_{it} is the credit variable for countries $i = 1,\ldots,N$ over periods $t=1,\ldots T$, and X_{it} a vector of the UMP policy variable and real GDP. Z_{it} and X_{it} are assumed to be integrated of order one. The parameters α_i and δ_i are, respectively, a country-specific constant and a deterministic trend. If added, then the cointegrating vectors may be heterogeneous across the countries of the panel. The slope coefficients β_i may vary across countries, also called the cointegrated vector, and ε_{it} is a vector of residuals, which is expected to be $I(0)$ if cointegration among credit and the UMP policy variable exists.

Moreover, in the presence of structural breaks, standard panel cointegration tests become inadequate because the relationship in Equation (3.8) is no longer linear. Another issue may arise with the heretofore tests, especially in applications that use macroeconomic and financial data with strong inter-economy linkages, is the common assumption of cross-sectional independence which leads to misleading results if not accounted for. In response to these issues, we decide to employ two additional panel cointegration tests. First, we use a panel bootstrap cointegration test by Westerlund and Edgerton (2007) for the null hypothesis of cointegration in the panel.[38] Second, we use Westerlund and Edgerton (2008) panel cointegration test for the null of no cointegration in the panel. The advantage of the latter test over others is that it allows simultaneously for heteroskedastic and serially correlated errors, country-specific trends, cross-sectional dependence and multiple breaks.[39]

3.5.2 Empirical results

After testing the behaviour of each series and finding that they have the same order of integration, i.e., $I(1)$, we proceed to perform the cointegration tests in both time series and panel format.

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[37] The Pedroni (1999, 2004) approach is considered as a semiparametric model with respect to the temporal data dependence, while Kao (1999) approach is based on the assumption of a parametric model, both approaches extend the Engle and Granger (1987) two-step residual cointegration tests, and require the innovations driving the model to be independent over time. Westerlund (2005) approach lie between the assumptions of semiparametric and parametric models in a way to accommodate the correlation in the residuals.

[38] Westerlund and Edgerton (2007) test is based on the sieve sampling scheme to approximate the dependence of the equilibrium errors using a finite order autoregressive mode, and it is able to accommodate for dependence within and between the cross-sectional units. The bootstrap draws of the test are made from the joint empirical distribution of the regression errors. Using Monte Carlo simulations for the data generating process, the authors show that the test perform well in small sample studies.

[39] Another appealing feature of this test is that it allows for the unknown breaks to be located at different dates for different units.

We start with the Trace test of Johansen (1988) for cointegration using the first principal component of the original credit variables and real GDP with each policy variable. Table 3.7 presents the results of the cointegration analysis between the first principal component of each of the three credit measures, total credit volume, credit-to-GDP ratio, and credit-to-GDP gap extracted from the samples of Euro, non-Euro countries, and the full cohort of countries, and its two alternative potential determinants of unconventional monetary policy of ECB.

Based on the Johansen (1988) Trace statistic, we find evidence of cointegrating relationships between the first principal component of all measures of credit variables and both total assets and the shadow rate. Therefore, ECB's implementation of UMP has a significant impact on credit aggregates in the Eurozone. To investigate whether ECB's policies affect other non-Euro countries, we report in panel (b) the results of the cointegration tests between the first principal component of their credit measures for non-Euro countries and the same ECB's policy variables previously considered. We only support a cointegrating relationship between the first principal component of credit and shadow rate. In contrast, total assets feature no long-run relationship with any of the common factors. These results seem to provide empirical support to the work presented by other scholars, such as, for example, Szczerbowicz (2015) who finds that ECB's UMP, measured by ECB's total assets, lowered market borrowing costs for banks, and thus support our finding of long-run relationship with credit volume. Also, Burriel and Galesi (2018) find that UMP shocks benefit most of the euro area members with substantial heterogeneity with spillover effects and to the whole union.

We, next, perform the Gregory and Hansen (1996) residual-based test for cointegration, which allows for the possibility of cointegration with a break under the alternative hypothesis when the timing of the shift is unknown. The results reported in Table 3.8 are for the Z_t and Z_a tests where the dependent variable is each type of credit for each cohort, and the independent variables are the policy variable, i.e., either the ECB's total assets or the shadow rate, and the real GDP. In all specifications, the statistics are lower than the critical values of both tests at 5% significance level. Hence, the results suggest that no cointegration exists between the variables in the long-run after considering one break only in the intercept with a trend.[40] As discussed in the methodology section, allowing for one break only may cause misspecifications about the long-run estimating relationships between the variables. To solve this issue, we also employ Maki (2012) approach and allow for multiple breaks in a time series context. The results for total credit, credit-to-GDP ratio and credit-to-GDP gap are presented in Table 3.9 - Table 3.11. In particular, Table 3.9 supports the existence of a cointegrating relationship at 5% significance level, once with multiple structural breaks in regime shifts and once with regime shifts and trend, between ECB's total assets and the common factor of total credit. As shown in panel

[40] The cointegration results do not change if we alter the specification to allow for a regime shift in the constant and slope.

(a), the null hypothesis of no cointegration cannot be rejected between total assets and credit for non-Euro and for the full samples. In panel (b), we consider the cointegrating relationship between the shadow rate and total credit. In this latter case, we find support for cointegration with regime shifts and trend at 10% significance level for the Euro and full sample, and at 5% for the non-Euro countries. Table 3.10 presents the results when the credit-to-GDP ratio is considered with the two policy variables, here we do not reject the null hypothesis. For the credit-to-GDP gap, the results in Table 3.11 support a cointegrating relationship at 5% significance level only for the Eurozone sample, between total assets and the gap, when the test considers multiple breaks with regime shifts and trend.

The empirical evidence using Maki (2012) confirms the existence of cointegration between both policy variables and the common factor of total credit in the presence of multiple structural breaks. Such a result raises concerns about the previous methods used to test for cointegration and assume invariant model parameters such as Johansen (1988) or allow for one break only such as Gregory and Hansen (1996). These two methods may not provide adequate patterns of the long-run relationship between the variables under security, especially if the observed period is subject to periods of multiple structural changes. Furthermore, employing cointegration analysis with multiple breaks is what differentiate our long-run analysis in this chapter from previous scholars.

Considering panel data cointegration, based on the three tests in Table 3.12, we find strong evidence of long-run equilibrium between the chosen policy variable and each credit variable (original data) in the full sample and subsamples. However, the results slightly vary from one test to the other. For example, weaker evidence of cointegration is found when using Kao (1999) test which, unlike Pedroni (1999); Pedroni (2004) and Westerlund (2005) tests, does not allow for time trend. We also find strong evidence of cointegration between the components of the credit aggregates and total assets, as the above tests reject the null at the 1% significance level. This pattern of results becomes slightly weaker when the shadow rate is considered in place of total assets.

However, as discussed earlier, such panel cointegration tests do not account for cross-sectional dependence; hence their size properties become distorted when such dependence is present. To handle this issue, we present two results of the bootstrap panel cointegration test by Westerlund and Edgerton (2007) where the acceptance of the null hypothesis points to the existence of cointegration. We consider a constant only equation in Table 3.13, and in Table 3.14 we consider a constant and trend in the cointegrating equation. We report in both tables the asymptotic p-value in the absence of dependence and the bootstrap p-value which is used in the case of dependence. Our focus to explore cointegration is based on the latter p-value because dependence is present in our data, as presented in Section 3.4.2. It can be seen from Table 3.13 that the null hypothesis of cointegration cannot be rejected between the policy variables and each credit measure in each estimation. In this case, we conclude that there is a long-run relationship between policy variables and credit. However, when we consider a constant and trend in each panel equation, then the null hypothesis of cointegration is rejected for almost all samples, as shown in Table 3.14.

We finalize our panel cointegration analysis by using Westerlund and Edgerton (2008) test that can handle cross-sectional dependence and multiple breaks simultaneously. Table 3.14 presents the results based on two statistics, $Z_{\tau}(N)$ and $Z_{\phi}(N)$. We focus on the former statistic as it has higher power and size accuracy for small samples and robust against different forms of serial correlation and dependence in the panel. We reject the null hypothesis of no cointegration in the panel at 5% only when total credit and total assets are considered and for the Eurozone countries. This result indicates that total credit and total assets comove in the long run over the sample period, and such finding is robust to the presence of common factors and multiple breaks. Other estimations do not reject the null hypothesis, and hence we do not find cointegration relationship in the other panels.

Table 3.7. Time series cointegration using the first principal components of credit

Panel (a): Euro			Panel (b): non-Euro			Panel (c): full cohort		
UMP and total credit			**UMP and total credit**			**UMP and total credit**		
Total assets			Total assets			Total assets		
H_0: r=0	37.75	Lag = 3	H_0: r=0	29.74**	Lag = 3	H_0: r=0	36.18	Lag = 3
H_0: r=1	12.11 **		H_0: r=1	12.31		H_0: r=1	12.53**	
Shadow rate			Shadow rate			Shadow rate		
H_0: r=0	56.71	Lag = 4	H_0: r=0	36.79	Lag = 2	H_0: r=0	51.07	Lag = 2
H_0: r=1	16.91**		H_0: r=1	13.65**		H_0: r=1	16.66**	
UMP and credit-to-GDP ratio			**UMP and credit-to-GDP ratio**			**UMP and credit-to-GDP ratio**		
Total assets			Total assets			Total assets		
H_0: r=0	30.78**	Lag = 2	H_0: r=0	45.63	Lag = 3	H_0: r=0	34.87	Lag = 2
H_0: r=1	8.26		H_0: r=1	12.90**		H_0: r=1	5.28**	
Shadow rate			Shadow rate			Shadow rate		
H_0: r=0	39.25	Lag = 2	H_0: r=0	54.49**	Lag = 2	H_0: r=0	37.73	Lag = 2
H_0: r=1	6.76**		H_0: r=1	22.45		H_0: r=1	8.72**	
UMP and credit-to-GDP gap			**UMP and credit-to-GDP gap**			**UMP and credit-to-GDP gap**		
Total assets			Total assets			Total assets		
H_0: r=0	28.66**	Lag = 3	H_0: r=0	50.20	Lag = 2	H_0: r=0	34.69	Lag = 3
H_0: r=1	9.834		H_0: r=1	16.31**		H_0: r=1	13.83*	
Shadow rate			Shadow rate			Shadow rate		
H_0: r=0	49.58	Lag = 4	H_0: r=0	37.83	Lag = 2	H_0: r=0	39.61	Lag = 2
H_0: r=1	10.91**		H_0: r=1	16.76**		H_0: r=1	13.59**	

Notes: Sample period 1999Q1 to 2018Q1 (N = 12/8/20, T=77). Trace test statistics applied to series at levels with critical value at 5% level equals to 34.55 for zero cointegrating relationships and 18.17 for one cointegrating relationship. All specifications include a constant and a trend. In all equations, the first principal component of real GDP is added to control for the business cycle. The number of cointegrating vectors in the Johansen (1988) Trace test is denoted by r. Lag length is determined by the Akaike Information Criteria with maximum lag length = 4. The results show significance only up to 1 cointegrating relationship; hence, we do not report where r=2. ** indicates rejection of the null at the 5%, significance level.

Table 3.8. Time series cointegration using the first principal components of credit with one structural break

Panel (a): Euro			Panel (b): non-Euro			Panel (c): full cohort		
UMP and total credit			UMP and total credit			UMP and total credit		
Total assets			Total assets			Total assets		
Z_t	-3.78	Lag = 0	Z_t	-3.83	Lag = 0	Z_t	-3.79	Lag =0
Z_a	-23.57	2014Q1	Z_a	-23.47	2014Q1	Z_a	-23.33	2014Q1
Shadow rate			Shadow rate			Shadow rate		
Z_t	-4.71	Lag = 1	Z_t	-5.01	Lag = 1	Z_t	-4.71	Lag =1
Z_a	-30.47	2008Q4	Z_a	-33.41	2007Q3	Z_a	-30.94	2008Q3
UMP and credit-to-GDP ratio			UMP and credit-to-GDP ratio			UMP and credit-to-GDP ratio		
Total assets			Total assets			Total assets		
Z_t	-2.38	Lag = 0	Z_t	-3.97	Lag = 0	Z_t	-2.97	Lag = 0
Z_a	-13.81	2013Q3	Z_a	-27.73	2008Q3	Z_a	-19.27	2008Q2
Shadow rate			Shadow rate			Shadow rate		
Z_t	-4.13	Lag = 0	Z_t	-4.15	Lag = 0	Z_t	-4.28	Lag = 1
Z_a	-27.82	2008Q1	Z_a	-27.01	2008Q1	-29.11	-29.11	2008Q1
UMP and credit-to-GDP gap			UMP and credit-to-GDP gap			UMP and credit-to-GDP gap		
Total assets			Total assets			Total assets		
Z_t	-3.62	Lag = 2	Z_t	-4.32	Lag = 0	Z_t	-3.92	Lag = 1
Z_a	-20.58	2008Q2	Z_a	-30.41	2008Q2	Z_a	-27.30	2008Q2
Shadow rate			Shadow rate			Shadow rate		
Z_t	-4.00	Lag = 2	Z_t	-4.11	Lag = 1	Z_t	-4.11	Lag = 2
Z_a	-24.72	2008Q4	Z_a	-25.70	2008Q4	Z_a	25.27	2008Q4

Notes: Sample period 1999Q1 to 2018Q1 (N = 12/8/20, T=77). Z_t and Z_a statistics are the residuals-based tests applied to series at levels with critical value at 5% level equals to -5.29 and -53.92 respectively. The null hypothesis is that the series are not cointegrated, and the alternative hypothesis is that the series are cointegrated with a possible break in the intercept and slope of the cointegrating regression. All specifications allow for a change in level and trend with an unknown date. In all equations the first principal component of real GDP is added to control for the business cycle. Lag length is determined by the Akaike Information Criteria with maximum lag length = 4. ** indicates rejection of the null at the 5% significance level.

Table 3.9. Time series cointegration test with multiple breaks for total credit

Panel (a): Total asset and total credit				
	Regime shift		Regime shift with trend	
	T-statistics	Break points	T-statistics	Break points
Eurozone	-5.751**	2005Q3 2010Q3 2014Q2	-6.735**	2008Q3 2012Q4 2014Q4
non-Euro	-4.527	2002Q1 2008Q2 2014Q2	-5.87	2004Q2 2008Q2 2010Q3
Full cohort	-5.096	2005Q3 2010Q3 2014Q2	-5.647	2008Q4 2011Q2 2014Q4
Panel (b): Shadow rate and total credit				
	Regime shift		Regime shift with trend	
	T-statistics	Break points	T-statistics	Break points
Eurozone	-4.579	2006Q4 2012Q1 2014Q2	-6.376*	2007Q3 2014Q2 2016Q3
non-Euro	-5.605*	2007Q1 2009Q2 2013Q4	-7.088**	2007Q1 2009Q1 2014Q2
Full cohort	-4.662	2008Q3 2012Q1 2013Q4	-6.514*	2007Q3 2013Q2 2015Q2

Notes: Sample period 1999Q1 to 2018Q1 (N = 12/8/20, T=77). T-statistic is the residual-based test for cointegration with multiple breaks applied to the series at level. The common factor of total credit is used here for each sample. Regime shift and regime shift with trend models have critical values at 5% and 10% equals to -5.703, -5.407 and -6.524, -6.267 respectively. The null hypothesis is that the series are not cointegrated, and the alternative hypothesis is that the series are cointegrated with up to three maximum breaks in the intercept and slope (regime shift). Lag length is determined by the Akaike Information Criteria with maximum lag length = 4. */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels.

Table 3.10. Time series cointegration test with multiple breaks for credit-to-GDP ratio

Panel (a): Total asset and credit-to-GDP ratio				
	Regime shift		Regime shift with trend	
	T-statistics	Break points	T-statistics	Break points
Eurozone	-5.071	2001Q1 2004Q4 2014Q4	-5.878	2001Q4 2008Q2 2011Q2
non-Euro	-3.890	2001Q2 2006Q1 2014Q4	-5.009	2003Q1 2006Q4 2011Q1
Full cohort	-4.592	2001Q1 2004Q4 2014Q4	-6.228	2007Q2 2009Q4 2014Q3
Panel (b): Shadow rate and credit-to-GDP ratio				
	Regime shift		Regime shift with trend	
	T-statistics	Break points	T-statistics	Break points
Eurozone	-4.456	2006Q2 2010Q4 2015Q1	-6.018	2007Q1 2009Q2 2014Q4
non-Euro	-4.674	2007Q4 2010Q3 2013Q3	-5.156	2005Q4 2009Q1 2011Q1
Full cohort	-3.898	2006Q1 2011Q1 2013Q2	-4.529	2009Q2 2011Q4 2016Q2

Notes: Sample period 1999Q1 to 2018Q1 (N = 12/8/20, T=77). T-statistic is the residual-based test for cointegration with multiple breaks applied to the series at level. The common factor of the credit-to-GDP ratio is used here for each sample. Regime shift and regime shift with trend models have critical values at 5% and 10% equals to -5.703, -5.407 and -6.524, -6.267 respectively. The null hypothesis is that the series are not cointegrated, and the alternative hypothesis is that the series are cointegrated with up to three maximum breaks in the intercept and slope (regime shift). Lag length is determined by the Akaike Information Criteria with maximum lag length = 4. */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels.

Table 3.11. Time series cointegration test with multiple breaks for credit-to-GDP gap

	Panel (a): Total asset and credit-to-GDP gap			
	Regime shift		Regime shift with trend	
	T-statistics	Break points	T-statistics	Break points
Eurozone	-4.231	2001Q2 2003Q3 2014Q4	-7.366**	2001Q4 2008Q2 2014Q3
non-Euro	-4.077	2001Q2 2006Q1 2015Q3	-6.193	2004Q2 2008Q2 2012Q3
Full cohort	-4.060	2001Q2 2003Q3 2014Q4	-4.599	2003Q1 2008Q2 2013Q3
	Panel (b): Shadow rate and credit-to-GDP gap			
	Regime shift		Regime shift with trend	
	T-statistics	Break points	T-statistics	Break points
Eurozone	-4.238	2008Q1 2010Q4 2015Q1	-5.370	2006Q4 2009Q3 2014Q4
non-Euro	-4.141	2006Q1 2010Q4 2015Q4	-5.128	2004Q3 2008Q1 2014Q3
Full cohort	-4.887	2006Q3 2011Q1 2015Q1	-6.039	2009Q3 2011Q4 2014Q3

Notes: Sample period 1999Q1 to 2018Q1 (N = 12/8/20, T=77). T-statistic is the residual-based test for cointegration with multiple breaks applied to the series at level. The common factor of the credit-to-GDP gap is used here for each sample. Regime shift and regime shift with trend models have critical values at 5% and 10% equals to -5.703, -5.407 and -6.524, -6.267 respectively. The null hypothesis is that the series are not cointegrated, and the alternative hypothesis is that the series are cointegrated with up to three maximum breaks in the intercept and slope (regime shift). Lag length is determined by the Akaike Information Criteria with maximum lag length = 4. */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels.

Table 3.12. Panel cointegration analysis using credit and UMP variables

Eurozone							
Policy variable: total assets							
	Kao			Pedroni			Westerlund
Variable	MDF[a]	DF[b]	ADF[c]	MPP[d]	PP[e]	ADF	VR[f]
Total credit	1.029	1.266	0.427	5.029***	6.558***	8.265***	4.542***
Credit-to-GDP ratio	1.351	1.288	0.053	4.638***	7.025***	11.17***	3.425***
Credit-to-GDP gap	1.609*	2.370***	1.609*	4.138***	5.617***	7.895***	3.375***
Policy variable: shadow rate							
Variable	MDF[a]	DF[b]	ADF[c]	MPP[d]	PP[e]	ADF	VR[f]
Total credit	-0.534	-1.625	-4.145***	3.305***	2.827***	3.349***	3.068
Credit-to-GDP ratio	-0.208	-2.143***	-2.213***	4.777***	5.269***	5.135***	2.475***
Credit-to-GDP gap	0.025	0.705	-0.413	4.487***	4.393***	4.389***	0.258
non-Euro countries							
Policy variable: total assets							
	Kao			Pedroni			Westerlund
Variable	MDF[a]	DF[b]	ADF[c]	MPP[d]	PP[e]	ADF	VR[f]
Total credit	0.267	0.496	-0.274	4.194***	5.89***	5.764***	4.529***
Credit-to-GDP ratio	0.182	-0.073	-0.808	4.221***	6.139***	7.369***	4.396***
Credit-to-GDP gap	0.950	1.176	-1.364	3.734***	4.983***	6.4247***	4.340***
Policy variable: shadow rate							
	MDF[a]	DF[b]	ADF[c]	MPP[d]	PP[e]	ADF	VR[f]
Total credit	-0.008	-0.201	-1.716	0.978	-0.091	0.452	1.225
Credit-to-GDP ratio	1.450	1.413	-0.6994	2.439***	1.537	3.291***	1.285
Credit-to-GDP gap	-0.066	0.104	-1.729***	3.410***	3.128***	4.828***	1.509
Full cohort							
Policy variable: total assets							
	Kao			Pedroni			Westerlund
Variable	MDF[a]	DF[b]	ADF[c]	MPP[d]	PP[e]	ADF	VR[f]
Total credit	1.034	1.351	-0.461	6.441***	8.569***	10.048***	6.424***
Credit-to-GDP ratio	1.193	0.863	-1.087	6.262***	9.324***	14.473***	5.555***
Credit-to-GDP gap	2.845***	3.846***	1.236	5.687***	7.764***	10.179***	5.059***
Policy variable: shadow rate							
Variable	MDF[a]	DF[b]	ADF[c]	MPP[d]	PP[e]	ADF	VR[f]
Total credit	-0.393	-1.475	-4.504***	3.239***	2.165***	2.879***	3.257***
Credit-to-GDP ratio	0.736	-1.250	-2.017***	5.549***	5.414***	6.059***	2.852***
Credit-to-GDP gap	0.949	1.596	-0.266	6.059***	5.884***	6.453***	0.790

Notes: Sample period 1999Q1 to 2018Q1 (N = 12/8/20, T=77). The reported values are test statistics for each cointegration under the null hypothesis of no cointegration in the panels. All tests adjusted for serial correlation in the residuals of the cointegration equations using the Bartlett kernel by Newey and West (1987) method. [abc] denote Modified Dicky-Fuller, Dicky-Fuller and Augmented Dickey-Fuller tests of Kao where AR parameter is the same for all panels without time trend specification. [de] are Modified Philips-Perron and Philips-Perron test statistics of Pedroni where AR parameter is panel specific with time trend specification. [f] is the variance ratio of Westerlund with time trend specification. In all equations, the natural logarithm of real GDP is added to control for the business cycle. Lag length is determined by the Akaike Information Criteria with maximum lag length = 4. */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels.

Table 3.13. Panel cointegration analysis using credit and UMP variables adjusted for dependence (constant only)

Variable	LM-stat	Asymptotic *p*-value	Bootstrap *p*-value
Eurozone			
Policy variable: total assets			
Total credit	21.90	0.000	0.697
Credit-to-GDP ratio	14.28	0.000	0.881
Credit-to-GDP gap	15.76	0.000	0.736
Policy variable: shadow rate			
Variable	LM-stat	Asymptotic *p*-value	Bootstrap *p*-value
Total credit	16.12	0.000	0.374
Credit-to-GDP ratio	8.773	0.000	0.945
Credit-to-GDP gap	10.69	0.000	0.594
non-Euro countries			
Policy variable: total assets			
Variable	LM-stat	Asymptotic *p*-value	Bootstrap *p*-value
Total credit	15.49	0.000	0.469
Credit-to-GDP ratio	12.86	0.000	0.684
Credit-to-GDP gap	12.22	0.000	0.699
Policy variable: shadow rate			
Variable	LM-stat	Asymptotic *p*-value	Bootstrap *p*-value
Total credit	10.31	0.000	0.447
Credit-to-GDP ratio	9.013	0.000	0.758
Credit-to-GDP gap	8.305	0.000	0.619
Full cohort			
Policy variable: total assets			
Variable	LM-stat	Asymptotic *p*-value	Bootstrap *p*-value
Total credit	26.76	0.000	0.430
Credit-to-GDP ratio	19.19	0.000	0.860
Credit-to-GDP gap	19.94	0.000	0.768
Policy variable: shadow rate			
Variable	LM-stat	Asymptotic *p*-value	Bootstrap *p*-value
Total credit	19.01	0.000	0.392
Credit-to-GDP ratio	12.49	0.000	0.930
Credit-to-GDP gap	13.53	0.000	0.651

Notes: Sample period 1999Q1 to 2018Q1 (N = 12/8/20, T=77). The reported LM-statistic values are Lagrange multiplier residual-based test of McCoskey and Kao (1998) under the null hypothesis of cointegration in the panels. Bootstrap draws are made from the joint empirical distribution of the regression errors and are based on 2000 replications. All equations contain a constant term only. Lag length is determined by the Akaike Information Criteria with maximum lag length = 4. */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels.

Table 3.14. Panel cointegration analysis using credit and UMP variables adjusted for dependence (constant and trend)

	Eurozone		
	Policy variable: total assets		
Variable	LM-stat	Asymptotic *p*-value	Bootstrap *p*-value
Total credit	81.94	0.000	0.000***
Credit-to-GDP ratio	52.77	0.000	0.000***
Credit-to-GDP gap	59.09	0.000	0.000***
	Policy variable: shadow rate		
Variable	LM-stat	Asymptotic *p*-value	Bootstrap *p*-value
Total credit	31.12	0.000	0.029**
Credit-to-GDP ratio	20.12	0.000	0.002***
Credit-to-GDP gap	22.63	0.000	0.001***
	non-Euro countries		
	Policy variable: total assets		
Variable	LM-stat	Asymptotic *p*-value	Bootstrap *p*-value
Total credit	60.44	0.000	0.000***
Credit-to-GDP ratio	46.01	0.000	0.000***
Credit-to-GDP gap	46.00	0.000	0.000***
	Policy variable: shadow rate		
Variable	LM-stat	Asymptotic *p*-value	Bootstrap *p*-value
Total credit	15.83	0.000	0.058*
Credit-to-GDP ratio	23.09	0.000	0.000***
Credit-to-GDP gap	20.58	0.000	0.000***
	Full cohort		
	Policy variable: total assets		
Variable	LM-stat	Asymptotic *p*-value	Bootstrap *p*-value
Total credit	101.7	0.000	0.000***
Credit-to-GDP ratio	69.98	0.000	0.000***
Credit-to-GDP gap	74.86	0.000	0.000***
	Policy variable: shadow rate		
Variable	LM-stat	Asymptotic *p*-value	Bootstrap *p*-value
Total credit	34.12	0.000	0.039**
Credit-to-GDP ratio	30.18	0.000	0.000***
Credit-to-GDP gap	30.55	0.000	0.000***

Notes: Sample period 1999Q1 to 2018Q1 (N = 12/8/20, T=77). The reported LM-statistic values are Lagrange multiplier residual based test of McCoskey and Kao (1998) under the null hypothesis of cointegration in the panels. Bootstrap draws are made from joint empirical distribution of the regression errors and are based on 2000 replications. All equations contain a constant term and trend. Lag length is determined by the Akaike Information Criteria with maximum lag length = 4. */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels.

Table 3.15. Panel cointegration analysis using credit and UMP variables adjusted for dependence and multiple breaks

		Eurozone		
		Policy variable: total assets		
Variable	$Z_{\tau}(N)^{a}$	$Z_{\phi}(N)^{a}$	$Z_{\tau}(N)^{b}$	$Z_{\phi}(N)^{b}$
Total credit	1.140(0.873)	1.794(0.964)	-2.084(0.019)**	-1.277(0.101)
Credit-to-GDP ratio	-0.830(0.203)	0.621(0.733)	-0.142(0.444)	0.751(0.774)
Credit-to-GDP gap	1.189(0.883)	1.547(0.939)	3.232(0.999)	3.010(0.999)
		Policy variable: shadow rate		
Variable	$Z_{\tau}(N)^{a}$	$Z_{\phi}(N)^{a}$	$Z_{\tau}(N)^{b}$	$Z_{\phi}(N)^{b}$
Total credit	1.936(0.974)	2.411(0.992)	0.724(0.765)	1.289(0.901)
Credit-to-GDP ratio	-0.522(0.301)	0.440(0.670)	0.277(0.609)	1.496(0.933)
Credit-to-GDP gap	1.067(0.857)	2.268(0.988)	-0.136(0.446)	0.028(0.511)
		non-Euro countries		
		Policy variable: total assets		
Variable	$Z_{\tau}(N)^{a}$	$Z_{\phi}(N)^{a}$	$Z_{\tau}(N)^{b}$	$Z_{\phi}(N)^{b}$
Total credit	5.070(1)	3.460(1)	1.594(0.945)	0.977(0.836)
Credit-to-GDP ratio	1.295(0.902)	1.543(0.939)	0.650(0.742)	0.945(0.828)
Credit-to-GDP gap	1.210(0.887)	1.747(0.960)	0.438(0.669)	0.986(0.838)
		Policy variable: shadow rate		
Variable	$Z_{\tau}(N)^{a}$	$Z_{\phi}(N)^{a}$	$Z_{\tau}(N)^{b}$	$Z_{\phi}(N)^{b}$
Total credit	-2.796(0.997)	1.937(0.974)	-1.573(0.058)*	-1.726(0.042)**
Credit-to-GDP ratio	0.727(0.766)	1.130(0.871)	1.070(0.858)	1.440(0.925)
Credit-to-GDP gap	1.722(0.957)	1.839(0.967)	1.921(0.973)	1.918(0.972)
		Full cohort		
		Policy variable: total assets		
Variable	$Z_{\tau}(N)^{a}$	$Z_{\phi}(N)^{a}$	$Z_{\tau}(N)^{b}$	$Z_{\phi}(N)^{b}$
Total credit	-0.487(0.313)	0.743(0.771)	0.507(0.694)	1.313(0.905)
Credit-to-GDP ratio	2.466(0.993)	2.525(0.994)	1.295(0.902)	1.825(0.966)
Credit-to-GDP gap	1.221(0.889)	1.842(0.967)	2.338(0.990)	2.555(0.995)
		Policy variable: shadow rate		
Variable	$Z_{\tau}(N)^{a}$	$Z_{\phi}(N)^{a}$	$Z_{\tau}(N)^{b}$	$Z_{\phi}(N)^{b}$
Total credit	0.347(0.636)	1.951(0.974)	0.249(0.598)	1.448(0.926)
Credit-to-GDP ratio	0.658(0.745)	0.509(0.694)	3.025(0.999)	2.961(0.998)
Credit-to-GDP gap	1.883(0.970)	2.293(0.989)	1.583(0.943)	1.788(0.963)

Notes: Sample period 1999Q1 to 2018Q1 (N = 12/8/20, T=77). The reported Lagrange multiplier statistics, $Z_{\tau}(N)$ and $Z_{\phi}(N)$ are normally distributed under the null hypothesis of no cointegration in the panels. p-values are in parentheses. [a] is the model estimated with no breaks and [b] is the model estimated with regime shift (break in both constant and slope). The number of common factors is determined using the information criterion proposed by Bai and Ng (2004) and the maximum number is set to 4. Lag length is based on the largest integer less than $4(T/100)^{2/9}$. */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels.

In this section, we focus on the long-run and attempt to establish a relationship between the series of ECB's UMP and credit variables in each sample of countries to investigate if UMP were successful in affecting private credit. We perform such analysis using cointegration in time series and panel data contexts. Using such methods, we find that the policy variables of ECB's UMP and the three credit measures are cointegrated. While cointegration tests with only one structural break do not present any significant long-run results between the variables, using cointegration tests that allow for multiple breaks, we find significant long-run relationships between the variables.

We further support our long-run evidence found in this section and continue to address the research question. However, we now focus on the short-run and use a different identification strategy to enhance our findings. We, therefore, decide to focus on a specific period, i.e., 2007-2018, and proceed to take the analysis further by following a vast body of literature and attempt to identify the effect of UMP on credit using a time series structural VAR approach.[41]

3.5.3 Structural Vector Autoregression

To analyze the macroeconomic effects of UMP shocks on credit aggregates using the common factor, we apply a Structural Factor Augmented VAR (SFAVAR) model.[42] Similar to the approach first introduced by Bernanke et al. (2005), who exploit the information from a factor of economic activity variables and augment it into a VAR to study the impact of monetary policy on output and prices.[43] Structural VARs are commonly used in the early and recent literature to gauge the effects of conventional and unconventional monetary policy innovations, see, e.g., Christiano et al. (1999); Peersman and Smets (2003); Fry and Pagan (2011); Conti (2017); Arias et al. (2019); Lewis and Roth (2019). While employing a minimum set of theoretical structures and assumptions about the economy, SVAR methodology allows us to identify the effects of monetary policy shocks dynamically. Our interest in this section is to analyze the contribution of UMP shocks to credit dynamics. Such shocks are identified by a set of restrictions using a Bayesian approach for estimation and inference.[44]

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[41] Since the variables of UMP and credit are $I(1)$ processes, one may consider Fully-modified OLS and canonical regression estimators or even VECM methods. However, these estimators may not be able to provide a reliable result in terms of direction and magnitude between the variables, i.e., it does not capture the macroeconomic effects of UMP, because the structural innovations of monetary policy shocks are usually identified using sign restrictions especially for relatively a short-time period and for the short-run. Hence, the application of structural VAR (Bernanke and Blinder, 1992).

[42] Throughout this section, we will refer to the Structural Factor Augmented VAR (SFAVAR) model as SVAR for brevity.

[43] For a recent survey on factor augmented VAR modelling in related literature, see, e.g., Doz and Fuleky (2020).

[44] Unlike the time series (frequentist) approach, Bayesian methods do not require the variables in the VAR model to be stationary, because the estimation and inference of the parameters depend on the prior distribution, hence the variables in the VAR model will enter as $I(1)$ processes (Koop, 2003).

3.5.3.1 *Specification*

The following reduced-form VAR system serves as our benchmark model:

$$Z_t = \alpha + A(L)Z_{t-1} + B\varepsilon_t \tag{3.9}$$

where Z_i is a vector of endogenous variables, α is a vector of constants, $A(L)$ a matrix polynomial in the lag operator L, and B is the contemporaneous impact matrix of mutually uncorrelated shocks ε_t. The vector of six endogenous variables includes real GDP, consumer prices, ECB total assets, financial market volatility as measured by the composite indicator of systemic stress (CISS) of Holló et al. (2012), and the spread between the Euro overnight index average (EONIA) rate and the main refinancing operations (MRO) rate. We further add the common factor of total credit to the VAR system, calculated using the PANIC method in Section 3.4.3, to investigate how the common factor of total credit interact with the above variables. All series except the CISS, spread, and the common factor is taken in logs and seasonally adjusted.[45] These variables are standard in the empirical literature on UMP, see, e.g., Gambacorta et al. (2014); Boeckx et al. (2017), and should account for the dynamics among the macroeconomic, financial, and monetary indicators.[46] [47]

3.5.3.2 *Identification of structural shocks*

An exogenous innovation to central bank balance sheet is one that is identified as an expansionary UMP shock. We isolate exogenous balance sheet shocks by using a mixture of zero and sign restrictions, where we implement the structural identification scheme based on Arias et al. (2018), who extend the sign restrictions approach proposed by Rubio-Ramirez et al. (2010).[48] [49]

Such a method requires making assumptions on central bank actions and the response of the real economy to these actions based on economic relevance, where the aim is to identify and isolate truly orthogonal UMP shocks. To ensure that our restrictions are valid and comparable to previous studies, we first follow Gambacorta et al. (2014) and Boeckx et al. (2017) by assuming that a UMP shock has only a lagged impact on output and prices, i.e., the contemporaneous impact on both variables is restricted to be zero. On the contrary, shocks to output and prices are allowed to have an

[45] Adding the composite indicator of systemic stress (CISS) as a general proxy for financial distress and economic turmoil is important to disentangle exogenous shocks to ECB balance sheet from endogenous responses to market imbalances, including financial risk and economic uncertainty. Failure to take into account such market risk perceptions and the uncertainty channel could fail to capture UMP shocks and hence bias the estimation of the SVAR model.

[46] All macroeconomic variables are obtained from Eurostat database, except for the CISS and total assets obtained from ECB database.

[47] We follow the procedure of Eickmeier et al. (2014) by normalizing and scaling the factor to have the same standard deviation and mean as credit growth series, calculated quarter-on-quarter, before entering the SVAR model.

[48] The estimation procedure is carried out by employing the Bayesian Estimation, Analysis and Regression (BEAR) toolbox developed by Dieppe et al. (2016).

[49] Imposing a sign restriction constrains the reaction of a specific variable to a structural shock to be either positive or negative, while a zero restriction constrains the response to be zero for the chosen period.

immediate effect on the central bank assets. Such assumption allows to isolate different monetary policy shocks, as well as aggregate supply from demand shocks and is found in early studies on monetary policy transmission channel (see, e.g., Bernanke and Blinder (1988); Peersman and Smets (2003); Eickmeier and Hofmann (2013)). Second, to disentangle exogenous shocks to central bank balance sheet from their endogenous response to financial distress arising from financial market uncertainty, we assume that an expansionary UMP shock does not increase financial market volatility. This restriction is in support of the assumption that central bank assets increase in response to a rise in financial market volatility.[50] In doing so, we assume that ECB's UMP aims to mitigate the concerns about financial and economic vulnerabilities captured by the stock market volatility. Third, we assume that an expansionary UMP decision does not increase the EONIA-MRO spread. Specifically, liquidity surplus in the response of UMP, i.e., the unlimited access of banks to central bank liquidity under the FRFA procedure, exercise downward pressure on EONIA rate, and hence the interest rate spread.[51] [52]

Regarding the common factor of total credit, we prefer to let the data speak by themselves. Hence, the response of credit to UMP is left unrestricted in the baseline SVAR model. This step is particularly relevant and will enable us to determine whether UMP is a driving force of private credit. If the transmission channel of ECB's UMP works through private lending, then one would expect to observe a positive response from the common factor of total credit to a positive shock in UMP. Furthermore, as argued by Paustian (2007), identifying additional shocks in the VAR by imposing restrictions on the other variables in the system through further assumptions, improves the precision of the estimates, leading to narrower confidence intervals. However, one concern that arises here is that invalid assumptions imposed on the other shocks may bias the IRFs to the shock of interest. Jointly with UMP shock, we identify a financial stress shock that increases the financial volatility index as in Lewis and Roth (2019) and Elbourne et al. (2018). This shock is notably important because UMP and financial stress are highly correlated, and UMP can be endogenously driven by vulnerabilities in the financial market (Gambacorta et al., 2014; Kremer, 2016). Similar to UMP shock restrictions, output and prices are sluggish in the response of financial and monetary disturbances, and therefore do not respond contemporaneously to the financial shock. In the latter

[50] This assumption is also in line with the interaction between financial distress and conventional monetary policy. See, e.g., Bekaert et al. (2013).

[51] One may argue that not all UMP measures imply downward pressure on the EONIA-MRO spread. To account for this, we employ the sign restriction in a weak form, i.e., smaller/larger or equal to zero (Boeckx et al., 2017).

[52] The fixed rate tender procedure with full allotment (FRFA) policy, which is effective since 15 October 2008, aims to stimulate lending to the real economy by allowing banks to obtain liquidity as much as needed given adequate collateral. Such policy is meant to work through MRO and LTRO rates (Bock et al., 2018).

case, interest rate spread increases, and ECB's balance sheet is assumed to expand in response to financial stress. A summary of the identifying restrictions is presented in Table 3.16 below.

Table 3.16. Structural shocks identification scheme

Shocks/variable	Output	Prices	ECB total assets	CISS	EONIA-MRO spread	C/F total credit
UMP	0	0	+	−	−	?
Financial stress	0	0	+	+	+	?

Notes: 0 indicates no immediate response, while '+' '(-)' indicates that the response is restricted to positive (negative) sign in the respective period. All sign restrictions are imposed on impact and the first period after the shock, i.e., the first quarter.

3.5.3.3 Estimation

The reduced-form VAR is estimated over the sample period 2007Q1 – 2018Q4 with four lags based on the usual information criteria.[53] We use Bayesian methods for estimation and inference which are well-suited for short data sets and help overcome the curse of dimensionality due to rich parametrization by imposing prior believes on the model parameters (Litterman, 1986). Furthermore, the prior can account for unit root behaviour by including autoregressive coefficient on the first own lag of each variable. The prior and posterior distributions of the reduced-form VAR belong to the Normal-Wishart family (Zellner, 1996).[54] The concept of the underlying algorithm with zero and sign restrictions is to compute the median IRFs from Gibbs sampling based on the procedure proposed by Uhlig (2005). In order to draw the "candidate truths" from the posterior, a joint draw is chosen from the posterior distributions for the unrestricted Normal-Wishart posterior of the VAR parameters in addition to a uniform distribution for the rotation matrices. If the restrictions presented in Table 3.16 are satisfied, and the draw of the VAR system is stationary, then the draw is kept. Otherwise, the draw is rejected by giving it a prior weight equals to zero (Peersman, 2005). The total number of iterations, i.e., the times that the SVAR coefficients are drawn, is 5,000.

3.5.3.4 Results

Figure 3.5 shows the IRFs of the estimated SVAR model that include – apart from the conventional measures of real output, prices, financial volatility, and interest rate spread – total assets of ECB balance sheet as a proxy of UMP and the common factor of total credit. Our model captures the macro-financial and monetary interaction following an expansionary UMP shock obtained from the SVAR model using the sign restrictions introduced in Table 3.16. Such shock is characterized by an increase in ECB's total assets of about 0.75%, which is significant up to three quarters. The solid

[53] We choose such period to capture the effectiveness of monetary policy starting from the Global Financial Crisis onward, where the ECB started their UMP programs.

[54] Similar to Bańbura et al. (2015), we adopt the sum-of-coefficients prior in our VAR settings, first introduced by Doan et al. (1984), to account for unit root behaviour in the data.

lines depict the median responses of the posterior distribution, and the dashed lines represent the 68% posterior credibility bounds. The responses of output and consumer prices are reconciled with our identification strategy, correctly signed and in line with the ECB asset purchases program, which aims to revive the Eurozone economy and support price stability. Both variables respond positively to a one-standard-deviation shock in ECB's total assets, output reaches 0.85% for the first quarter after the shock, and consumer prices reach 0.025%, which is slightly significant for the first four quarters, and gradually decrease towards the baseline at longer horizons. These results are qualitatively similar to those from the literature on the macroeconomic effects of UMP which concludes that asset purchases have a positive impact on economic activity and inflation (see, e.g., Gambacorta et al. (2014); Boeckx et al. (2017), and Murgia (2020) who find that output is more responsive to monetary policy shocks compared to prices, and Elbourne et al. (2018) who find no significant effect on prices.[55] However, since we use quarterly and not monthly data, there remain some differences in the magnitude, peak, and duration of the shock.

Moreover, an expansionary UMP shock decreases the levels of financial distress, as the CISS features a response that remains negative for the first three quarters, reaches its lowest of -1.5% on impact, and then returns to baseline rapidly after six quarters. The common factor of total credit, which we purposely left it unrestricted, responds positively to an expansionary UMP shock, with such a response being positive on impact, becomes significant only after four quarters. This result shows that the transmission of UMP through the credit channel exists with a lag up to a year. Finally, the interest rate spread shows a negative response and reaches -5.8% on impact, and remains significant up to four quarters, and returns to fade out after seven quarters. We take this result as evidence of the negative impact of UMP on interest rates, which is in line with the literature (Kapetanios et al., 2012).

Looking at the forecast error variance decomposition in Figure 3.6 that takes into accounts the magnitude of the different shocks of the SVAR system, it can be noted that the financial stress shock identifies a large proportion of variation in forecasting the common factor. The UMP shock comes in the second place, in terms of proportion, which gradually contributes to more variability of the common factor over time. These findings are important in our analysis. They reveal that the common factor of private credit was substantially driven by financial stress and UMP surprises during the crisis period. However, such stress in the financial markets depresses banks' liquidity, adversely affects the balance sheets of both lenders and borrowers, and eventually cuts lending for all types of loans provided by banks. This scenario poses challenges to the effectiveness of the bank lending channel of monetary policy and eventually hampers the central bank's actions to revive the real economy,

[55] As mentioned earlier, the literature so far has not addressed the role of the common factor(s) into the analysis of UMP. We believe that this departure from the current literature to be our main contribution in short-run analysis of this chapter.

which may explain the limited impact on prices in our analysis (Ivashina and Scharfstein, 2010; Acharya et al., 2020).

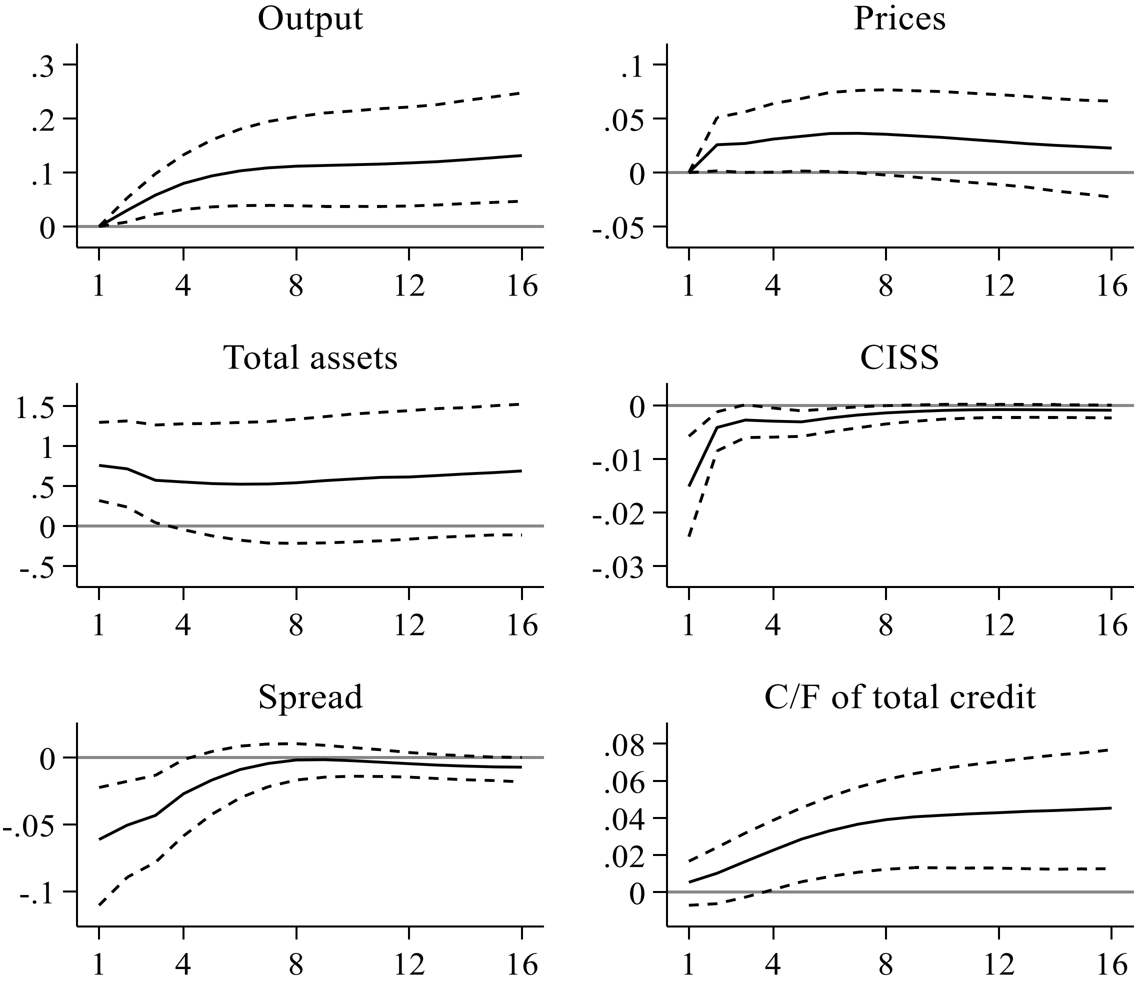

Figure 3.5. Median IRFs of real output, prices, ECB total assets, financial volatility index (CISS), interest rate spread and the common factor of total credit following a one-standard-deviation shock in UMP. Lag length = 4. The dashed lines denote the 68th percentile of the posterior distribution over a period of 16 quarters. IRFs obtained from SVAR model estimated over the period 2007Q1-2018Q4.

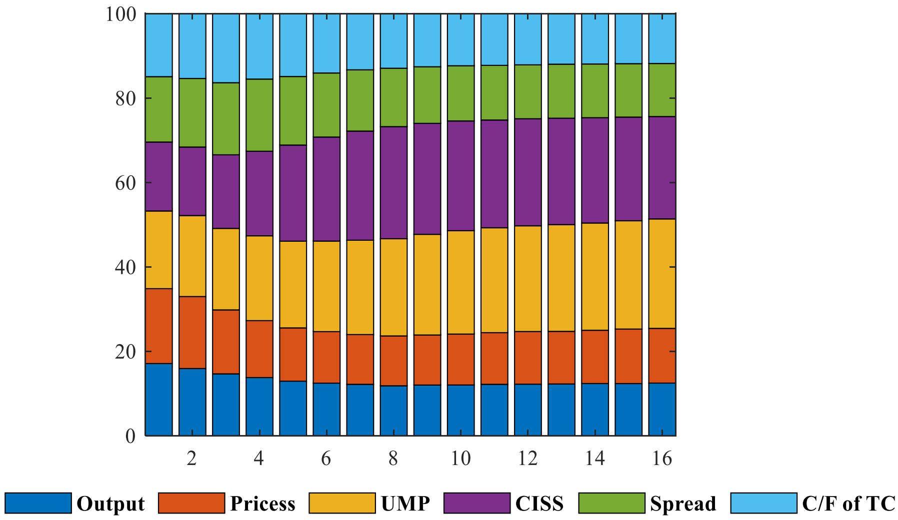

Figure 3.6. Forecasting error variance decomposition (FEVD) for the common factor of total credit, over a period of 16 quarters, due to UMP and financial stress shocks (restricted), and real output, prices, interest rate spread and the common factor of total credit shocks (unrestricted). FEVD obtained from SVAR model estimated over the period of 2007Q1-2018Q4.

3.5.3.5 Robustness

We perform several modifications of our baseline SVAR estimation to check its ability to capture the effects of UMP. First, we estimate the same variables under the same restrictions using one lag, the results remain intact, except for the common factor of total credit becomes less significant due to wider error bands. The results with one lag order are presented in Figure 3.7 in Appendix B.[56] Second, instead of using ECB's total assets, we use the volume of the longer-term refinancing operations (LTROs), which are used to safeguard liquidity and money market conditions during the crisis. With the remaining settings of the baseline SVAR intact, Figure 3.8 shows that the sign of the median IRFs remains similar to the baseline results. However, a UMP shock is now more plausible with an increase of 3% on impact. In return, output and prices respond positively and significantly. Third, alongside the UMP and financial stress shocks, identified using the heretofore mentioned restrictions, we impose restrictions on the other variables, namely, output, prices, interest rates spread, and we leave the common factors unrestricted. In this latter case, IRFs results remain similar to the baseline with no significant changes.

In a fourth robustness check, we replace the variable of ECB's total assets with the shadow rate, which is used by previous scholars as a measure of UMP (see, e.g., Conti (2017); Elbourne et al. (2018).

[56] Please see Table 3.17 in Appendix B for the lag selections based on different criteria.

Similar to the baseline estimation, we define UMP shock as an expansionary surprise that reduces the shadow rate on impact. Our approach and identification strategy here are similar to Conti (2017) who proxies UMP with the shadow rate using quarterly data for the US. However, while the author defines a contractionary UMP shock, which increases the shadow rate on impact, we assume an expansionary shock, which decreases the shadow rate, and is in line with Elbourne et al. (2018). Further, the reason for this choice is to make the results comparable with the findings obtained using the total assets variable as in our benchmark model in Section 3.5.3.1, where we also assume an expansionary UMP shock. We also follow Conti (2017) and assume that UMP shocks increase output and prices while decreasing both the financial stress index and interest rate spread. We impose the sign restrictions only on impact which can be argued by the fact that the shadow rate already captures the UMP innovations on the announcement, and not only at implementation (with a lag) as in the total assets variable (De Rezende and Ristiniemi, 2020). Similar to the baseline model, we leave the common factor of total credit unrestricted to let the data speak.

The results in Figure 3.9, show that an expansionary UMP shock is associated with a 1.2% decline in the shadow rate on impact, which stays significant for the first two quarters, and turns insignificant afterwards. In response to such UMP shock, we observe a significant increase in output around 0.52% on impact, where such response increases until it stabilizes around 1.2% after four quarters. Similarly, prices increase by 0.05%, and clusters around 0.75% after the first quarter following the shock. Next, we notice that both CISS indicator and the interest rate spread respond negatively and reach -1% and -6% respectively, and after four quarters, both responses fade out towards the baseline. Such responses are very similar to the ones obtained from the baseline model. Next, the response of the common factor of total credit has the expected sign. We find that UMP shock increases the common factor by around 2%, which becomes slightly significant only after five quarters.

Overall, and based on our alternative specifications – using the shadow rate to identify UMP – we can conclude that our results from both policy variables show similar tendencies, and are correctly signed, even for the common factor that is left unrestricted. The magnitude of the responses, however, seems to be noticeably larger for the robustness using the shadow rate, this can be due to the duration of the identified shocks which was restricted only on impact. Overall, the relative responses are plausible and comparable with the baseline model, were both specifications support the notion that the UMP is successful in increasing lending to the private sector and can be seen as evidence of the credit channel of UMP.[57]

[57] In all of our alternative specifications of the baseline model, we notice no remarkable change to the forecast error variance decomposition.

3.6 Conclusions

In this study, we contribute to the recent literature on the effects of ECB's unconventional monetary policy on the macroeconomy by shedding light on the long-run comovement between aggregate credit and ECB's total assets and shadow rate, and by using a structural VAR approach to study the transmission mechanism of UMP through the credit channel. This study is one of the few attempts to gauge the effects of the ECB's policies on the provision of private credit by banks. We do so by focusing on a cohort of Euro and non-Euro economies over the period 1999Q1-2018Q1 to study the evolution of link between different credit aggregates and UMP variables. By using Panel Analysis of Idiosyncratic Component (PANIC) methods, we show that there is convergence among different measures of credit such as total credit, credit-to-GDP ratio, and credit-to-GDP gap, such convergence can signal the presence of a common monetary policy that derive credit during the period under study.

Our findings show that there is an association between ECB's policy variables and credit through long-run equilibrium. However, one should be wary regarding the long-run results, as we witness a vanishing effect when considering the same relationship through cointegration tests that account for only one structural break in the data over the full sample. When using methods that account for multiple breaks, we are able to detect a long-run relationship in the Eurozone countries sample for the part that uses time series analysis. This finding is also supported for the same sample using methods that account for cross-sectional dependence and multiple breaks in a panel data context.

Considering a short-run analysis, we further augment the common factor of total credit into a structural VAR model once using total assets, and we check the robustness of the baseline specification another time using the shadow rate. In both cases, we find that a one-standard-deviation shock in the policy variable increases the common factor by around 2%, which is significant only after four quarters. This finding indicates that UMP policy is capable of boosting the economy through an increase in private lending, and it can be seen as evidence of the transmission channel of UMP through lending that materializes only after a lag. The other results on the macro effects of UMP, i.e., the effects on output, prices, interest rate spread, and financial volatility are significant and consistent with the literature.

While this study provides an analysis at the macro-level for the different banking industries, it can also be extended to a micro-level dimension by studying the effects of the same UMP indicators on individual banks. Additionally, one may separate credit into different types based on the borrowing sector. Further research can incorporate ECB's capital measures while studying the credit channel of

UMP to disentangle the increase in credit due to either UMP shock, reduction in capital requirements, or both. This is in our agenda for future research.

Appendix B

- **Principal component analysis**

PC aims to reduce the dimensionality of a set of data using the least square method. Thus, we reduce the credit series of all countries to fewer components that capture the essential patterns and information in the original data (Jolliffe, 1986). The goal here is to find the components $z = [z_1, z_2, \dots, z_i]$, which is a linear representation of the credit variables $x = [x_1, x_2, \dots, x_i]$. The first component z_1 accounts for the maximum possible variance of the original series, with the subsequent components that detect the patterns that are not captured by the first component. Hence, these components are not correlated with each other by definition (Wold et al., 1987). We obtain the Principal Components (PCs) of total credit, credit-to-GDP ratio, and credit-to-GDP gap series for the full set of countries, as well as the partition into Euro and non-Euro countries. In doing so, we choose the components with eigenvalues that are higher than one as it has a better prediction power compared to other components (Nunnally et al., 1967). In all cases, the first component does an excellent job in explaining a high proportion of the original data, usually above 96.5%. Hence, the first component is chosen to carry the cointegration analysis in a time series context.

Table 3.17. VAR lag length selection criteria.

Lag	LogL	LR-stat	Akaike	Schwarz	Hannan-Quinn
0	-458.5	NA	12.36	12.51	12.42
1	34.14	906.5	-0.110	0.816*	0.259
2	78.65	75.95	-0.630	1.068	0.047*
3	106.3	43.56	-0.702	1.769	0.284
4	132.5	37.76*	-0.735*	2.509	0.560

Notes: LR-stat is the sequential modified likelihood ratio test statistic. * indicates lag order selection by the criterion at 5% significance level.

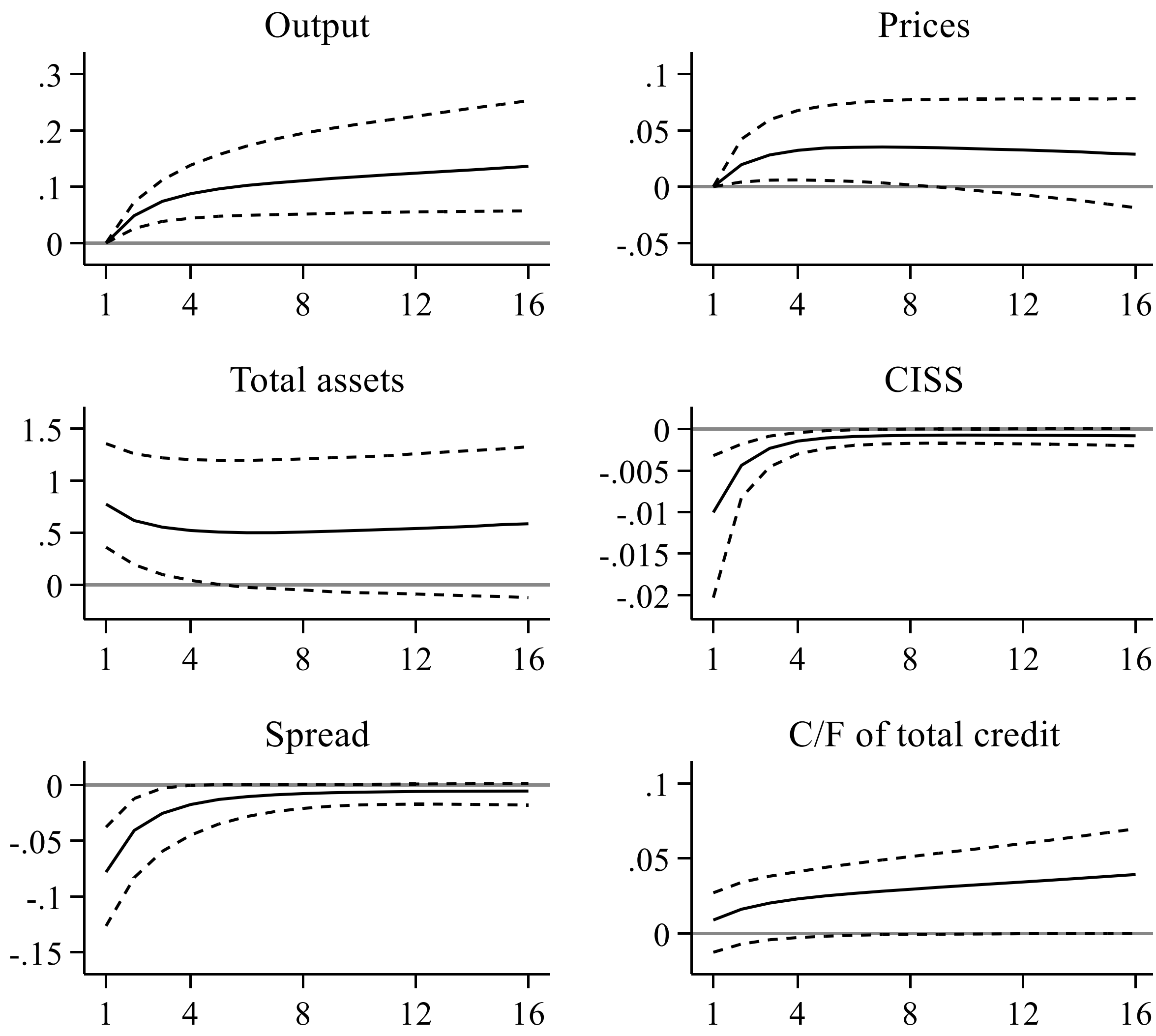

Figure 3.7. Median IRFs of real output, prices, ECB total assets, financial volatility index (CISS), interest rate spread and the common factor of total credit following a one-standard-deviation shock in UMP. Lag order = 1 based on the LR-statistic and Akaike information criteria. The dashed lines denote the 68th percentile of the posterior distribution over a period of 16 quarters. IRFs obtained from SVAR model estimated over the period 2007Q1-2018Q4.

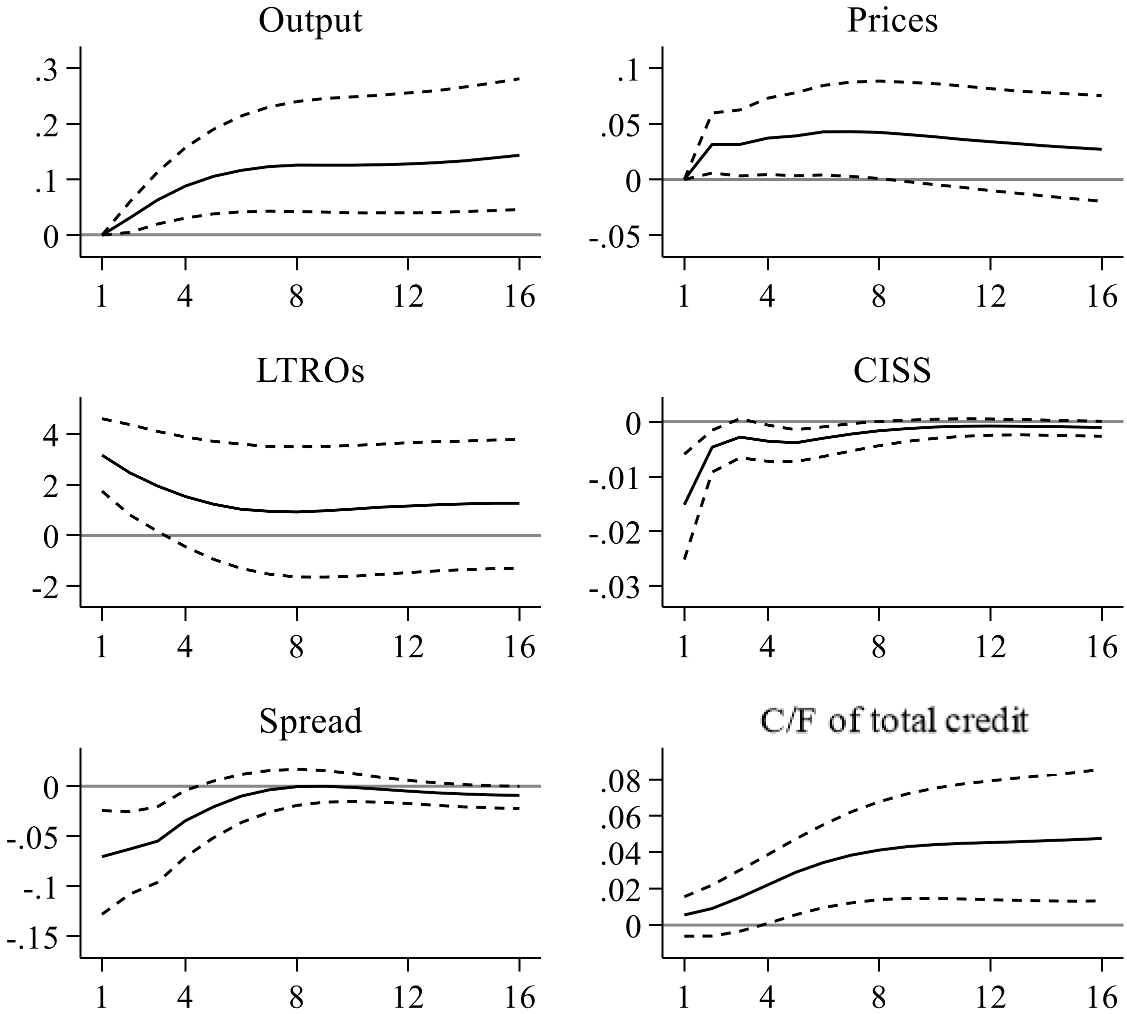

Figure 3.8. Median IRFs of real output, prices, ECB's long-term refinancing operations (LTROs), financial volatility index (CISS), interest rate spread and the common factor of total credit following a one-standard-deviation shock in UMP. Lag order = 4 based on the LR-statistic and Akaike information criteria. The dashed lines denote the 68th percentile of the posterior distribution over a period of 16 quarters. IRFs obtained from SVAR model estimated over the period 2007Q1-2018Q4.

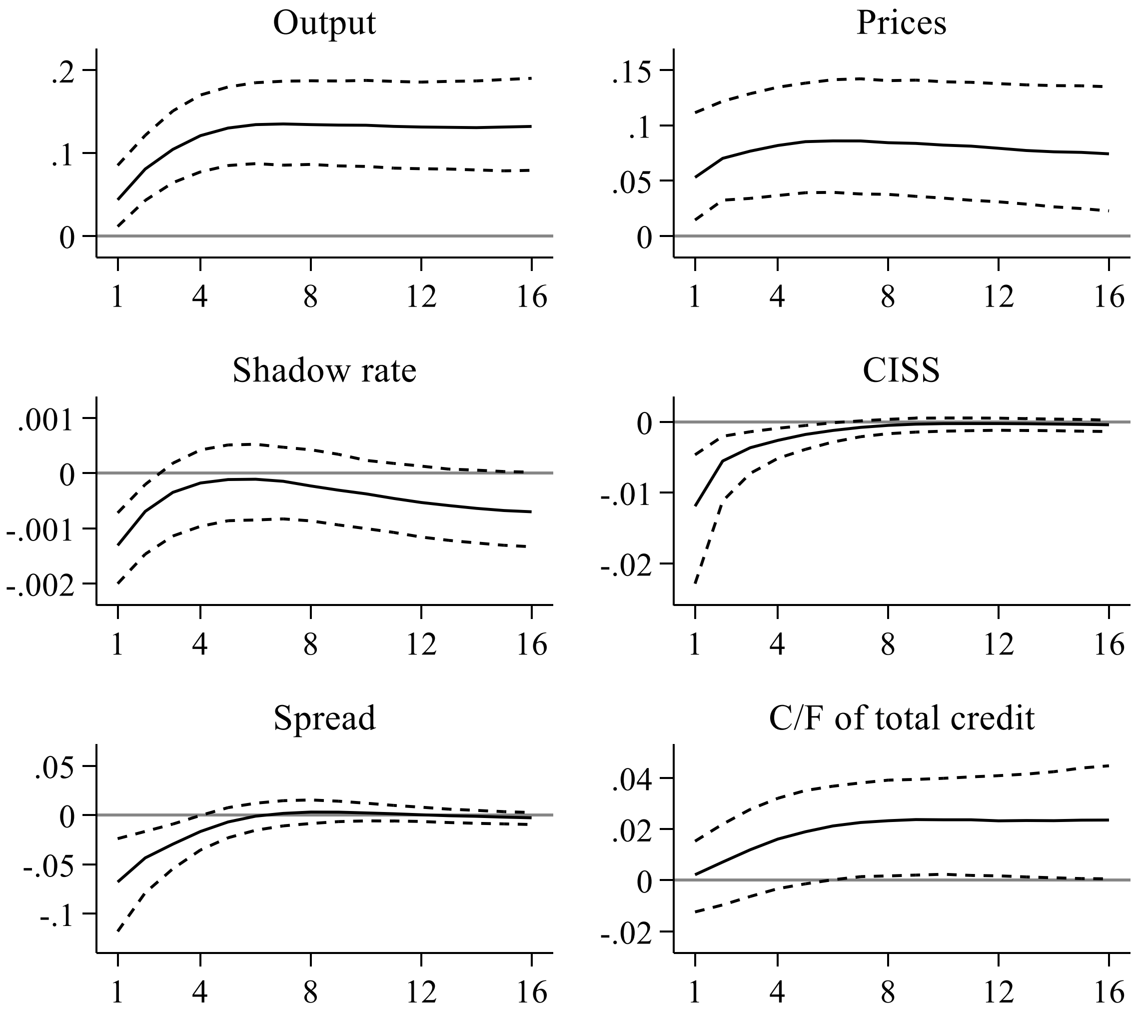

Figure 3.9. Median IRFs of real output, prices, shadow rate, financial volatility index (CISS), interest rate spread, and the common factor of total credit following a one-standard-deviation shock in UMP using the shadow rate. Lag order = 4 based on the LR-statistic and Akaike information criteria. The dashed lines denote the 68th percentile of the posterior distribution over a period of 16 quarters. IRFs obtained from SVAR model estimated over the period 2007Q1-2018Q4.

Chapter 4. On the credit and growth nexus: Idiosyncratic and common factors in the long- and short-run

4.1 Introduction

Over the last two decades, the macroeconomic dynamics of credit in relation to growth have climbed to the top of the agenda for macroeconomists and policymakers alike. One of the problematic issues is that credit booms often go hand in hand with risky leveraged bubbles, and they lead to unintended consequences such as resource misallocation and recessions (Asea and Blomberg, 1998; Jordà et al., 2013). The credit-growth nexus is complex, varying across countries and time, and also characterized by global common factors that are acknowledged as being one of the main sources of correlation in the credit series, through which countries become prone to shocks originating from outside their frontiers (Chudik et al., 2018). The role of such factors appears to have gained traction over time, possibly because growing financial globalization and integration have led to an increase in capital flows, cross-border lending, and surge in global banks. In response to such interconnectedness in financial markets, monetary policy has increasingly become concerned with fighting international crises, especially in advanced economies (Igan et al., 2011; Breitung and Eickmeier, 2016).

The extent to which credit movements are global or idiosyncratic matters for policymakers to control and monitor the flow of funds, apply appropriate policy measures and evaluate the merits of policy actions that target financial stability. For example, if a significant fraction of aggregate credit in a set of countries with different economic policies and institutional environments is due to the global common factor, this implies that policies targeting credit at the local level might be ineffective.

Moreover, from a purely methodological point of view, the fact that credit aggregates are characterized by a factor structure poses challenges to empirical methods used to gauge their dynamics, as the presence of cross-sectional dependence affects the statistical properties of standard panel estimators. Previous work on the role of credit aggregates has treated cross-sectional dependence mainly by using nonparametric methods, i.e., supplementing the baseline panel specifications with cross-sectional averages (hereafter CSA) of the observed variables (Pesaran, 2006).[58] The CSA approach has been regarded as a valid remedy for detecting common factors, and for mitigating dependence. However, the same approach suffers from a number of shortcomings, as

[58] Dependence across individual units can take two main forms. Either it depends on the distance between units, i.e., spatial dependence, where nearby units are more related than the far ones, or it depends on the cross-sectionally invariant common factors where individual units are observed at the same time, and therefore subject to the same set of common global shocks that do not depend on distance (Croissant and Millo, 2019). In this chapter, we refer the latter type.

it is not able to detect any heterogeneity in the response of units to common factors, and as long as the factor number increases the accuracy of CSA drops down.

Sul (2019) shows that the principal component approach (hereafter PC) can be more accurate than the CSA if the number of common factors in the panel data of interest is larger than one. The PC estimation has been widely used to reduce the dimensionality of the panel data by transforming the original data into a smaller set of linear combinations (see also Chapter Three). Hence, this chapter takes cross-sectional dependence as key information in the analysis rather than '*passively*' account for its behaviour. A key advantage of PC over CSA is that the former makes it possible to disentangle the dynamics of credit aggregates into the common component(s) – affecting the cross-section of countries simultaneously or with lags – and idiosyncratic component(s) that feature the dynamics of country-specific factors only and can be at the origin of diverging economic developments (Eickmeier, 2009).[59]

This empirical choice is particularly important for two reasons. First, albeit the increase in credit cycles synchronization that has been a trend for quite sometimes globally, there are still significant remaining asymmetries across countries. Such asymmetries lead to divergence and should be accounted for to achieve successful and appropriate policy measures (Aikman et al., 2015). Second, the detection of common factors enables the researcher to account for cross-sectional dependence and, at the same time, to detect asymmetries occurring in the responses to common shocks. Observing such heterogeneity when working with large economies allows us to observe if one country dominates the factor structure over others, and therefore, presents appropriate inference of the results.

After controlling for the common factors in the data, we study the nexus between credit and economic growth by using panel ARDL for the long-run, and panel VAR (PVAR) embedded with Generalized Method of Moments framework for the short-run analysis. Both of these methods control for potential non-stationarity and endogeneity among the series under scrutiny (Chudik and Pesaran, 2015). Endogeneity is a critical concern in the empirical literature due to the possibility of feedback effects between financial and real sectors. Goodhart and Hofmann (2008) argue that the interplay between monetary aggregates and the macro-economy is multi-faceted. Governments, households and firms might adjust their borrowing habits and leverage structure in response to changing economic conditions, which are in turn correlated with the supply of credit (Beck et al., 2000; Demirci et al., 2019). Therefore, high indebtedness may have an adverse impact on economic growth, and low GDP growth could also lead to high debt (Beck et al., 2016; Chudik et al., 2016).

[59] The common components can be interpreted as either common shock, aggregation factor, leader, and macro shocks such as the world interest rate, oil price, technological development, primary stock market crash or pandemic.

In this chapter, we study the link between credit and growth in 22 countries for the period between 2000Q1 and 2019Q4. We do so by focusing on private credit aggregates, as well as public debt. To the best of our knowledge, we are the first to uncover the non-stationarity properties of these aggregates. First, we model the factor structure of credit by using the PC approach, finding that there are important global common factors for the household credit and public debt series, while corporate credit features more idiosyncratic dynamics. In particular, household credit can be represented by three common factors, and public debt by two, therefore, the underlying factor structure of both types of credit cannot be assessed based on a single indicator as seen in other studies using CSA. The results also show that credit developments in individual countries present remarkable heterogeneities in both their common factor and country-specific compositions with asymmetric transmissions of common shocks. Using the de-factored series to account for CSD in a panel ARDL framework, we find that economic growth is a driver of credit variables in the long-run, and such effects of growth on credit aggregates are negative and stronger on public debt, whereas it is weaker for private credit. More specifically, a 1 percentage increase in economic growth leads to a decline of 0.55% in public debt, and of 0.11% and 0.24% in household and corporate credit, respectively. Similar dynamics of the link between credit and growth is found in the short-run using panel VAR (PVAR) framework, where the results show that growth Granger-causes private and public debt, and credit does not Granger-cause growth. On the contrary, when we reconsider our overall empirical framework using the data without filtering out the common factors, i.e., with the presence of CSD, we find that household and corporate credit, but not public debt, Granger-causes economic growth. This intriguing finding takes a new look and calls into question the role of the common factors in transmitting monetary policy shocks to the real economy, which eventually affects the global sustainability of credit aggregates.

The remainder of this chapter is organised as follows. Section 4.2 discusses the literature on credit determinants in relation to economic growth. Section 4.3 describes the dataset. Section 4.4 presents the empirical methods. Section 4.5 discusses the empirical results. Finally, Section 4.6 concludes.

4.2 Literature review

Given the recent and unprecedented credit growth worldwide, the finance and growth nexus has sparked crucial questions on the mutually reinforcing interaction between the real and finance sides of the economy. A feature of the existing studies is that the question as to whether there is any nexus between credit and economic growth is tackled by implicitly assuming that private credit or public debt explains growth, i.e., one-way direction.

To begin with, Hofmann (2004) analyses the determinants of aggregate bank credit to the private sector in a standard vector error correction model (VECM) of 16 industrialized economies using quarterly data from 1980 to 1998, finding that positive effects of real GDP and negative effects of interest rates on credit, and that property prices are an important determinant of the long-run borrowing capacity of the private sector. In a similar vein, Goodhart and Hofmann (2008) study the dynamic interaction between credit, house prices and economic activity in a panel VAR context for 17 countries over a period spanning from 1973 to 2006. They find a multidirectional causality link between credit and economic activity; they also argue that such relationship arises through housing wealth and collateral effects on credit demand and supply. This finding is also noted by Aron et al. (2012) who study the influence of the credit channel on the consumption function in the UK, US, and Japan while controlling for the housing collateral effects on consumption.

Several studies in the macro-finance literature that seeks to address the factors influencing economic agents' indebtedness classify the factors into credit demand and supply factors. At the demand-side, households' need for credit may be driven by their ability to smooth consumption taking into account saving, demography, wealth and the business cycle (Coletta et al., 2019). Scholars have often rationalized the modus operandi of such demand-side factors by recurring to the Modigliani (1986) life-cycle hypothesis. A boost in household demand for credit today can also be caused by the anticipation of higher income tomorrow, which could be driven by technology, natural resource discovery, or trade shocks (Aguiar and Gopinath, 2007). However, sudden boosts in household credit are often temporary and followed by a decline in subsequent economic growth, because typically when credit booms stall, frictions such as nominal rigidities and monetary policy constraints exacerbate the decline in subsequent growth (Guerrieri and Lorenzoni, 2017).

On the supply-side, credit is sensitive to changes in interest rates which affect lending constraints. This link is highlighted in various studies on the transmission channel of monetary policy where a central bank uses interest rates to control the supply of credit (Kashyap et al., 1993; Bernanke, 2005; Capolupo, 2018). For example, Adrian et al. (2010) study the links between monetary, financial, and business cycles, showing that changes in interest rates affect the profitability and risk-taking capacity of financial intermediaries, and eventually the supply of credit. Such results still hold nowadays in the context of near-zero interest rates, as discussed in the literature on quantitative easing (Kapetanios et al., 2012; Bowman et al., 2015).

Subsequently, many scholars have shown that inflation is an important factor for financial development, as it can affect economic agents' decisions to borrow (Debelle, 2004) and, at the same time, it impairs the ability of financial intermediaries to extend credit to borrowers. For example, Caglayan and Xu (2016) find that banks behave conservatively when inflation rises.

A number of studies investigate the credit-growth nexus by focusing on both household and government debt. In this regard, Reinhart and Rogoff (2010) show how the link between public indebtedness and growth is not linear, with growth that falls significantly once debt-to-GDP levels surpass the threshold of 90%. They obtain such result for a large cohort of 44 advanced and emerging economies, using simple comparisons of the average growth rate of debt-to-GDP ratios, featuring a strong homogeneity assumption, and without accounting for cross-sectional dependence that exists across countries due to the presence of global common factors. Taking these last shortcomings into consideration, the seminal work of Chudik et al. (2017) also focuses on the relationship between public debt, inflation and economic growth. Their work presents a theoretical contribution by developing tests for threshold effects in the context of dynamic heterogeneous panel models with cross-sectional dependence in the disturbance terms. Using an Auto-Regressive Distributed Lag (ARDL) model on a sample of 40 countries from 1965 to 2010, they find significant negative effects of public debt and inflation on growth in the long-run. However, they show that such a relationship does not vary with the level of government indebtedness, so that there is no evidence of threshold effects between public debt and growth.

Several authors highlight the importance of household credit expansion to the real economy, and in particular, an elevated household credit which amplifies the business cycle, causes higher default rates and triggers severe recessions (Mian et al., 2020; Verner and Gyöngyösi, 2020). Incorporating household credit in the literature, Lombardi et al. (2017) study the long- and short-run effects of household credit on economic growth and consumption. Using cross-sectional (CS) augmented ARDL approach, developed by Chudik and Pesaran (2015), on 54 economies from 1990 to 2015, they show that household credit-to-GDP boosts consumption and GDP growth within a time horizon of one year. In the long-run, however, a 1 percentage point increase in the household credit-to-GDP ratio tends to lower growth by 0.1 percentage point, so that the build-up of household credit is a drag on GDP growth. The conventional view is that credit can stimulate aggregate demand and output in the short run via productivity and technology shocks that increase expected future income. However, in the long-run households might borrow excessively due to over-optimism, and that could lead to the build-up of financial vulnerability that eventually stagnates growth. Such type of long-run dynamics is also documented, for instances, in Jordà et al. (2013); Mian et al. (2013).

Further, Mian et al. (2017) study the effect of household and corporate debt on GDP growth for a panel of 30 countries from 1960 to 2012. Their analysis is based on panel VAR and shows that a shock to household debt boosts GDP growth in the short-run (between one and two years), then growth slows down quite substantially in the medium-run (between three and six years), and becomes lower than the pre-shock levels in the long-run. Additionally, opposed to household debt which initially boosts GDP, corporate debt leads to immediate negative effects on GDP which reverts after five years, and quicker than the effect of household debt, concluding that corporate and household debt feature very different impacts on GDP growth in both the short and medium run.

Recently, Sleibi et al. (2020) study the nexus between shocks to large banks' lending, real output growth and aggregate leverage, measured by the credit-to-GDP gap, on a panel of 15 advanced economies from 1989 to 2016. By using panel VAR method, they show that shocks to banks' lending tend to deviate credit-to-GDP ratio from its long-term trend by 4.5 percentage points after one year, thus exposing the banking system to the risk of high rates of loan defaults. Such evidence shows that the credit-to-GDP gap conveys information on the build-up of systemic financial vulnerabilities. They also find that positive shocks to real output growth tend to intensify aggregate leverage by four percentage points up to two years which could undermine the stability of the financial system. This finding is also consistent with the literature on the procyclicality of credit that documents how credit is amplified and becomes more attractive to borrowers during the expansionary phases of the economic cycle.

Moreover, a related strand of literature acknowledges that "too much finance" may not benefit growth and some highlight "vanishing effects" between both measures. In this vein, Beck et al. (2006) use a panel fixed effects regression on a sample of 63 countries over the period 1960-1997 and find no evidence between private credit and real volatility. They argue that financial intermediaries have no overall effect on growth volatility because financial intermediaries have contradicting effects on the propagation of real and monetary shocks so that the overall effect is insignificant. Our work is also related to Aghion et al. (2005) who perform split-sample regressions on a sample of 71 countries over the period 1960-1995. They suggest that financial development and growth relationship is limited or not significant for high-income economies that are close or at the productivity frontier.

Furthermore, Beck et al. (2012) carry out an analysis on data from 45 countries for the period 1994-2005 using cross-country regressions averaged over ten years, they argue that the relationship between finance and economic growth could depend on whether credit is being used to finance investment opportunities and productive assets or for household consumption. They find no significant effects between household credit and growth. They show that corporate credit drives the relationship between financial development and economic growth because the financial systems foster growth by alleviating firms' financing constraints. Such a result points out that the relationship between finance and economic growth could depend upon the type of credit provided.

Using quantile regressions on a sample that covers 72 countries from 1980 to 2008, Demirguc-Kunt et al. (2013) show that the association between aggregate bank credit and economic growth is decreasing, while they do not test for causality, they argue that services provided by banks become less important when economies become richer. On the contrary, services provided by securities market become more important for economic activity. Arcand et al. (2015) estimate cross-country regressions for the period 1970-2010 and find that at high levels of financial depth, more finance is associated with less growth, i.e., the "vanishing effects" of financial development, especially in the last twenty years when the financial sector has grown rapidly. Their argument is that the vanishing effect is not necessarily driven by a change in the fundamental relationship between financial development and economic growth, but by the non-linearities in the empirical settings that do not allow for such relationship between finance and growth. The vanishing effects are also documented in Rousseau and Wachtel (2011), who argue that the link between finance and growth has weakened considerably over time. They suggest that excess financial deepening, as manifested in a credit boom, can be problematic in both developing and developed countries because it weakens the banking system. Recent scholars link financial development, measured by private credit, with the innovation-led growth hypothesis. In this regard, Beck et al. (2016) assess the relationship between financial innovation, bank development and growth. Using panel regressions based on annual data from 32 countries over the period 1996-2010, they find an insignificant result on the interaction of growth opportunities with private credit. They argue that such a result is not surprising as their sample is limited to mostly high-income countries where recent research has shown that there is no significant relationship between financial development and economic growth. They also find that financial innovation is significantly related to growth, suggesting that it is not so much the level of financial deepening but the innovative activity of financial intermediaries that drives the finance-growth link in high-income countries. In a similar fashion, Zhu et al. (2020) gauge non-linearities between financial development, innovation and growth using linear GMM and dynamic panel threshold on 50 countries over the period 1990-2016. They find that innovation exhibits an insignificant effect on output growth when private credit exceeds a threshold level of about 60% as a share of GDP. Their results suggest that private credit may have a diminishing effect on the rate of innovation, which transmits to productivity and slows down aggregate growth. The implication is that as credit market expands, banks credit facilities may prevent firms from involving in risky projects to easily access finance. Hence, the less investment in productive capital may prolong and reduce the effects of innovation on growth.

Other scholars find no causality from debt to growth. For example, Lof and Malinen (2014) examine the relationship between growth and public debt in a dynamic context using bivariate panel VAR framework for 20 and 10 developed countries over the periods 1954-2008 and 1905-2008. They find no evidence for a robust effect of debt on growth. Surprisingly, the authors find a significant negative reverse causality from growth towards debt, which is primarily driving the negative correlation between both variables. De Vita et al. (2018) study the same relationship on 13 countries over the period 1970-2014 while considering the nonlinear properties of the data. Using causality tests, they find no robust evidence in most of the countries in their sample. Kempa and Khan (2017) analyse the spillover of public debt and economic growth in the Euro area using a GVAR model for the period 1991-2014 and find no evidence of debt shocks impacting on growth dynamics. Puente-Ajovín and Sanso-Navarro (2015) investigate the causal relationship between debt and growth using panel bootstrap Granger causality test for 16 countries for the period 1980-2009. Their findings do not support the idea that government debt causes growth, but they find causal relationship running from growth to debt. Other studies that confirm the negative relation between public debt and economic growth include Guajardo *et al.* (2014); Dosi *et al.* (2015).

A close look at the literature on credit and growth relationship, however, reveals that it is not conclusive. The focus of most studies has been specific to address one type of credit in relation to economic activity and limited on the link that runs from credit towards output and mainly in one direction, i.e., attempting to explain movements in output growth by using household credit and public debt. These studies leave the factor structure of both variables unexplored. In contrast to previous literature, we do not take any a priori stance in term of the causality link between finance and growth and aim to uncover the direction between both of them. We fill this gap by analysing the factor behaviour of household, corporate and public debt using PC analysis. In a second stage, we study the nexus between credit and growth by augmenting the de-factored data into panel ARDL and panel VAR frameworks. Our methods account for unobserved common factors, endogeneity, and heterogeneity across the countries under scrutiny.

4.3 Data

We gather a country-level balanced panel data set for three different credit aggregates: households, non-financial corporates, and public debt. We collect quarterly data for as many as 22 countries over the period 2000Q1-2019Q4 (N=22 and T=80).[60] The source of the credit variables is the Bank of International Settlements (BIS) database, "Credit to non-Financial Sector". The BIS database provides a larger sample of countries on private credit; however, we exclude countries with credit series starting after the year 2000 to preserve our time dimension, which eventually limits the sample size. According to the BIS, credit here is defined as loans and debt instruments from banks

[60]Addressing cross-sectional dependence using fairly long-time dimension is crucial for obtaining consistent estimates of the unobserved common factor(s), see, e.g., Sul (2019) and Bai and Ng (2004). Therefore, having quarterly data is advantageous in this chapter and similar to Lombardi *et al.* (2017) who study the growth and finance nexus using data of the same frequency.

and non-banks institutions measured at the end of each quarter in a given year. Private non-financial credit is partitioned into households (including non-profit institutions sever households) and non-financial corporates. Household credit includes, *inter alia*, consumer, real estate, automobile, credit card and student loans, while non-financial corporate credit includes mainly commercial and industrial (C&I) loans. On the lending side, credit comprises financing from all sources, including domestic banks, other domestic financial corporates, non-financial corporates and non-residents (see, e.g., Dembiermont et al. (2013)). Government debt includes currency and deposits which represents the bulk of broad type of debt, i.e., special drawing rights (SDR), insurance, pension and standardized guarantee schemes and other accounts receivable or payable.[61] [62] We then retrieve macroeconomic variables, such as real GDP, consumer prices, and long- and short-term interest rates from the Organization for Economic Co-operation and Development (OECD) database. Table 4.1 reports the summary statistics of the aforementioned variables, while Figure 4.1-Figure 4.3 display the diagrams of the individual series.

Table 4.1. Summary statistics

Variable	Mean	Std. Dev.	Minimum	Maximum	Obs.
ΔC^{hh}	0.658	2.14	-32.75	19.783	1,738
ΔC^{cor}	0.316	2.123	-10.29	14.033	1,738
ΔC^{pub}	0.309	3.364	-27.81	31.92	1,738
ΔY	0.428	0.867	-7.007	4.395	1,738
ΔP	0.505	0.736	-2.869	6.034	1,738
$\Delta Rate^{short}$	-0.068	0.477	-5.050	4.412	1,738
$\Delta Rate^{long}$	-0.067	0.477	-7.527	5.703	1,738

Notes: Sample period 2000Q1-2019Q4 for 22 countries (N=22, T=80). Credit variables are normalized by GDP and adjusted for breaks. All variables are transformed by log changes and multiplied by 100 to report changes in percentages or percentage points, except for short and long-rates presented only in growth terms. Δ denote quarter-on-quarter changes. The variables C^{hh}, C^{cor}, C^{pub}, Y, P, $Rate^{short}$, $Rate^{long}$ denote household credit-to-GDP, non-financial corporate credit-to-GDP, public debt-to-GDP, real output, consumer prices, three-month short-term rate and ten-year government bond long-term rate, respectively.

[61] We use break-adjusted data provided by the BIS, because changes in the underlying data source, coverage or measurement may induce breaks in the series.

[62] Consistent with previous studies on cross-country debt, we normalize credit by GDP at the same period. By doing so we are able to capture aggregate indebtedness relative to the size of the economy, (see, e.g., Jordà et al. (2013); Mian et al. (2017))

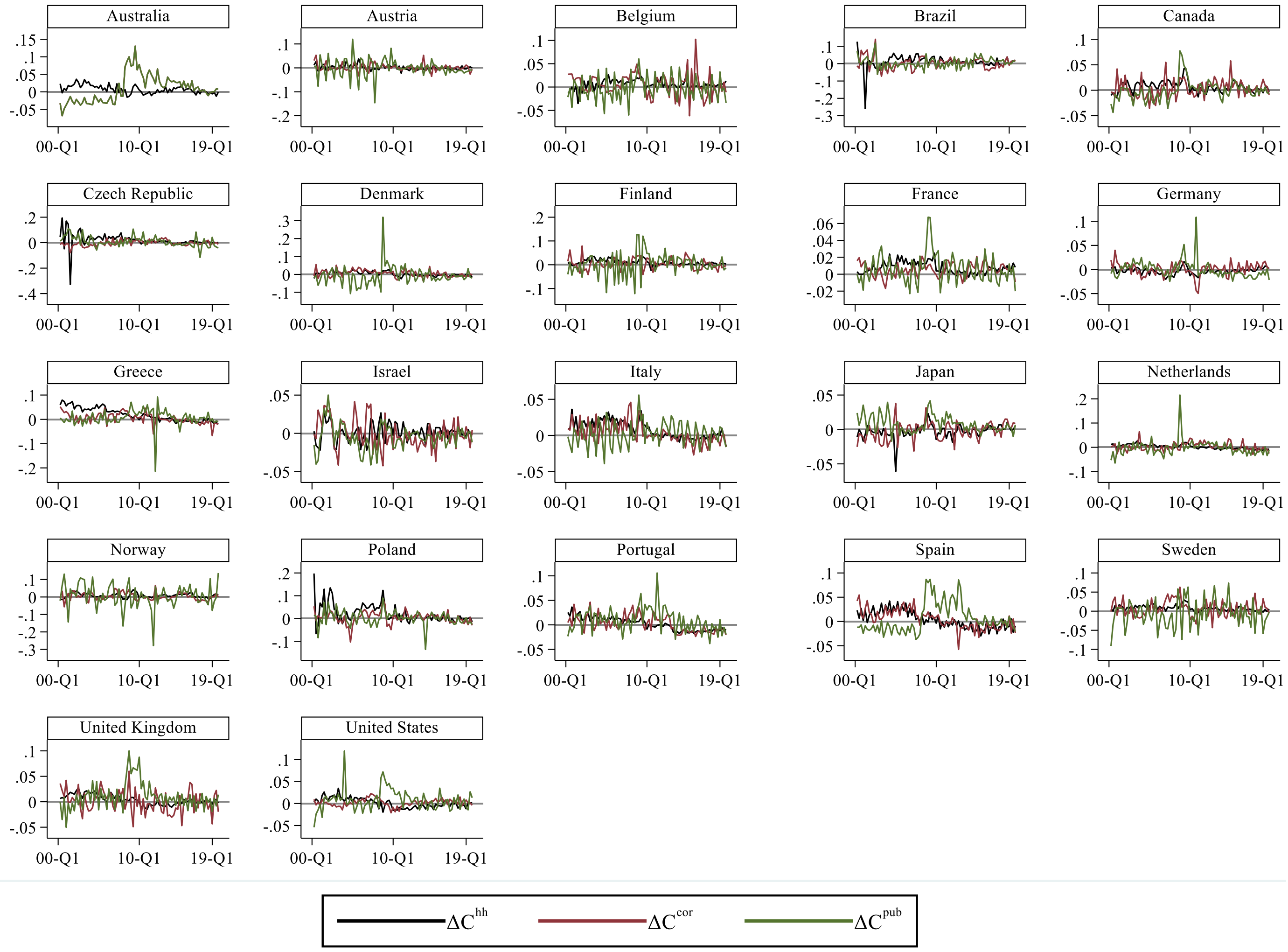

Figure 4.1. Household credit-to-GDP (hh), non-financial corporate credit-to-GDP (cor) and public debt (pub) in log difference for 22 countries during the 2000Q1-2019Q4 period (*N*=22, *T*=80).

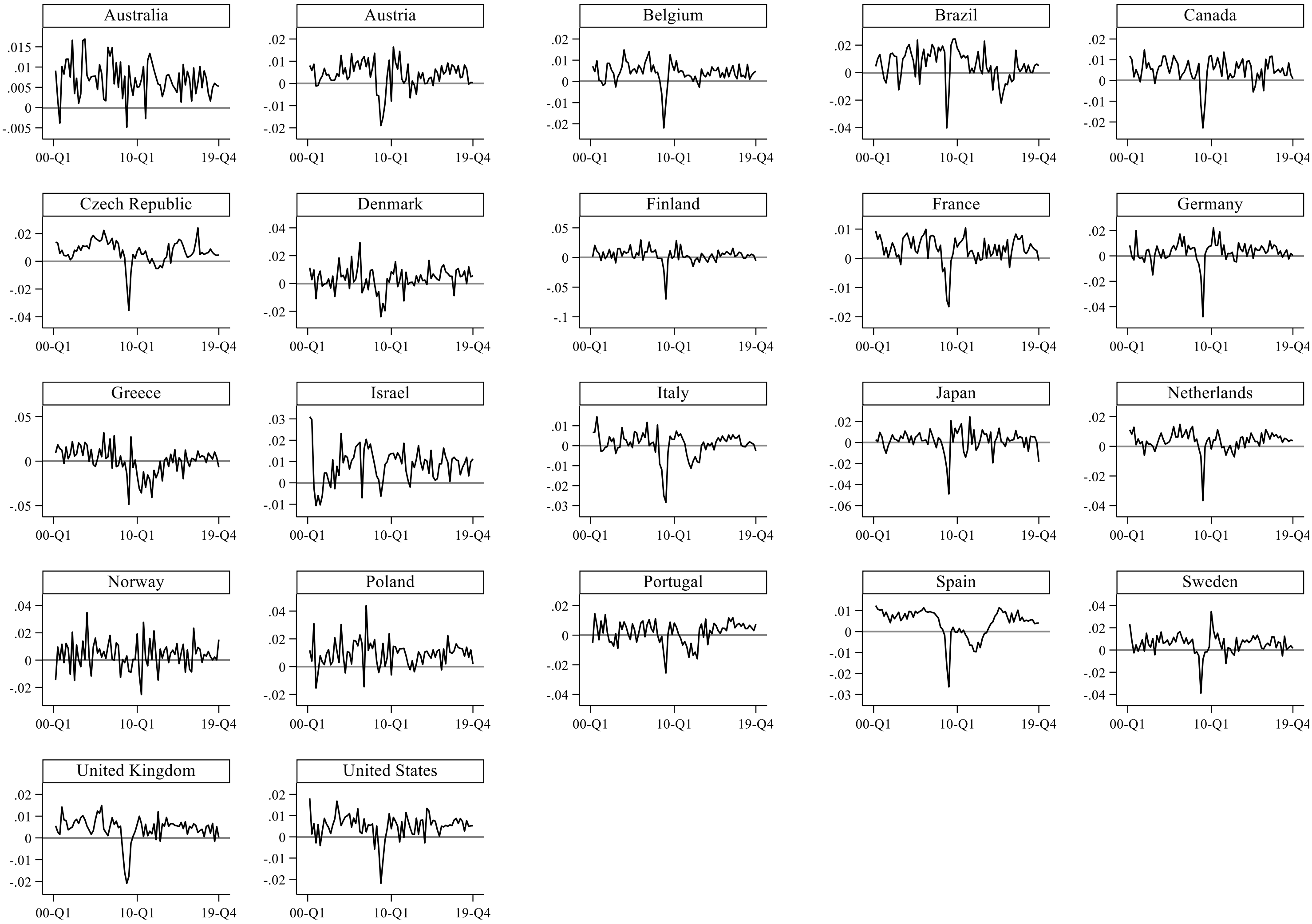

Figure 4.2. Real output growth measured as quarter-on-quarter for 22 countries during the 2000Q1-2019Q4 period (N=22, T=80).

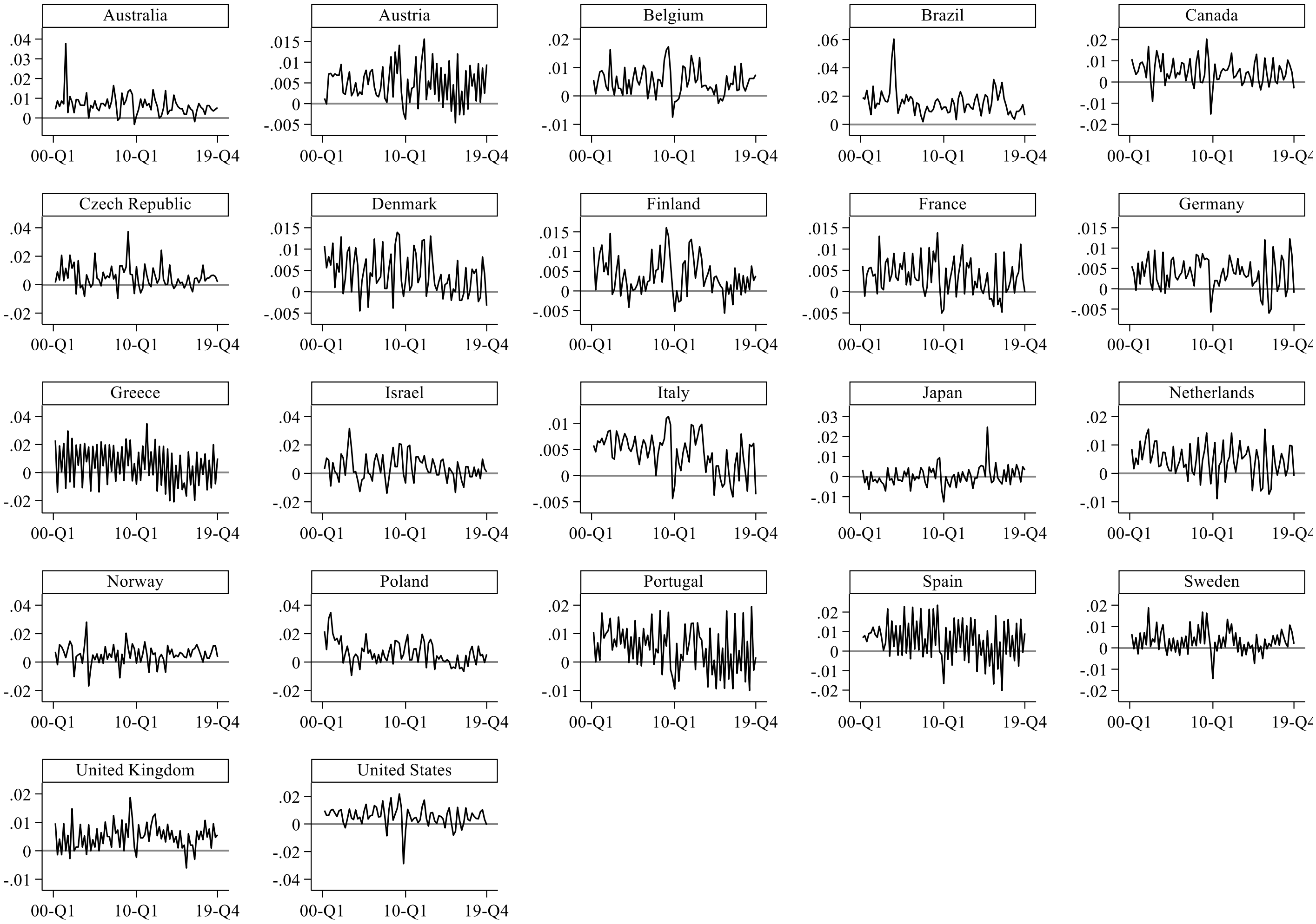

Figure 4.3. Inflation rate measured as quarter-on-quarter change in consumer prices for 22 countries during the 2000Q1-2019Q4 period (*N*=22, *T*=80).

4.4 Empirical methodology

4.4.1 Common factors and idiosyncratic components

As also discussed in Chapter Three, a crucial issue that inherently arises in the context of panel data analysis is cross-sectional dependence (hereafter CSD), whereby the individual units are interdependent, albeit with different intensities. A possible explanation for the pervasive nature of CSD in the variables of interest is that they are driven by unobserved global common factors. If this issue is not properly tackled, then the disturbances of the estimated panel model become correlated, yielding results that are biased and inconsistent (Sarafidis and Wansbeek, 2012; Moon and Weidner, 2017). In this chapter, we treat CSD as a source of information, rather than a nuisance that should be eliminated. We do so by using Panel Analysis of Non-Stationarity in Idiosyncratic and Common components (PANIC) approach due to Bai and Ng (2004) (hereafter BN) to detect the common factors driving the cohorts of series under scrutiny. One advantage of the PANIC method is that it enables to synthesize the time series properties of a several series into a much smaller number of estimated latent variables extracted using the PC approach.[63] In doing so, we disentangle the series under scrutiny into two components, global common factors and country-specific (idiosyncratic) components. A second desirable feature of this approach is that it makes it possible to uncover the source of possible unit roots in the data, i.e., to what extent the non-stationarity is due to the common factor F_t, the idiosyncratic components υ_{it}, or both.[64]

We define this relationship algebraically:

$$Z_{it} = c_i + \Lambda_{i1}F_{1t} + \Lambda_{i2}F_{2t} + \dots + \Lambda_{ik}F_{kt} + \upsilon_{it} = c_i + \Lambda'_i\zeta_t + \upsilon_{it}. \tag{4.1}$$

where the variable Z_{it} is observed series over *i*=1,2,…,*m* units, and *t*= 1,2,…,*T*, is explained in terms of k unobserved common factors, $\zeta_t = (F_{1t}, F_{2t}, \dots, F_{kt})'$, c_i are fixed effects. The factors influence each cross-section unit differently through the factor loadings $\Lambda'_i = (\Lambda_{i1}, \Lambda_{it}, \dots, \Lambda_{ik})'$. Equation (4.1) implies that Z_{it} is cross-sectionally correlated with $Z_{i+1,t}$ by sharing the same common factors F_{kt}. The common factors F_{kt} are mutually orthogonal, cross-sectionally invariant, responsible for comovement in the underlying panel, and uncorrelated with the idiosyncratic error υ_{it}. The latter is allowed to be weakly correlated across units and provides valuable information on the behaviour of

[63] PANIC method and the principal component approach have been successfully used as a statistical foundation for modelling the factor structure of panel data. See, among others, Arsova (2020) on exchange rates pass-through on import prices, Greenaway-McGrevy et al. (2018) on exchange rates, García-Cintado et al. (2015) on inflation rates, Byrne et al. (2012); Byrne et al. (2013) on interest rates and commodity prices comovement, respectively, Byrne and Fiess (2016) on capital flows, Stock and Watson (2002) on the factor structure of multiple macroeconomic indices, and Eickmeier (2009) on output and price comovement and heterogeneity in the Euro area.

[64] The stationarity of common factors F_{kt} is assessed by means of univariate unit root tests, whereas stationarity of the idiosyncratic components υ_{it} is assessed by means of pooled Fisher-type test.

each unit (Bai and Ng, 2004; Sul, 2019).[65] Furthermore, to avoid spurious regression results and enable standard inference for the de-factoring process, the factors are obtained by first differencing the raw data, extracting the principal components from the differenced data and then re-cumulating the principal component back to levels (Bai and Ng, 2004; Reese and Westerlund, 2016).[66] Similar to the factors, the residuals are also re-cumulated to deliver estimates of the idiosyncratic components for each cross-sectional unit. We apply this procedure to each of the seven variables in our panel. As discussed later on in Section 4.5, the country-specific components υ_{it} exhibit high persistence over time, thus signaling that they retain substantial information content. In the light of this, it becomes plausible to focus on the dynamics of Z_{it} after removing the common factors F_{kt}, so that our variable of interest becomes the de-factored time series Z_{it}^{d} for each unit *i*.

4.4.2 Factor number identification

Since the number of common factors is unknown, it has to be estimated and then used as a prior for the estimation of Equation (4.1). The literature presents two broadly methods that utilize the PC approach to identify the true number of latent factors. One method is based on penalty functions such as the three information criteria of Bai and Ng (2002), i.e., IC_1, IC_2, IC_3, Hallin and Liška (2007), and Ahn and Horenstein (2013) criteria. The other method, proposed by Onatski (2010), estimates the number of factors from the distribution of eigenvalues. Following Sul (2019), let Z_{it} be a panel data of interest, $\tilde{Z}_{it}$ be the deviation from its time series mean, $\hat{\Sigma}_T$ be the sample ($T\times T$) covariance matrix, and $\hat{\Sigma}_N$ be the sample ($N\times N$) covariance matrix. In our case, $N<T$, therefore, the k^{th} largest eigenvectors from $\hat{\Sigma}_N$ become the PC component for the factor loadings, then to estimate the common factors, we regress $\tilde{Z}_{it}$ on the *k* estimated eigenvectors for each *t*. The estimated PC for the factor loadings are obtained from the regression of $\tilde{Z}_{it}$ on the eigenvectors for each i. Define ϱ_i as the i^{th} largest eigenvalue of the $(NT)^{-1}\hat{z}^{d\prime}\hat{z}^{d}$ matrix, where $\hat{z}^{d}$ is the $T \times N$ matrix of residuals Z_{it}^{d}. Therefore, the maximum number of eigenvalues becomes h, where $h=\min[N,T]$. Bai and Ng (2002) IC minimize the following statistic:

$$IC_{BN} = \arg min \left[\ln\left(\sum_{i=k+1}^{h} \varrho_i\right) + k \times \rho(N,T)\right]. \quad (4.2)$$

[65] Equation (4.1) is referred to as the "static form" of the factor model because the factors appear to enter only contemporaneously, however, this is a notational artifact since the factors contain current and past values of the dynamic form of the factors (Clements et al., 2012).

[66] Prior to the factor extraction process, the raw data are de-meaned to account for the observed time trend across *i*. The data are also standardized to remove the excessive heteroskedasticity in the panel. Such pre-whiting procedure is required for consistent estimation of the factor number, see, e.g., Greenaway-McGrevy et al. (2012). Further, the PC estimator of the factor is consistent even with certain types of unknown breaks or time variation in the factor loading (Stock and Watson, 2009).

where $0 \leq k \leq k_{max}$, $\rho(N,T)$ is the penalty or threshold function that is based on sample size and k_{max} is the maximum number of assigned factors. IC_{BN} is developed under the assumption that N, T $\rightarrow\infty$ with some degree of correlation in the errors allowed. However, Hallin and Liška (2007) argue that in a finite sample, these criteria select a different factor number. They redefine the penalty functions to include a multiplicative constant, for example, IC of BN to be written as $ck \times \rho(N,T)$ for any finite $c > 0$, where c is an arbitrary positive constant. The issue here is that the number of factors becomes heavily dependent on the value of c. The authors suggest a method to select c by using various subsamples. Ahn and Horenstein (2013) propose a method that is free from the choices of penalty functions $\rho(N,T)$. They proposed 'Eigenvalue Ratio' $ER(k) = \max \varrho_k/\varrho_{k+1}$, and 'Growth Ratio' $GR(k) = \max ln[1+\varrho_k/V_k]/ln[1+\varrho_{k+1}/V_{k+1}]$, where $0 \leq k \leq k_{max}$, $V_k = \sum_{i=k+1}^{h} \varrho_k$, while the eigenvalue for $k = 0$ is unknown, they suggest a 'mock eigenvalue', $\varrho_0 = \sum_{i=1}^{h} \varrho_{0i}/\ln(h)$. Finally, Onatski (2010) proposes a method for consistent factor number estimation defined as:

$$\hat{k}(\delta) = \max\{i \leq k_{max} : \varrho_i - \varrho_{i+1} \geq \delta\}. \tag{4.3}$$

where δ is a fixed positive number, see Onatski (2010) for the calibration procedure of δ. Further, Bai and Ng (2002) IC_2 criterion has been the most used, although in some cases it may overestimate k. Greenaway-McGrevy et al. (2012) argue that IC_2 is robust with various data subsamples. In this chapter, we opt to present the results of different criteria and subsamples to make sure that the selected factor number is stable over both time and criteria.

Moreover, Greenaway-McGrevy et al. (2012) discuss the importance of pre-whitening the data Z_{it} across i before applying the information criterion and the factor extraction process. For example, such pre-whitening procedure consists of taking the first difference of the data, de-meaning to account for the observed time trend, and standardizing each i by its own standard deviation to remove the excessive heteroskedasticity in the panel. This last procedure can be particularly important if one series has a relatively large variance compared to the other series in the panel. However, if the heterogeneity of the variances comes from the factor loadings Λ_{ik}, then standardization may lead to overestimation. In our analysis, we will report the results with and without standardization to present a robustness comparison. Since the data are differenced, a final step in the BN approach in recovering the common factors F_{kt} and the idiosyncratic errors v_{it} is to take the cumulative sum of each component separately, in doing so, they are scaled back to the original series.

4.4.3 Variance decomposition

Once the panel is disentangled into common and idiosyncratic components F_{kt} and υ_{it} , it is worth to investigate how much the estimated common factors explain the time-varying fluctuations of the panel data of interest. Let Z_{it}^{+} be the standardized sample of the panel data Z_{it}, then $\tilde{Z}_{it}^{+}$ can be rewritten as:

$$\tilde{Z}_{it}^{+} = \frac{\tilde{Z}_{it}}{\hat{\sigma}_i} = \frac{1}{\hat{\sigma}_i}\left(\Lambda_i'\tilde{\mathrm{F}}_t + \tilde{\upsilon}_{it}\right). \tag{4.4}$$

where '~' stands for the deviation from its time series mean, and $\hat{\sigma}_i^2$ is the variance of $\tilde{Z}_{it}$. Let $V(Z_{it})$ be the true time series variance of Z_{it}. Then in case of a single factor, the variance can be decomposed into:

$$V\left(\tilde{Z}_{it}^{+}\right) = 1 \simeq \Lambda_i^2/\sigma_i^2 + V(\tilde{\upsilon}_{it})/\sigma_i^2. \tag{4.5}$$

where Λ_i^2/σ_i^2 is the fraction explained by the common factors, also referred to R_i^2 or the goodness of fit.[67] If the dependence from the common factor is negligible, then this part must be small, and $V(\tilde{\upsilon}_{it})/\sigma_i^2$ is the fraction explained by idiosyncratic errors for each i. As more common factors are identified, and thus, added to the estimation, then the fraction explained by the common factors increases and approaches unity. Therefore, an adequate estimation of the number of factors is important before applying the variance decomposition in Equation (4.5).

4.4.4 Panel Autoregressive Distributed Lag (ARDL) model

To analyse the credit-growth nexus, we rely on a Panel Autoregressive Distributed Lag (ARDL) approach with Pooled Mean Group (PMG) estimator, first proposed by Pesaran and Smith (1995), that incorporates heterogeneous dynamic panels. The panel ARDL approach is particularly suited for our empirical analysis because it is able to disentangle the long-and short-run effects of the variables of interest. Additionally, the long-run estimates are valid regardless of whether the regressors are exogenous, or endogenous, and irrespective of whether the underlying variables are stationary or $I(1)$ (Pesaran, 1997; Pesaran et al., 1999; Chudik et al., 2016). These features are crucial as endogeneity could be important in our empirical application. Such endogeneity issues can be compelling in our analysis as the credit market is vulnerable to macroeconomic fluctuations with feedback effects on economic activity that are amplified during events of credit booms and busts (Baltas et al., 2017; Sleibi et al., 2020). Furthermore, since we feed the panel ARDL specifications only after the variables under scrutiny are de-factored (to account for unobserved common factors that are correlated with the regressors), we can be confident that cross-sectional dependence is no longer an issue.

[67] R_i^2 can also be obtained of a regression of the credit series on the common factor and a constant, so that $R_i^2 \approx \Lambda_i^2/\sigma_i^2$.

We specify the panel ARDL($p,q,q,\ldots,q$) model as follows:

$$y_{it} = \alpha_i + \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta'_{ij} x_{i,t-j} + \varepsilon_{it}, \tag{4.6}$$

where i = 1, 2, …, N represents the cross-sectional units; t = 1, 2,…, T represents time (quarterly) periods; y_{it} is the dependent variable; $x_{i,t}$ is a k-dimensional vector of explanatory variables for each i; p and q are the lag length of the dependent and independent variables respectively; α_i represent the country-specific effects; the coefficients of the lagged dependent variables, λ_{ij}, are scalars; and δ_{ij} are k-dimensional coefficient vectors. The disturbances ε_{it} is a vector of residuals that are independently distributed across i and t, with zero means and variances σ_i^2.

Equation (4.6) can be rewritten through model reparameterization based on Pesaran et al. (1999) as follows:

$$\Delta y_{it} = \alpha_i + \phi_i y_{i,t-1} + \beta'_i x_{it} + \sum_{j=1}^{p-1} \lambda^*_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \delta^{*\prime}_{ij} \Delta x_{i,t-j} + \varepsilon_{it}, \tag{4.7}$$

where

$$\phi_i = -\left(1 - \sum_{j=1}^{p} \lambda_{ij}\right), \qquad \beta_i = \sum_{j=0}^{q} \delta_{ij},$$

$$\lambda^*_{ij} = -\sum_{m=j+1}^{p} \lambda_{im}, \qquad j = 1,2,\ldots,p-1,$$

$$\delta^*_{ij} = -\sum_{m=j+1}^{q} \delta_{im}, \qquad j = 1,2,\ldots,q-1.$$

By further grouping the variables, Equation (4.7) can be rewritten as an error-correction equation:

$$\Delta y_{it} = \alpha_i + \phi_i\left(y_{i,t-1} - \theta'_i x_{it}\right) + \sum_{j=1}^{p-1} \lambda^*_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \delta^{*\prime}_{ij} \Delta x_{i,t-j} + \varepsilon_{it}\,. \tag{4.8}$$

where $\theta_i = -(\beta_i/\phi_i)$ is the long-run coefficient attached to the x_{it} variable. In contrast, $\lambda^*_{ij}$and $\delta^{*\prime}_{ij}$ are short-run coefficients relating credit to its past values and the macroeconomic variables, respectively. Finally, the coefficient of the error-correction mechanism impact ϕ_i presents the speed of adjustment of credit toward the long-run equilibrium following a change in x_{it}. A significant and negative value of ϕ_i, i.e., ($\phi_i < 0$), is an endorsement of long-run association between the variables of interests. As shown in Pesaran et al. (1999), Equation (4.8) can be consistently estimated using the Pooled-Mean-Group (PMG) estimator, which allows the intercepts, short-run parameters, and error variances to differ freely across groups, but constrains the long-run parameters to be identical. These assumptions are important in our empirical analysis, given that the underlying credit accumulation is accompanied by future output growth under the neoclassical models (Mian et al., 2017), which is conventional in studies relating the level of credit to other macroeconomic variables in the long-run (see, among others, Lang and Welz (2018); Baba et al. (2020)).[68]

4.4.5 Panel Vector Autoregression

To investigate the short-run dynamics between credit and growth, we use a panel Vector Autoregression (PVAR) methodology estimated using the Generalized Methods of Moments (GMM) framework. In particular, our approach follows that of Abrigo and Love (2016) who introduce a PVAR estimation based on the early work of Sims (1980). In a VAR model, all variables are treated as endogenous and interdependent, although in some cases exogenous variables might be included.

Furthermore, modelling the dynamics of credit and growth variables into a PVAR allows us to look at the Impulse Response Functions (IRFs) of different types of shocks, observing the response of the credit after simulating innovations to growth, and vice versa. We apply orthogonalized impulse responses because the actual variance-covariance matrix of the errors is unlikely to be diagonal. A careful identification procedure for the PVAR is needed to isolate shocks to each of the variables. We choose a causal ordering of the variables and follow the standard procedure of Cholesky decomposition. It is fairly standard where VAR models are used in the monetary transmission and macro-finance literature to adopt an order where real variables are placed first followed by financial variables, i.e., output and prices before interest rates (see, e.g., Christiano et al. (1998) and Assenmacher-Wesche and Gerlach (2008)). Previous studies place credit as last in the VAR under the assumption that monetary variables respond immediately to a real shock (see, e.g., Goodhart and Hofmann (2008)). On the contrary, Leroy and Lucotte (2019) place credit before interest rates and after real output as the bank interest rate pass-through is sluggish in the short term, hence the lack of immediate response from credit to a shock in interest rates. In our case, we use the deviations of credit relative to output and not the absolute term of credit as done by previous authors.

In our specification, we assume that the channels through which monetary policy operates render a lag before influencing the cyclical fluctuations in economic activity as proposed by Friedman (1961). Therefore, real GDP growth is placed at the front-end of the PVAR, reflecting that the banking

[68] The PMG estimator, estimated through a maximum likelihood procedure, is seen as an intermediate tool between the mean group (MG) and the simple pooled estimators, therefore, and for the purpose of our study, the PMG estimator offers the best available compromise to combine consistency and efficiency. This choice is important when the long-run coefficients are expected to be homogenous across countries, while the short-run dynamics depends on country-specific characteristics such as monetary and fiscal adjustment mechanisms, financial markets imperfections and relative price and wage flexibility (Pesaran et al., 1999; Loayza and Rancière, 2006).

system responds immediately to a shock in output and if there is a feedback effect is likely to happen with a lag.[69] The resulting order of a four-variable PVAR model is: real GDP growth, public debt-to-GDP ratio, household credit-to-GDP ratio, corporate credit-to-GDP ratio. At a later stage, we add inflation rate and short-term interest rate to observe if our results hold, we further perform a robustness check and consider a reversed order similar to Lof and Malinen (2014). We also aim to study the direction of transmission and causality between our variables using Granger (1969) causality tests. Following Love and Zicchino (2006) we can specify PVAR model as follows:[70]

$$Z_{it} = \Gamma_0 + \Gamma_1 \sum_{j=1}^{q} Z_{i,t-j} + \varepsilon_{it}, \tag{4.9}$$

where, Z_{it} is a $k \times 1$ vector of stationary variables of each of the i countries, $i = 1, 2, 3, \ldots 22$. The subscript t denotes time. Γ_0 is a vector of constants, Γ_1 is a matrix of parameters corresponding to the coefficients attached to Z_{it-j}, the vector of lagged endogenous variables. The disturbance ε_{it} is a vector of residuals/shocks and a country-specific variance, σ_i^2.

Equation (4.9) imposes the restriction that the underlying structure is the same for each cross-sectional unit. However, this constraint is likely to be violated in practice and the identification would be affected by unobserved heterogeneity. To account for this, it is possible to introduce fixed effects, f_i:

$$Z_{it} = \Gamma_0 + \Gamma_1 \sum_{j=1}^{q} Z_{i,t-j} + f_i + \varepsilon_{it}. \tag{4.10}$$

However, introducing fixed effects would create biased coefficients, especially when the mean-difference procedure is used to estimate the model since the fixed effects are correlated with the regressors when including lags of the dependent variables. To avoid this problem, we use forward mean-differencing, also known as the Helmert procedure (Arellano and Bover, 1995). This procedure removes only the mean of all the future observations for each country-year and preserves the orthogonality between transformed variables and lagged regressors so that the application of GMM becomes valid when using lagged regressors as instruments to estimate the coefficients. For analysing the IRFs, we estimate their confidence intervals based on Monte Carlo standard errors with 1,000 simulations.[71] We set the time horizon of the IRFs to twelve quarters.

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[69] Following the standard approach in the literature, the assumption here is to follow a causal ordering of the variables. For example, the variables that come earlier in the ordering affect the subsequent variables contemporaneously as well as with a lag, while the variables that come later affect the previous variables only with a lag.

[70] A lag length of four was selected based on the minimization of the Akaike Information Criterion (AIC).

[71] Following Love and Zicchino (2006), we randomly generate a draw of the coefficients of our model using the estimated coefficients and their variance-covariance matrix. Then, we re-calculate the impulse responses. We repeat this procedure

4.5 Empirical results

4.5.1 Cross-sectional dependence

We start our analysis by investigating the possible existence of cross-correlation in each of the variables under scrutiny. Gauging the cross-sectional dependence in our panel is an important preliminary step to ensure we can make valid inference out of our long- and short-run estimates (see, e.g., Banerjee et al. (2004); Phillips and Sul (2003); Phillips and Sul (2007)). As mentioned earlier, dependence may occur in the data if, for instance, one variable is correlated across countries where the variations are driven by unobserved common factors. For this aim, we apply Pesaran (2015) test for CSD, which is based on the average pairwise correlation coefficient of the residual across units.[72] Table 4.2 shows that the null hypothesis of weak CSD is soundly rejected for all variables, suggesting, therefore, the presence of strong cross-correlation in all panels.[73] It can be noted that household credit has the largest absolute cross-correlation of 0.31, followed by 0.24 for public debt, and corporate credit with a lesser degree of correlation of 0.15.[74] The presence of strong dependence paves the way to the application of PANIC method in the following section.

Table 4.2. Cross-sectional dependence

Variable	CD t-statistic	$\overline{\hat{\rho}_{ij}}$	$\left\lvert\overline{\hat{\rho}_{ij}}\right\rvert$
ΔC^{HH}	36.98***	0.27	0.31
ΔC^{Cor}	12.73***	0.09	0.15
ΔC^{Pub}	28.43***	0.21	0.24
ΔC^{Ratio}	18.43***	0.14	0.18
ΔY	49.82***	0.37	0.37
ΔP	51.72***	0.38	0.39
$\Delta Rate^{long}$	63.07***	0.47	0.5
$\Delta Rate^{short}$	80.65***	0.6	0.6

Notes: This table presents the results of CD test of Pesaran (2015) under the assumption of covariance stationary. Sample period 2000Q1-2019Q4 for 22 countries (*N*=22, *T*=80). $\overline{\hat{\rho}_{ij}}$ denotes the average pairwise residual correlation coefficient between the (*i*,*j*) units once the original series are filtered using AR(1) specifications. $\left\lvert\overline{\hat{\rho}_{ij}}\right\rvert$ denotes the absolute value pairwise correlation. Asterisk (***) indicates rejection of the null hypothesis of weak cross-sectional dependence at 1% significance level.

1,000 times. We generate 5th and 95th percentiles of this distribution that we use as confidence interval for the impulse-responses.

[72] Averaging has to be performed across pairwise correlations between the same variables residuals in order to avoid the underestimation of the correlation, which would lead to an oversized panel test. We present the absolute value of the correlations because in simple averaging, positive and negative correlations will cancel out, which would lead to underestimation of the true degree of cross-sectional correlation.

[73] The literature distinguishes between two types of CSD, weak and strong. While the former refers to the dependence that decreases in a distance-decaying fashion due to either spill-over or spatial effects, the latter is pervasive, does not depend on distance between units and arises due to unobserved common factors (Pesaran and Tosetti, 2011).

[74] We note that there is a lower correlation between corporate credit in our panel. In the following sections, therefore, we use different information criterions on the existence of a common component in corporate credit to buttress this evidence.

4.5.2 Factor analysis

Following the framework set out in Section 4.4.1, we disentangle each series into two components, common factor F_{kt}, and idiosyncratic components υ_{it} using the BN methodology. The benefit of such a framework is providing a clear image and a better understanding of the dynamics and comovements among the variables under scrutiny. We allow up to five factors and rely on the three information criteria suggested by Bai and Ng (2002) and the procedures of Onatski (2010) (hereafter ON) and Ahn and Horenstein (2013) (hereafter AN) ratios, presented earlier as ER and GR, to determine the optimal number of common factors in each panel. Using PC analysis, the factor extraction process is applied to the data in first difference. While there is no clear theory on whether to standardize the data or not, we perform the analysis first by using the de-meaned data only and then repeat the same exercise by using the standardized series. The two sets of estimates are displayed in Table 4.3 and Table 4.4, respectively. The evidence on the de-meaned data shows that in most of the cases, the first two information criteria of BN select the maximum number of factors allowed, for instance, five for household credit, three factors for corporate credit, and five for public credit, which are robust across subsamples. Such recommended numbers match ON and AN procedures only for household and corporate credit. In all cases, ER and GR indicate the same number of common factors. Furthermore, in most cases, the null hypothesis of unit root is not rejected for the first common factor for household and public debt but not for corporate credit. Similarly, the null hypothesis of unit root is not rejected for all of the idiosyncratic components for the three types of credit, indicating that non-stationarity arises from both global common components and country-specific drivers. The results for output and prices are similar, it seems that both variables are driven by non-stationary common factors, and while the non-stationarity of output is also driven by country-specific component, prices appear to have stationary idiosyncratic component signalling that the source of non-stationarity comes from common factors only.

The results of the factor analysis after standardizing the data are more conservative. We notice that the number of factors recommended by different procedures dropped noticeably. For example, the ON and AN procedures recommend only one factor for household credit and public debt and only one factor for corporate debt using the ON procedure and the first two of BN criterion over the full sample period. In fact, the ON procedure recommends only one factor in most cases equivalent to the AN procedure except for corporate debt, where the latter indicate no factors. For output and prices, the IC_3 of BN, ON and AN procedures recommend one factor only for both variables. Moreover, the first common factor explains up to 38.2%, 16.6% and 28.8% for household, corporate and public debt respectively for the total panel of countries, while the results show that the rest of variations are country-specific. Similar results are found for output and prices, the first common factor explains up to 44% and 45% for each variable, respectively. Similar variations for output and prices common factors are also found in Arsova (2020).

Furthermore, the null hypothesis of non-stationary idiosyncratic component is soundly rejected for all variables; on the other hand, the results show that the first and second common factors, and the third factor for some variables, are non-stationary – except for some sub-samples – concluding that the source of unit root comes from global components that are shared among all variables.

It can be seen that applying various data transformations provides different results in terms of the number of factors for each panel. While we want to ensure the quality and an adequate approximation of the factors, we follow Sul (2019) and proceed with the standardized data, after transforming the data in first differences and using the recommended number of factors provided by IC_2 of BN approach for the recent of the analysis.

Table 4.3. PANIC analysis for de-meaned series.

Sample	F_{kt}	v_{it}	IC_1	IC_2	IC_3	ON	ER	GR
C^{hh}								
2000-2019	-0.171, -1.359, -3.867*, -2.455, 2.046 [0.362, 0.246, 0.155, 0.099, 0.041]	-1.452	5	5	4	5	5	5
2000-2008	-4.085*,-3.147*,-2.211,-1.002,-4.420* [0.471, 0.216, 0.175, 0.037, 0.026]	6.923**	5	5	3	3	3	3
2009-2019	-1.889,-1.499,-2.251,-4.940*,-1.585 [0.363, 0.159, 0.140, 0.078, 0.046]	6.691**	5	4	0	4	4	4
C^{cor}								
2000-2019	-3.184*, -0.857, -3.800*,-1.180, -0.626 [0.196, 0.149, 0.125, 0.070, 0.057]	2.228	3	3	0	3	3	3
2000-2008	-0.099,-2.438,0.795,-3.640*,-2.551 [0.271, 0.179, 0.083, 0.075, 0.060]	3.233**	2	2	0	3	3	3
2009-2019	0.482, -2.913*, -3.780*, 0.900, -2.160 [0.194, 0.152, 0.105, 0.093, 0.071]	3.939**	2	2	0	1	1	1
C^{pub}								
2000-2019	-2.476, -3.306*, -3.482*, -0.201,-4.021* [0.262, 0.192, 0.120, 0.065, 0.064]	-2.290	5	5	0	0	3	3
2000-2008	-2.675, -2.273, -0.460, -2.189, -3.710* [0.336, 0.197, 0.138, 0.091, 0.064]	-1.738	5	5	0	0	3	3
2009-2019	-2.082, -3.016*, -4.086*, -2.850, -1.021 [0.276, 0.186, 0.117, 0.092, 0.065]	1.421	5	5	0	2	2	2
C^{ratio}								
2000-2019	-0.390, -1.436, -3.597*-1.732,-1.507 [0.235, 0.166, 0.105, 0.089, 0.068]	0.552	5	5	0	1	1	1
2000-2008	-0.899,-1.454,0.511,-3.260*,-2.614 [0.316, 0.175, 0.110, 0.068, 0.062]	5.507**	5	3	0	4	1	1
2009-2019	-1.041,-2.484,-1.997,-1.787m-3.262* [0.195, 0.159, 0.113, 0.100, 0.084]	-1.403	5	2	0	0	0	0
Y								
2000-2019	-2.264, -2.201, -2.296, -1.322, -1.076 [0.396, 0.131, 0.078, 0.070, 0.059]	-0.754	5	5	1	2	1	1
2000-2008	-0.414,1.119,-2.583,-1.724,-1.708 [0.418, 0.116, 0.087, 0.071, 0.065]	-0.519	5	1	1	1	1	1
2009-2019	-2.923*,-3.776*,-2.396,-1.628,-1.058 [0.236, 0.172, 0.138, 0.110, 0.085]	0.197	5	5	0	1	1	1
P								
2000-2019	1.598, -2.269*, -3.378*, -3.416*,-0.309 [0.455, 0.143, 0.095, 0.076, 0.037]	4.617**	5	4	1	4	1	1
2000-2008	-2.246, -0.561, -1986, -5.248*,-2.470 [0.382, 0.148 ,0.133, 0.110, 0.043]	3.803**	5	4	0	4	1	1
2009-2019	-3.926*,-4.696*,-4.022*,-2.831,-2.756 [0.535, 0.152, 0.079, 0.057,0.028]	7.315**	4	4	1	5	1	2

Notes: This table presents the results of unit root tests on the factors and panel unit root tests on the idiosyncratic components using Bai and Ng (2004) PANIC method. Sample period 2000Q1-2019Q4 for 22 countries (N=22, T=80/37/43). IC_1, IC_2, IC_3 are the number of factors recommended by Bai and Ng (2004) information Criteria. ON is the number of factors recommended by Onatski (2010), ER and GR are the number of factors recommended by Ahn and Horenstein (2013) procedure. Asterisk (**) indicates rejection of the null of unit root at 5% significance level. The unit root tests for the factor and the idiosyncratic components have t-statistics of -2.82 and -1.64, respectively. Eigenvalues in square brackets [.].

Table 4.4. PANIC analysis for de-meaned and standardized series.

Sample	F_{kt}	υ_{it}	IC_1	IC_2	IC_3	ON	ER	GR
C^{hh}								
2000-2019	-2.234, -1.094, -3.430* [0.382, 0.119, 0.087]	10.66**	5	3	1	1	1	1
2000-2008	-0.506, -3.607*, -4.182* [0.244, 0.156, 0.124]	11.15**	4	3	0	0	1	4
2009-2019	-3.653*, -4.239*, -4.549* [0.393, 0.141, 0.085]	9.517**	3	2	1	2	1	1
C^{cor}								
2000-2019	-0.746, -2.764, -2.324 [0.166, 0.114, 0.082]	7.136**	1	1	0	1	0	0
2000-2008	0.410, -2.679, -2.608 [0.2037 0.1102 0.1065]	6.544**	1	0	0	1	1	1
2009-2019	-2.461, -4.312*, -1.387 [0.1691 0.1348 0.1002]	10.21**	1	0	0	0	0	0
C^{pub}								
2000-2019	-2.377, -2.332, -5.946* [0.2878 0.1195 0.0826]	3.810**	2	2	0	1	1	1
2000-2008	-3.782*, -1.198, -1.026 [0.2791 0.1809 0.1058]	10.13**	3	2	0	2	2	2
2009-2019	-1.766, -3.309*, -3.696* [0.2984 0.1212 0.0750]	8.243**	2	1	0	2	1	1
C^{ratio}								
2000-2019	-0.574, -2.654, -2.278 [0.2239 0.1007 0.0795]	8.403**	1	1	0	1	1	1
2000-2008	1.735, -3.624*, -2.033 [0.1511 0.1373 0.1143]	6.084**	0	0	0	0	0	0
2009-2019	-1.919, -3.098*, -2.575 [0.1870 0.1632 0.0972]	9.398**	2	2	0	2	0	2
Y								
2000-2019	-2.301, -1.798, -1.341 [0.4400 0.0746 0.0657]	5.046**	1	1	1	1	1	1
2000-2008	-0.299, -1.057, -1.867 [0.2682 0.1267 0.0894]	4.761**	1	1	1	1	1	1
2009-2019	-1.552, -2.837*, -2.203 [0.4917 0.0950 0.0660]	6.178**	2	2	1	1	1	1
P								
2000-2019	-2.059, -2.577, -3.143* [0.4496 0.1243 0.0764]	4.992**	4	4	1	1	1	1
2000-2008	-3.565*, -4.852*, -1.836 [0.4143 0.1579 0.0785]	5.655**	4	2	4	2	1	1
2009-2019	-4.305*, -2.536, -3.672 [0.4832 0.1240 0.0923]	4.543**	5	4	1	4	1	1

Notes: This table presents the results of unit root tests on the factors and panel unit root tests on the idiosyncratic components using Bai and Ng (2004) PANIC method. Sample period 2000Q1-2019Q4 for 22 countries (N=22, T=80/37/43). IC_1, IC_2, IC_3 are the number of factors recommended by Bai and Ng (2004) information Criteria. ON is the number of factors recommended by Onatski (2010) , ER and GR are the number of factors recommended by Ahn and Horenstein (2013) procedure. Asterisk (*) indicates rejection of the null of unit root at 5% significance level. The unit root tests for the factor and the idiosyncratic components have t-statistics of -2.82 and -1.64, respectively. Eigenvalues in square brackets [.].

Figure 4.4 displays the evolution of the first global common factor extracted from each type of credit over the full sample period. In order to facilitate interpretation, we follow a similar approach to Eickmeier et al. (2014) and normalize all factors. In particular, each factor is scaled to have the same standard deviation as its corresponding credit growth.[75] Furthermore, the graph reveals how the three factors capture the effects of the Global Financial Crisis, reacting with similar dynamics especially for the two types of private credit. For example, the common factors of household and corporate credit seem to be moving together, they appear to be positive before the crisis period, and become negative during the crisis where monetary policy is loose. We also notice that there are two trends in private credit, a downward trend until 2009Q3, a build-up period of non-performing loans related to a vulnerable banking sector and weak macroeconomic conditions, and a positive trend,

[75] Credit growth for each type of credit is computed as quarter-on-quarter growth of the average credit of all 22 countries.

afterwards, where major central banks implement asset purchase programs to steer financial conditions and growth. However, it seems that the comovement in household credit recovers slightly faster than corporate credit, as the former becomes positive in 2012Q3 while the later takes additional six quarters (until 2014Q1) to become positive. Such dynamics signal the characteristics of comovement in household borrowing which is largely elastic with respect to credit supply shocks, as a result, credit shocks work faster through household as opposed to the corporate sector (Mian et al., 2017). The common factor of public debt takes a different dynamic. It goes upward and reaches its peak in 2008Q3 and then it decreases and reaches a negative value in 2010Q1 and turns positive only from 2019Q3 onward.

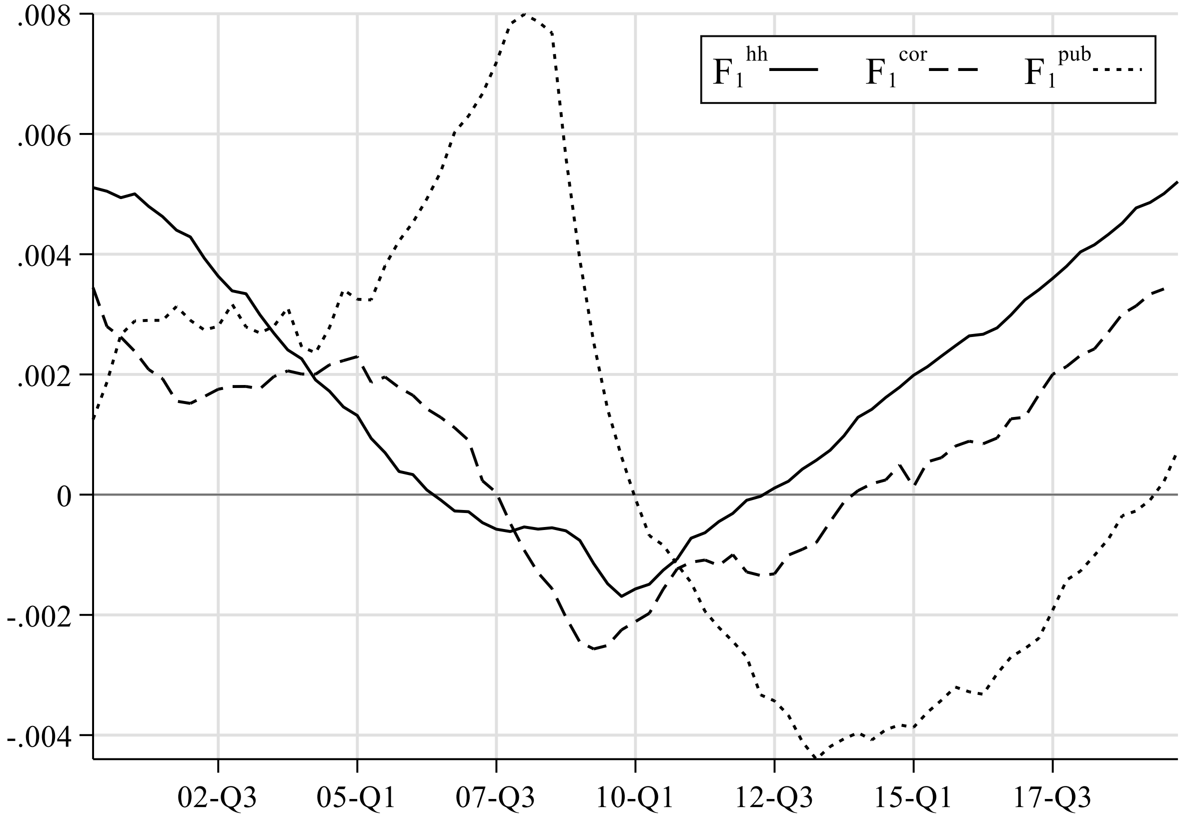

Figure 4.4. Extracted common factors (first) from household credit (hh), corporate credit (cor) and public debt (pub) using BN approach. Sample period 2000Q1-2019Q4 for 22 countries (*N*=22, *T*=79). Data is standardized

After estimating the factor structure of the variables, we proceed to check how much such factors can explain the time-varying fluctuations of the observed panel data. We follow Sul (2019) and carry out variance decomposition of the data in the first difference and calculate the coefficient $R_i^{2,}$ which takes values close to one whenever variations in the raw series are completely dominated by common factors. The results presented in Table 4.5 show that the common factor for household credit explains a significant fraction of the fluctuations in most of the countries in our sample with some degree of heterogeneity. Four countries are found to be significantly dominated by common factors, i.e., R_i^2 > 80%, namely, Greece, Spain, Italy and Portugal. Other countries with high variation explained by the factor include Canada, UK, Finland and the Netherlands, with an average R_i^2 of 75%. On the other end, Brazil, Poland and Austria are less tied by the common factor, as they feature an R_i^2< 25%. Such a result indicates that country-specific characteristics or local determinants are more important than the global common factor in shaping the evolution of household credit for these last three countries.

Unlike household credit, corporate credit seems to be less driven by the common factors, where the largest variation explained by such factors can be found in Spain (as much as 46%) and the lowest for Czech Republic (close to zero). Differences in labour markets and the role of institutional factors and bankruptcy laws could generate such marked differences across countries in the evolution of corporate credit. All in all, this finding shows that household credit is remarkably tied together across countries; on the contrary, corporate credit features more idiosyncratic behaviour.

While there is little theoretical and empirical research on the cross-country difference between household and corporate credit comovement, some scholars have investigated why household credit is so strongly interlinked across countries. One potential reason is the strong link between households' balance sheet and the housing market where mortgage borrowing and changes in house prices expose households to potentially large interconnectedness across economies. As a result, households in different countries face the same high sensitivity to shocks in the global housing market. In contrast to households, corporates have access to other forms of collateral in their financing decisions, and therefore, they are less exposed to the housing market (Mian et al., 2013; Jordà et al., 2016). Another reason could be related to the similarity in household characteristics regarding their financing decisions and behavioural biases in response to increases in the availability of credit, with such characteristics being over-confidence about the ability to repay debts and the risk associated with future income (Brunnermeier and Parker, 2005; Agarwal et al., 2018). In contrast to household, corporate credit is less elastic with respect to credit supply shocks since corporates face more sophisticated decisions regarding their leverage and financing positions that are expected to be more rational and realistic in the assessment of debt service costs and future cash flows (Mian et al., 2017). Nevertheless, the findings of household and corporate credit variance decomposition are consistent with the observed pairwise cross-country correlations presented earlier in Table 4.2, where household credit shows less idiosyncratic forces compared to corporate credit.

Regarding public debt, the common factors are important in Italy, Belgium, Spain, and rather irrelevant for Brazil and Norway. Likewise, for output, the common factor is important in France, the Czech Republic, and Italy, and less important in Australia, Norway, and Poland. These last three countries seem to be less tied with the global business cycle. We also notice that the US output is less affected by the common factor in comparison to other countries, with an R_i^2 coefficient as low as 42.6%. Country-specific factors are likely important in inducing variations in US output. We make sense of this last result by noticing that the significant idiosyncratic shocks to US output can be, per se, a source of disturbance to the rest of the world via trade and financial markets interlinkages, whereas the opposite is less likely to happen (Kwark, 1999; Nadal-De Simone, 2002). The common factors for prices show more persistence than for output, it dominates the variation in Greece, France, United States, and United Kingdom, with only Australia featuring a common factor variation lower than 50%. For a sense of aggregation, these results give an average common variation, i.e., the goodness of fit, $\overline{R^2}$ of 44% and 71% for output and prices, respectively. This finding is expected as central banks tend to react to output growth and inflation which comove together internationally (Breitung and Eickmeier, 2016), and confirms the findings of previous studies that a considerable variation of output and prices dynamics is driven by global common factors (see, e.g., Kose et al. (2003); Ciccarelli and Mojon (2010); Eickmeier et al. (2014).

Finally, we notice that both interest rates, long-and short-term rates, are strongly dominated by the common factors with the majority of countries' variations being explained by 95%, which is in line with the findings of Byrne et al. (2012).[76] We take this high degree of correlation in interest rates as evidence of the similarity in the systemic reaction of monetary policy to maintain macroeconomic stability in individual countries, hence convergence of monetary policy strategies across the globe. Alternatively, it may reflect the significant role of monetary policy in one country, for example, US monetary policy, which may give a rise to global monetary policy spillover to other countries (Hofmann and Bogdanova, 2012).

The variance decomposition presents interesting results, with some degree of heterogeneity, about the comovement of the three types of credit, output, and prices across countries. This fact, coupled with the presence of cross-sectional dependence, renders strong and valid evidence on the importance of disentangling each variable into common and idiosyncratic components for a meaningful estimation of the dynamic behaviour of our panel data. We build on these findings to further investigate the finance and growth nexus in the long- and short-run. We do so by first removing the common factors from the original series to mitigate the issue of CSD and obtain unbiased estimates out of our panel ARDL framework.

[76] For a comprehensive discussion on the evidence of global factors and comovement in inflation rates and interest rates, see, e.g., Rogoff (2006); Borio and Filardo (2007); Ciccarelli and Mojon (2010).

Table 4.5. Variance decomposition of the common factors in individual countries

	C^{hh}	C^{cor}	C^{pub}	C^{ratio}	Y	P	$Rate^{long}$	$Rate^{Short}$
Austria	0.231	0.180	**0.569**	0.235	**0.604**	**0.678**	**0.960**	**0.997**
Australia	**0.619**	0.020	**0.551**	0.239	0.017	0.376	**0.829**	**0.930**
Belgium	**0.696**	0.300	**0.761**	0.181	**0.656**	**0.673**	**0.942**	**0.997**
Brazil	0.134	0.002	0.007	0.001	0.227	**0.784**	**0.982**	**0.994**
Canada	**0.784**	0.036	**0.630**	0.018	0.434	**0.773**	**0.865**	**0.887**
Czech Republic	0.347	0.001	0.210	0.004	**0.703**	**0.775**	**0.871**	**0.909**
Germany	0.353	0.073	0.227	0.012	**0.560**	**0.648**	**0.957**	**0.997**
Denmark	**0.578**	0.217	**0.531**	0.396	0.315	**0.774**	**0.899**	**0.889**
Spain	**0.832**	0.463	**0.654**	**0.734**	**0.648**	**0.782**	**0.906**	**0.997**
Finland	**0.743**	0.114	0.349	0.096	**0.611**	**0.692**	**0.960**	**0.997**
France	**0.686**	0.192	**0.576**	0.085	**0.781**	**0.878**	**0.962**	**0.997**
United Kingdom	**0.753**	0.196	**0.642**	0.358	**0.503**	**0.806**	**0.881**	**0.899**
Greece	**0.860**	0.285	0.231	**0.543**	0.195	**0.880**	**0.922**	**0.911**
Israel	0.459	0.043	0.159	0.075	0.214	**0.556**	**0.993**	**0.967**
Italy	**0.826**	0.341	**0.724**	**0.566**	**0.761**	**0.713**	**0.916**	**0.997**
Japan	0.334	0.009	0.328	0.045	0.401	**0.510**	**0.966**	**0.991**
Netherlands	**0.717**	0.004	**0.524**	0.086	**0.646**	**0.613**	**0.949**	**0.997**
Norway	**0.601**	0.256	0.012	0.101	0.031	**0.590**	**0.891**	**0.891**
Poland	0.217	0.136	0.301	0.113	0.057	**0.715**	**0.911**	**0.933**
Portugal	**0.813**	0.312	0.268	**0.521**	0.424	**0.774**	**0.890**	**0.997**
Sweden	**0.697**	0.338	0.334	0.221	0.465	**0.758**	**0.881**	**0.858**
United States	**0.686**	0.154	0.374	0.296	0.426	**0.829**	**0.909**	**0.939**
$\overline{R^2}$	0.589	0.167	0.407	0.224	0.440	0.708	0.920	0.953

Notes: This table examines the degree to which the optimal common factors explain the variation in each country's macro variable, i.e., credit, output, prices, long- and short-term rates. Sample period 2000Q1-2019Q4 for 22 countries (*N*=22, *T*=80) using differenced and standardized data. This ratio is from Equation (4.6) (i.e., $R_i^2 = 1 - V(\tilde{v}_{it})/\sigma_i^2$). If all variations are idiosyncratic then $R_i^2 \to 0$. We highlight in bold cross-sectional units where the common factor explains substantial degree of variability of the original series (i.e., $R_i^2 \geq 0.5$). $\overline{R^2}$ is the average variation, corresponds to the aggregate variation explained by the recommend number of factors for each variable across *N* and *T* and equals to the sum of each factor's eigenvalue reported in Table 4.4

4.5.3 Long-run analysis

Having identified the common factors of different types of credit and delineated their time series behaviour, in this section, we examine the long-run effects of economic growth, inflation and interest rate on credit variables, namely, household, corporate and public debt. Our framework is similar to the panel ARDL frameworks applied in Lombardi et al. (2017) and Chudik et al. (2017) which is designed to detect any long-run relationship between the series in growth terms. However, it also differs in two important features. First, while previous scholars account for dependence using nonparametric methods, i.e., cross-sectional averages, we use the PC approach in place of cross-sectional averages to detect the common factors responsible for the comovement among the series of interest, and then use such common factors to carry out the de-factoring of the original series. This approach is novel in the literature on credit and growth, and previous studies on dependence in panels have shown that it is more suited than standard cross-sectional averages whenever the number of factors r is larger than one. Second, we take a broader stance and produce the analysis on three different types of credit, and question the effects of economic growth on credit, and not only the other way around. Additionally, our panel ARDL specification allows for slope heterogeneity in the short-run, between growth and credit, taking into account country-specific factors that could affect the nexus between both the two sides of the economy such as, *inter alia*, institutional framework, law and regulatory system, and therefore allow for a significant degree of cross-country heterogeneity.[77] One of our interests is in the speed of adjustment ϕ, which is expected to be negative, less than one and significant in order for the variables to share an association in the long-run. Since we test the relationship between variables in growth terms and moderately persistent, we expect the speed of adjustment to be high.

We start by investigating the long-run association between the macro variables and the three credit variables using the Pool Mean Group (PMG) estimator in a panel ARDL framework presented earlier in Equation (4.8). Table 4.6 and Table 4.7 present the averages estimates of the long-run effects of the inflation rate, short-run rate and output growth (denoted by Δp, Δr^{short}, and Δy) on credit growth, where the estimate of the speed of adjustment in the error correction mechanism is denoted by ϕ.[78] For comparison, we start by using the original series without de-factoring, i.e., Z_{it}, and as we move on, we replace the original series with their de-factored counterparts. The estimates obtained from the panel ARDL are reported in three cases, (a), (b) and (c), in Table 4.6. Column (a) depicts the results when only output growth variable is included in the model, column (b) when both output growth and inflation rate are included, and column (c) when output, inflation and short-term rates are considered together. The results across all specifications suggest an inverse long-run association between inflation rate, short-term rate, output growth with household credit. The coefficients of output growth are, in most cases, negative and always statistically significant when considered with the other macro variables. In the case of corporate credit and public debt, the inflation rate seems to be diverging from the long-run and only significant at 10% level for corporate credit, in contrary in the case of household credit, it is significant at 1% level. The speed of adjustment ϕ, is negative, below one and statistically significant for the three variables. However, such results are likely to suffer from cross-sectional dependence due to the presence of unobserved common factors in the original series, as previously highlighted in Table 4.2. Therefore, in the analysis that follows, we estimate our panel setting using

[77] Sufficient lags are required for the consistency of the ARDL approach, however, specifying a relatively large number can lead to estimates with poor small sample properties (Chudik et al., 2017). The number of lags here is set to three for all variables/countries. Such selection is based on the minimum AIC, and it is appropriate for our specification to capture the feedback effects running from credit to output growth.

[78] Note that our aim is to uncover the association between credit growth and output growth in the long-run, and not in levels. This approach is adopted from Chudik et al. (2017).

the de-factored series Z^d_{it}. In doing so, we depart from the standard approach used in the literature of using cross-sectional averages to account for dependence.

The results in Table 4.7 provide further evidence on the existence of an inverse relationship between economic growth and the growth of the three credit variables in the long-run. We note that the coefficients of economic growth are smaller for the three types of credit compared to using the data with the presence of dependence. For example, a 1% increase in economic growth is associated with a decrease by 0.11% in household credit as reported in column (c), the effect is almost doubled for corporate credit with a decrease by 0.24% and a decrease of 0.55% for public debt. Such smaller effects – compared to the presence of dependence – highlight the role of global common factors between the countries in amplifying the effect of economic growth on credit.

The inflation rate is only significant for corporate credit at 1% significance level with positive coefficients of 0.356 and 0.330 in column (b) and (c) respectively. Such a result indicates that a higher inflation rate is associated with high corporate lending in the long-run. However, the panel ARDL analysis addresses associations which do not necessarily indicate causality. Regarding the short-term rate, the result is insignificant for the three variables. The finding regarding the insignificance of interest rate is expected, because the common factors of short-term rate – that are removed – explain a significant degree of comovement for individual countries, leaving little, if any, of country-specific variations, and therefore, does not catch up with the other macro variables in the system. As discussed earlier, such comovement in short-term rate can be proxy for global monetary policy, in which if eliminated, the effect of short-term on credit disappear, which is in our case. The speed of adjustment of 56.2%, 63.6%, 71.2% for household, corporate and public debt respectively, always remain negative, lower than one in absolute term, and statistically significant at the 1% level. The above figures indicate that public debt is faster than household and corporate credit in converging towards the equilibrium with economic growth. As argued by Chudik et al. (2017), such relatively quick speed of adjustment is in line with the low persistence of economic growth. However, this does not mean that the effects of economic growth will be very quick on the *level* of credit. A remarkable note regarding the results in Table 4.7 where the common factor is removed; while the effect of economic growth appears to be smaller (and significant) the speed of adjustment appears to be faster (almost doubled in the case of household credit) towards the long-run equilibrium between growth and credit. Our results indicate that the presence of global common shocks is associated with a slower speed of adjustment between financial and the real sectors at the country level, this result does not change even after considering inflation rate, short-term rate with output growth jointly together where the speed of adjustment between 56.2% and 71.2%, compared to 25.2% and 63%, for the three credit measures, respectively, before removing the common factor.

Table 4.8 and Table 4.10 present the empirical results for each type of credit with the same set of macro variables when the panel ARDL of Equation (4.8) contains 1, 2 and 4 lags. We carry out estimations for different lag order to check if the results are consistent across time.

For household credit in Table 4.8, the speed of adjustment varies with the number of lags, taking values from 74.5% to 58.6% which remains negative and statistically significant in all cases and across different estimations. Inflation rate and short-term rate are found to depart from the long-run equilibrium, economic growth is negative and significant, which is consistent with the results in the previous table. Furthermore, the inflation rate seems to pick up convergence towards long-run equilibrium with economic growth and corporate credit, as shown in Table 4.9, with values ranging between 0.306 and 0.41. In the case of public debt in Table 4.10, inflation rate and short-term rate seem to negatively affect public debt at two lags, significant at 5% level. However, this effect becomes insignificant at four lags. We also notice that economic growth coefficient varies between -0.357 and -0.592 signalling that the effect of growth is highest on public debt compared to the other two types of private credit.

For robustness, and to ensure that our long-run analysis is not undermined by the framework of de-factoring, we present in Table 4.11 the results where the dependent variable is economic growth, and the independent variables are inflation rate, short-term rate and each type of credit as in Chudik et al. (2017) and Lombardi et al. (2017). We also perform the analysis across different lags, i.e., 2, 3, 4 to check if the results are persistent. Panel (a) shows that household credit is no longer significant towards long-run equilibrium with economic growth, despite the significance of the speed of adjustment. This result signals that the presence of common factors decides the direction of the relationship between credit and growth. Further, while the inflation rate is negative and significant in the three cases, short-term rate is negative but only significant at 5% level when considering 4 lags. This finding indicates that a tightening monetary policy, which increases short-term rate, negatively affect output growth, which is consistent with the literature on bank lending channel.

A different pattern occurs when corporate credit is considered. Panel (b) shows that corporate credit shares a negative association with economic growth at different lags. More specifically, we find that a one percentage point increase in corporate credit is associated, in the long-run, with lower economic growth of almost 0.134 percentage point after four quarters, this finding is significant at 1% level. The pattern of results is, however, slightly different for the public debt where the negative link between output growth and public debt still holds. Empirical estimates of panel (c) show that a 1 percentage point increase in public debt is associated with lower output growth of 0.10 percentage point at four lags, and 0.15 percentage point at three lags. This is very close to Chudik et al. (2017) who report an impact of -0.120 of public debt on growth.

Further, one may argue that the long-term rate might be more suitable than short-term rates in our estimations since the average maturity of public debt tranches is around three years or longer. Therefore, in a final step, we replace the short-term with the long-term rate variable. The results presented in Table 4.12 show similar pattern as when the short-term rate is considered.

Table 4.6. PMG estimates of long-run effects between credit and growth

	ΔC^{hh}			ΔC^{cor}			ΔC^{pub}		
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
ΔY	-1.041***	-0.845***	-0.550**	-0.199	-0.119	-0.436**	-3.223***	-3.190***	-2.886***
	(0.155)	(0.200)	(0.239)	(0.128)	(0.140)	(0.173)	(0.183)	(0.189)	(0.214)
ΔP		1.924***	2.039***		0.274	0.471*		0.116	-0.108
		(0.359)	(0.363)		(0.256)	(0.255)		(0.217)	(0.232)
ΔR^{short}			-2.896***			1.473***			-1.217***
			(0.484)			(0.319)			(0.315)
ϕ	-0.298***	-0.252***	-0.252***	-0.573***	-0.564***	-0.547***	-0.670***	-0.649***	-0.630***
	(0.055)	(0.047)	(0.059)	(0.074)	(0.073)	(0.072)	(0.068)	(0.065)	(0.060)
$N \times T$	1650	1650	1650	1650	1650	1650	1650	1650	1650

Notes: This table is built on the ARDL specification of Equation (4.8) where the dependent variable is either ΔC^{hh} , ΔC^{cor} , ΔC^{pub} and vector X contains the series of prices (P), short-rate (R^{short}), output (Y). Lags order of p and q is set to three according to minimum AIC. ϕ is the speed of adjustment. Sample period 2000Q1-2019Q4 for 22 countries (N=22, T=80) without de-factoring. */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels. Standard errors in parentheses. All estimations contain a constant, but not reported for brevity.

Table 4.7. PMG estimates of long-run effects between the three types of credit and growth

	ΔC^{hh}			ΔC^{cor}			ΔC^{pub}		
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
ΔY	-0.110***	-0.104**	-0.115***	-0.259***	-0.235***	-0.241***	-0.598***	-0.589***	-0.549***
	(0.042)	(0.043)	(0.041)	(0.076)	(0.072)	(0.071)	(0.061)	(0.060)	(0.063)
ΔP		0.035	0.025		0.356***	0.333***		-0.001	-0.045
		(0.067)	(0.067)		(0.097)	(0.097)		(0.073)	(0.075)
ΔR^{short}			-0.037			0.099			-0.170
			(0.085)			(0.126)			(0.103)
ϕ	-0.623***	-0.583***	-0.562***	-0.662***	-0.656***	-0.636***	-0.760***	-0.752***	-0.712***
	(0.054)	(0.049)	(0.049)	(0.075)	(0.074)	(0.071)	(0.066)	(0.064)	(0.060)
$N \times T$	1628	1628	1628	1628	1628	1628	1628	1628	1628

Notes: This table is built on the ARDL specification of Equation (4.8) where the dependent variable is either household, corporate or public debt (ΔC^{hh} , ΔC^{cor} , ΔC^{pub}) and vector X contains the series of prices (P), short-rate (R^{short}), output (Y). Lags order of p and q is set to three according to minimum AIC. ϕ is the speed of adjustment. Sample period 2000Q1-2019Q4 for 22 countries (N=22, T=80) after de-factoring using Equation (4.1). */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels. Standard errors in parentheses. All estimations contain a constant, but not reported for brevity.

Table 4.8. PMG estimates of long-run effects between household credit and growth

	Lag = 1			Lag = 2			Lag = 4		
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
ΔY	-0.199***	-0.196***	-0.196***	-0.196***	-0.198***	-0.193***	-0.135***	-0.129***	-0.119***
	(0.033)	(0.033)	(0.033)	(0.032)	(0.032)	(0.032)	(0.041)	(0.040)	(0.038)
ΔP		0.078	0.060		0.0678	0.0422		-0.004	-0.001
		(0.052)	(0.052)		(0.056)	(0.056)		(0.064)	(0.064)
ΔR^{short}			0.074			0.039			0.016
			(0.058)			(0.065)			(0.085)
ϕ	-0.745***	-0.726***	-0.709***	-0.729***	-0.702***	-0.689***	-0.649***	-0.613***	-0.586***
	(0.060)	(0.060)	(0.057)	(0.078)	(0.074)	(0.073)	(0.060)	(0.055)	(0.056)
$N \times T$	1672	1672	1672	1650	1650	1650	1606	1606	1606

Notes: This table is built on the ARDL specification of Equation (4.8) where the dependent variable is household credit (C^{hh}) and vector X contains the series of prices (P), short-rate (R^{short}) and output (Y). Lag order of p and q is set to 1, 2 and 4 in each column. ϕ is the speed of adjustment. Sample period 2000Q1-2019Q4 for 22 countries (N=22, T=80) after de-factoring using Equation (4.1). */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels. Standard errors in parentheses. All estimations contain a constant, but not reported for brevity.

Table 4.9. PMG estimates of long-run effects between corporate credit and growth

	Lag = 1			Lag = 2			Lag = 4		
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
ΔY	-0.248***	-0.220***	-0.211***	-0.351***	-0.314***	-0.312***	-0.172**	-0.140*	-0.120
	(0.064)	(0.063)	(0.064)	(0.070)	(0.069)	(0.068)	(0.081)	(0.073)	(0.075)
ΔP		0.306***	0.322***		0.395***	0.409***		0.378***	0.351***
		(0.080)	(0.081)		(0.084)	(0.083)		(0.102)	(0.102)
ΔR^{short}			-0.0643			-0.0358			0.116
			(0.089)			(0.103)			(0.137)
ϕ	-0.704***	-0.707***	-0.699***	-0.705***	-0.706***	-0.697***	-0.656***	-0.665***	-0.626***
	(0.055)	(0.057)	(0.056)	(0.065)	(0.070)	(0.070)	(0.072)	(0.075)	(0.070)
$N \times T$	1672	1672	1672	1650	1650	1650	1606	1606	1606

Notes: This table is built on the ARDL specification of Equation (4.8) where the dependent variable is corporate credit (C^{cor}) and vector X contains the series of prices (P), short-rate (R^{short}) and output (Y). Lag order of p and q is set to 1, 2 and 4 in each column. ϕ is the speed of adjustment. Sample period 2000Q1-2019Q4 for 22 countries (N=22, T=80) after de-factoring using Equation (4.1). */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels. Standard errors in parentheses. All estimations contain a constant, but not reported for brevity.

Table 4.10. PMG estimates of long-run effects between public debt and growth

	Lag = 1			Lag = 2			Lag = 4		
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
ΔY	-0.357***	-0.365***	-0.364***	-0.436***	-0.467***	-0.452***	-0.592***	-0.582***	-0.560***
	(0.041)	(0.042)	(0.041)	(0.046)	(0.046)	(0.047)	(0.064)	(0.064)	(0.066)
ΔP		-0.0117	-0.0268		-0.133**	-0.141**		-0.0225	-0.0269
		(0.053)	(0.053)		(0.057)	(0.057)		(0.077)	(0.080)
ΔR^{short}			-0.130**			-0.154**			-0.003
			(0.066)			(0.075)			(0.127)
ϕ	-0.941***	-0.928***	-0.921***	-0.962***	-0.930***	-0.913***	-0.758***	-0.729***	-0.682***
	(0.055)	(0.055)	(0.056)	(0.069)	(0.067)	(0.066)	(0.065)	(0.064)	(0.062)
$N \times T$	1672	1672	1672	1650	1650	1650	1606	1606	1606

Notes: This table is built on the ARDL specification of Equation (4.8) where the dependent variable is public debt (C^{pub}) and vector X contains the series of prices (P), short-rate (R^{short}) and output (Y). Lag order of p and q is set to 1, 2 and 4 in each column. ϕ is the speed of adjustment. Sample period 2000Q1-2019Q4 for 22 countries (N=22, T=80) after de-factoring using Equation (4.1). */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels. Standard errors in parentheses. All estimations contain a constant, but not reported for brevity.

Table 4.11. PMG estimates of long-run effects between growth and credit using short-term rate

	Dep. ΔY								
	Panel (a)			Panel (b)			Panel (c)		
	Lag = 2	Lag = 3	Lag = 4	Lag = 2	Lag = 3	Lag = 4	Lag = 2	Lag = 3	Lag = 4
ΔP	-0.159***	-0.147***	-0.158**	-0.161***	-0.159***	-0.122*	-0.157***	-0.151***	-0.132**
	(0.053)	(0.055)	(0.063)	(0.054)	(0.056)	(0.064)	(0.052)	(0.054)	(0.063)
ΔR^{short}	-0.0180	-0.131	-0.233**	-0.020	-0.083	-0.156	-0.083	-0.180**	-0.216**
	(0.072)	(0.084)	(0.098)	(0.071)	(0.085)	(0.097)	(0.073)	(0.086)	(0.098)
ΔC^{hh}	-0.0369	0.004	0.012						
	(0.048)	(0.053)	(0.062)						
ΔC^{cor}				-0.055*	-0.088**	-0.134***			
				(0.032)	(0.035)	(0.038)			
ΔC^{pub}							-0.131***	-0.151***	-0.096*
							(0.046)	(0.048)	(0.057)
ϕ	-0.835***	-0.811***	-0.753***	-0.825***	-0.809***	-0.759***	-0.838***	-0.837***	-0.771***
	(0.081)	(0.092)	(0.086)	(0.081)	(0.090)	(0.082)	(0.077)	(0.086)	(0.083)
$N \times T$	1650	1628	1606	1650	1628	1606	1650	1628	1606

Notes: This table is built on the ARDL specification expressed in Equation (4.8), dependent variable is output (Y) and vector X contains the series of prices (P), short-rate (R^{short}) and each credit variable. Lag order of p and q is set to 2, 3 and 4 in each column. ϕ is the speed of adjustment. Sample period 2000Q1-2019Q4 for 22 countries (N=22, T=80) after de-factoring using Equation (4.1). */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels. Standard errors in parentheses. All estimations contain a constant, but not reported for brevity.

Table 4.12. PMG estimates of long-run effects between growth and credit using long-term rate

	Dep. ΔY								
	Panel (a)			Panel (b)			Panel (c)		
	Lag = 2	Lag = 3	Lag = 4	Lag = 2	Lag = 3	Lag = 4	Lag = 2	Lag = 3	Lag = 4
ΔP	-0.177***	-0.163***	-0.174***	-0.180***	-0.173***	-0.133**	-0.182***	-0.168***	-0.150**
	(0.053)	(0.057)	(0.064)	(0.055)	(0.058)	(0.066)	(0.053)	(0.055)	(0.063)
ΔR^{long}	-0.0566	-0.0496	-0.288**	-0.0730	-0.111	-0.281**	-0.107	-0.135	-0.262**
	(0.083)	(0.097)	(0.114)	(0.085)	(0.099)	(0.116)	(0.081)	(0.093)	(0.111)
ΔC^{hh}	-0.0587	-0.0133	-0.008						
	(0.049)	(0.054)	(0.063)						
ΔC^{cor}				-0.053*	-0.093***	-0.154***			
				(0.032)	(0.036)	(0.039)			
ΔC^{pub}							-0.139***	-0.146***	-0.0965*
							(0.047)	(0.048)	(0.056)
ϕ	-0.823***	-0.793***	-0.751***	-0.815***	-0.790***	-0.757***	-0.828***	-0.826***	-0.775***
	(0.080)	(0.088)	(0.083)	(0.078)	(0.082)	(0.076)	(0.075)	(0.085)	(0.082)
$N \times T$	1650	1628	1606	1650	1628	1606	1650	1628	1606

Notes: This table is built on the ARDL specification expressed in Equation (4.8), dependent variable is output (Y) and vector X contains the series of prices (P), long-rate (R^{long}) and each credit variable. Lag order of p and q is set to 2, 3 and 4 in each column. ϕ is the speed of adjustment. Sample period 2000Q1-2019Q4 for 22 countries (N=22, T=80) after de-factoring using Equation (4.1). */**/*** indicate rejection of the null hypothesis at 10%, 5% and 1% significance levels. Standard errors in parentheses. All estimations contain a constant, but not reported for brevity.

4.5.4 Short-run analysis

4.5.4.1 Impulse response functions

In this section, we opt to estimate a panel VAR (PVAR) in first difference to present the short-run dynamics of the relationship between the three different types of credit and output using the de-factored data.[79][80] The PVAR we estimate has four lags chosen based on the minimum of AIC.[81] We follow Goodhart and Hofmann (2008) and order real variables first followed by financial variables under the assumption that monetary variables respond immediately to a real shock. Our interest is to study if there is a bi-directional or unidirectional relationship between credit and growth in the short-run. Similar to the panel ARDL approach, we consider the PVAR estimation once with the original data where CSD is present and once with de-factored data.

First, we start with the original dataset, i.e., without de-factoring. The results in the left panel of Figure 4.5 show the response of each type of credit to a one-standard-deviation shock in growth, in all three cases, the response of credit variables is negative and significant. The right panel of Figure 4.5 presents the response of output growth to a one-standard-deviation shock in each of the credit variables. Regarding household credit, output reacts positively and significantly up to 0.1 percentage points. Such effect lasts as long as nine quarters; after that, it stays positive but becomes insignificant. Corporate credit has the opposite effects compared to household credit. It is quite evident that growth responds negatively to a positive shock in corporate credit and reaches 0.1 percentage points staying significant up to eight quarters. Our results are qualitatively similar to Mian et al. (2017), who argue that corporate and household credit shocks have statistically distinct effects on growth in the short-run. Regarding a positive shock in public debt, there is a slightly significant response of growth, which is negative and reaches 0.05 percentage points only for the first quarter.

Our second exercise in the short-run analysis is to consider the same PVAR setting, i.e., same order and use each variable in the first difference, however, this time with the de-factored data. The right panel of Figure 4.6 depicts that the response of output growth to a one-standard-deviation shock in each of the credit variables is statistically insignificant. A slight exception is the response of growth to public debt, in which growth responds negatively and significantly only at quarter four, after that, the response stays negative but insignificant. The left panel of Figure 4.6 reveals that output growth

[79] Our PVAR and the panel ARDL are both comparable to each other in the sense that both models are estimated in first difference.

[80] Our short-run analysis in this chapter is different from previous literature mainly in two features. First, while previous authors use variables' averages to model cross-sectional dependence, we use principal component analysis. As seen before, the PC approach has the desirable feature of remaining robust to multiple factors structure in the data. Second, we use household and corporate credit besides public debt for comparison, while current literature presents the results of only one type of credit, see, e.g., Chudik et al. (2017) on public debt and Lombardi et al. (2017) on household credit and

[81] All eigenvalues of the dynamic matrix in the PVAR system are within the unit circle, satisfying stability conditions of our estimation.

responds negatively to a positive shock in each of the credit variables which is similar to the results obtained using the de-factored data presented in the left panel of Figure 4.5. For example, a one-standard-deviation shock in household credit triggers a negative and significant impact of 0.05 points on growth which lasts as long as four quarters. The negative effect of growth on corporate credit is larger and reaches 0.1 points in the third quarter. Similarly, public debt responds negatively to a positive shock in growth with the largest impact of 0.1 points in the second quarter, and such impact stays negative until the end of the forecast horizon. In summary, the IRFs results provide a prima facie evidence that a negative relationship holds between credit and output growth and runs from the former to the latter and not the other way around. Such results are quantitatively and qualitatively similar to the ones obtained by Lof and Malinen (2014). However, the authors did not model cross-sectional dependence in their VAR analysis, which is one of the contributions of this chapter.

4.5.4.2 Granger-causality tests

We proceed to test for the direction of causality among credit and growth variables. Table 4.13 displays the results of the Granger-causality tests obtained from two PVAR estimations. The results in panel (a) are obtained using the de-factored data, while panel (b) represents the results obtained from the data with the presence of the common factors. As anticipated by the IRFs previously set out, we find that output growth Granger-cause household, corporate and public debt. However, such a relationship is not bi-directional, so that each type of credit does not Granger-cause growth using the de-factored data. However, we find that household and corporate credit significantly Granger-cause output growth using the data without de-factoring. In both cases, we did not find evidence that public debt Granger-causes output growth, which signals that such a link between both variables is in the form of association rather than causality.

4.5.4.3 Variance decomposition

In Table 4.14 - Table 4.17, we report the results of variance decompositions analysis, which highlight the importance of credit variables in explaining output growth and vice versa. In line with previous results, all credit variables have relatively low forecast power for output growth using the de-factored data. Specifically, 0.345%, 0.288% and 0.570% of the error variance forecast of output growth, over a time of twelve quarters, can be explained by household, corporate and public debt, respectively. Unsurprisingly, output growth has relatively higher forecasting power in explaining each type of credit. Such value equals to 3.430% and 3.034% of the error variance forecast of household and corporate credit and reaches up to 6.054% of public debt over a time of twelve quarters. On the other hand, Table 4.18 - Table 4.21 present the results without de-factoring. In line with the findings of the IRFs and Granger-causality for the same set of variables, we find that 7.301% and

3.444% of the error variance forecast of output growth, over a time of twelve quarters, can be explained by household and corporate credit. Public debt has a low forecast power of 0.510% over twelve quarters for output growth. However, 9.611% of the error variance forecast of public debt can be explained by output growth over twelve months.

In summary, the short-run results from IRFs, Granger-causality and variance decomposition are parallel to the findings of the long-run analysis using panel ARDL approach. We notice that removing the global common factors from each variable in the dataset has a significant impact on our findings, especially on the direction that goes from output growth to credit variables. This evidence signals the significant role of the common factors in propagating monetary shocks that originate from the financial sector towards the real side of the economy.

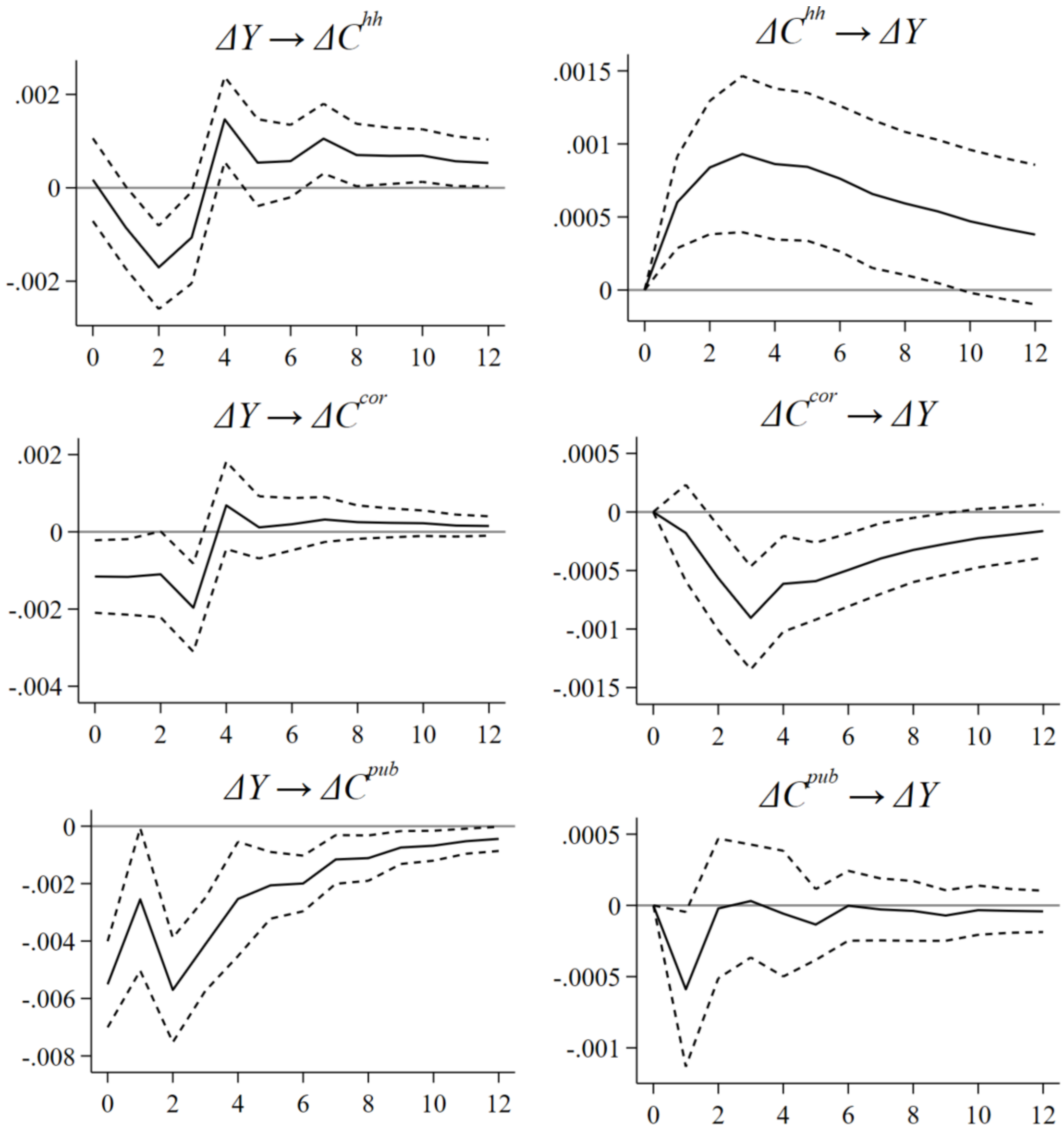

Figure 4.5. Household, corporate, and public debt (left) IRFs (solid lines) following a one-standard-deviation shock in output growth. Output growth (right) IRFs following a one-standard-deviation shock in credit variables. The dashed lines denote the upper and lower bounds of the 95% confidence intervals. All variables are not de-factored. IRFs obtained from PVAR model estimated on the panel data of 22 countries over the period 2000Q1-2019Q4 for 22 countries (N=22, T=80).

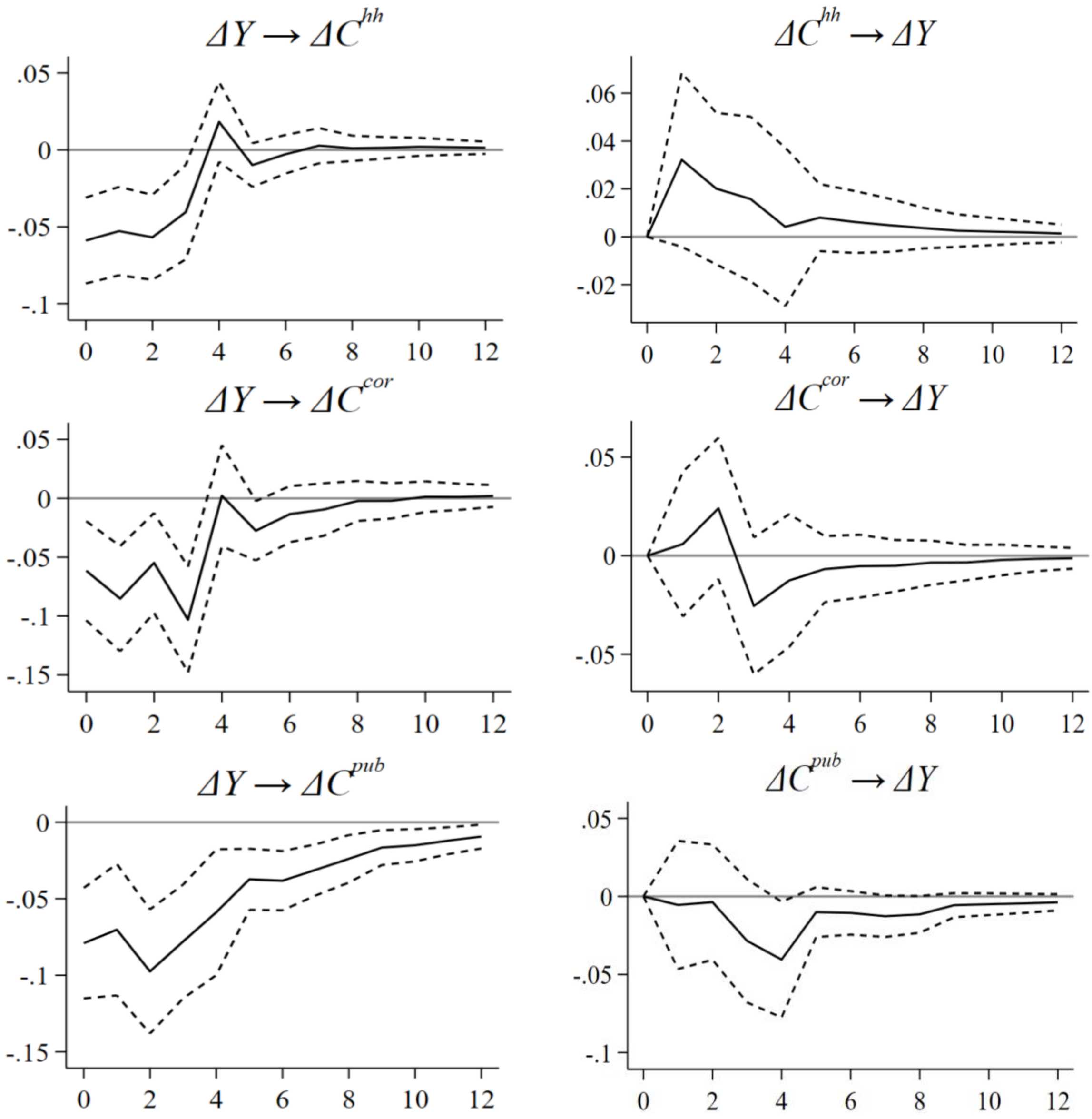

Figure 4.6. Household, corporate, and public debt (left) IRFs (solid lines) following a one-standard-deviation shock in output growth. Output growth (right) IRFs following a one-standard-deviation shock in credit variables. The dashed lines denote the upper and lower bounds of the 95% confidence intervals. All variables are de-factored using Equation (4.1). IRFs obtained from PVAR model estimated on the panel data of 22 countries over the period 2000Q1-2019Q4 for 22 countries (N=22, T=80).

Table 4.13. Granger-causality results

	Panel (a)		Panel (b)	
Null hypothesis	χ^2	p-value	χ^2	p-value
Output growth does not Granger-cause household credit	24.60***	0.000	44.07***	0.000
Output growth does not Granger-cause corporate credit	30.31***	0.000	25.39***	0.000
Output growth does not Granger-cause public debt	35.95***	0.000	39.18***	0.000
Household credit does not Granger-cause output growth	3.949	0.413	29.97***	0.000
Corporate credit does not Granger-cause output growth	6.072	0.194	19.46***	0.001
Public debt does not Granger-cause output growth	4.997	0.288	5.170	0.270

Notes: *** indicates rejection of the null at the 1% significance level. Lag length = 4 is selected based on the minimum of AIC. Granger-causality test are based on a likelihood ratio statistic that follows a χ^2 distribution with one degree of freedom. Panel (a) represent the results obtained from the de-factored data, while panel (b) results obtained using the original data. Sample period 2000Q1-2019Q4 for 22 countries (*N*=22, *T*=80).

Table 4.14. Variance decomposition of output growth over different time horizons

Horizons	Household credit	Corporate credit	Public debt	Output
3	0.276%	0.117%	0.001%	99.60%
6	0.330%	0.273%	0.482%	98.92%
9	0.342%	0.284%	0.555%	98.82%
12	0.345%	0.288%	0.570%	98.80%

Notes: Each time horizon (in quarters) shows the proportion of forecast error variance of output growth explained by household, corporate, public debt and output growth itself. For each row, figures add up to 100. Sample period 2000Q1-2019Q4 for 22 countries (*N*=22, *T*=80).

Table 4.15. Variance decomposition of household credit over different time horizons

Horizons	Household credit	Corporate credit	Public debt	Output
3	96.62%	0.149%	0.359%	2.880%
6	95.84%	0.186%	0.491%	3.429%
9	95.85%	0.201%	0.516%	3.428%
12	95.85%	0.204%	0.521%	3.430%

Notes: Each time horizon (in quarters) shows the proportion of forecast error variance of household credit explained by household, corporate, public debt and output growth. For each row, figures add up to 100. Sample period 2000Q1-2019Q4 for 22 countries (*N*=22, *T*=80).

Table 4.16. Variance decomposition of corporate credit over different time horizons

Horizons	Household credit	Corporate credit	Public debt	Output
3	1.444%	95.94%	0.801%	1.791%
6	1.606%	93.64%	1.707%	3.042%
9	1.674%	93.44%	1.881%	3.040%
12	1.699%	93.34%	1.933%	3.034%

Notes: Each time horizon (in quarters) shows the proportion of forecast error variance of corporate credit explained by household, corporate, public debt and output growth. For each row, figures add up to 100. Sample period 2000Q1-2019Q4 for 22 countries (*N*=22, *T*=80).

Table 4.17. Variance decomposition of public debt over different time horizons

Horizons	Household credit	Corporate credit	Public debt	Output
3	0.127%	0.037%	95.98%	3.868%
6	0.325%	0.271%	93.97%	5.497%
9	0.387%	0.290%	93.30%	5.954%
12	0.400%	0.292%	93.24%	6.054%

Notes: Each time horizon (in quarters) shows the proportion of forecast error variance of public debt explained by household, corporate, public debt and output growth. For each row figures add up to 100. Sample period 2000Q1-2019Q4 for 22 countries (*N*=22, *T*=80).

Table 4.18. Variance decomposition of output growth over different time horizons

Horizons	Household credit	Corporate credit	Public debt	Output
3	1.618%	0.536%	0.529%	97.37%
6	4.721%	2.644%	0.516%	92.19%
9	6.451%	3.266%	0.506%	89.77%
12	7.301%	3.444%	0.510%	88.74%

Notes: Each time horizon (in quarters) shows the proportion of forecast error variance of output growth explained by household, corporate, public debt and output growth itself. For each row, figures add up to 100. Sample period 2000Q1-2019Q4 for 22 countries (*N*=22, *T*=80) data without de-factoring.

Table 4.19. Variance decomposition of household credit over different time horizons

Horizons	Household credit	Corporate credit	Public debt	Output
3	98.13%	0.751%	0.166%	0.947%
6	97.43%	0.769%	0.268%	1.532%
9	96.89%	0.960%	0.360%	1.791%
12	96.46%	1.162%	0.417%	1.955%

Notes: Each time horizon (in quarters) shows the proportion of forecast error variance of household credit explained by household, corporate, public debt and output growth. For each row, figures add up to 100. Sample period 2000Q1-2019Q4 for 22 countries (*N*=22, *T*=80) data without de-factoring.

Table 4.20. Variance decomposition of corporate credit over different time horizons

Horizons	Household credit	Corporate credit	Public debt	Output
3	3.062%	94.05%	1.915%	0.965%
6	3.049%	93.10%	1.943%	1.906%
9	3.092%	93.02%	1.958%	1.929%
12	3.137%	92.93%	1.970%	1.954%

Notes: Each time horizon (in quarters) shows the proportion of forecast error variance of corporate credit explained by household, corporate, public debt and output growth. For each row, figures add up to 100. Sample period 2000Q1-2019Q4 for 22 countries (*N*=22, *T*=80) data without de-factoring.

Table 4.21. Variance decomposition of public debt over different time horizons

Horizons	Household credit	Corporate credit	Public debt	Output
3	0.221%	0.325%	92.11%	7.341%
6	0.516%	0.587%	89.77%	9.128%
9	0.721%	0.962%	88.77%	9.542%
12	0.885%	1.144%	88.36%	9.611%

Notes: Each time horizon (in quarters) shows the proportion of forecast error variance of public debt explained by household, corporate, public debt and output growth. For each row, figures add up to 100. Sample period 2000Q1-2019Q4 for 22 countries (*N*=22, *T*=80) data without de-factoring.

4.5.5 Robustness

We perform a battery of robustness checks to ensure the stability of our results. First, with respect to the common factor analysis, we extract the factors without applying any transformation to the data, i.e., standardization. We then obtain the series after de-factoring and apply the long-and-short run analysis. We find no difference in terms of final the results. We also exclude countries where the common factor dominates the series, i.e., R^2 > 70%, and exclude countries where the common factor is less relevant, i.e., R^2 < 25%., and once we exclude Brazil, and another time the US, because the former considered the least developed economy, and the latter is the most advanced and leading economy in our sample.

We further estimate the common factor using annual datasets from Jordà et al. (2017) for private credit and from Chudik et al. (2017) for public debt to observe any differences in the dynamics of the extracted factors. We find no substantial difference to the commonalities between countries concerning the common factor analysis. Second, we estimate the panel ARDL on different lags as presented in Section 4.5.3 and estimate the PVAR model with different order where we place credit series before output growth. While the main results in Figure 4.7 and Figure 4.8 in Appendix C remain similar to the baseline estimation, minor changes emerge in the response of output growth to credit. In particular, output growth responds negatively on impact to a shock in household credit and public debt, respectively. However, in the period after the shock, the response becomes insignificant. This result is due to the choice of causal ordering presented in the robustness check, i.e., output growth before credit, which is uncommon in the literature on the nexus between finance and growth using causal ordering.

4.6 Conclusions

This chapter models cross-sectional dependence in aggregate credit through the lens of a multi-factor structure framework using a principal component approach and considers the relationship between private and public debt with output growth. We examine the factor structure of household, corporate and public debt using a panel of 22 major economies over the period 2000Q1-2019Q4. We find considerable differences between the common factors of the three different types of credit. While household credit and public debt have two and three common factors respectively, which together account for of 58.9% and 40.7% variation on average for each type of credit, corporate credit is less correlated across countries with only an average commonality of 16.7%.

Remarkably, the asymmetry between the three types of credit concerning the global common factor continues to be evident across individual countries. While for some countries' household credit is characterized by high commonalities, explaining up to 86% in Greece, other countries are less tied with the common factor, explaining as low as 21.7% in Poland. Albeit the manifest of recent financial globalization, the results offer compelling evidence for the distinction in institutional frameworks and bankruptcy laws among the countries in our sample, which could be a source of economic divergence as the case in corporate credit. Nevertheless, our identification framework suggests that empirical models addressing credit in cross-countries studies should incorporate the fact that credit features a multi-factor structure rather than represent it using a single factor indicator, i.e., cross-sectional averages. To the best of our knowledge, we are the first to uncover this for the three types of credit.

In a second stage analysis, we study the nexus between credit and growth. We find that the relationship goes from growth towards credit and not the other way around using the de-factored data from the first empirical stage. In particular, we find that growth is a drag on credit variables, and again with considerable differences, depending on the type of credit. Public debt seems to be substantially affected by growth, followed by household credit. Since the common factor is removed, this result implies that the negative long-run association between credit and economic growth is mainly driven by the negative effect of growth on credit in the short-run.

However, when using the same empirical methods without filtering out the common factors from the data, i.e., with the presence of cross-sectional dependence, we find significant evidence on the link that goes from credit to growth. This interesting finding signals that the developments in the global system, i.e., the common factors, are responsible for the propagation of shocks from the financial sector to the real economy in individual countries. Given the interlinkages between financial markets, we argue that academics and policy practitioners should model credit as global rather than a local phenomenon when working on a panel data framework.

Our results imply that for credit to converge towards more sustainable levels, i.e., credit levels that are consistent with the economy's expansion, and for the economy to benefit from future waves of financial market development where banks' balance sheets, confidence and expectations become stronger, it may be relevant for individual countries, first, to continue using borrowers and lenders macroprudential policies which have the ability to foreshadow financial imbalances and strains.

Second, the global interconnectedness in credit requires central banks to systematically cooperate between them to reach flexible, and yet resilient credit dynamics that are consistent with the global growth, and, to remove country-specific barriers towards financial openness and technological advancements. These strategies are not only essential to build a sustainable environment for households to borrow and consume but also for corporates who require a longer time horizon on whether to invest or not and where to invest.

In future work, credit dependence can be further investigated in two directions. First, it would be interesting to incorporate country-specific variables to account for the differences in financial openness and institutional quality and to observe the heterogeneity between countries in this regard with a special focus on house prices. Second, it is useful to address the common factors in relation to global determinants such as oil prices, world GDP growth, among others, to search for the sources of comovement found in our chapter.

Appendix C

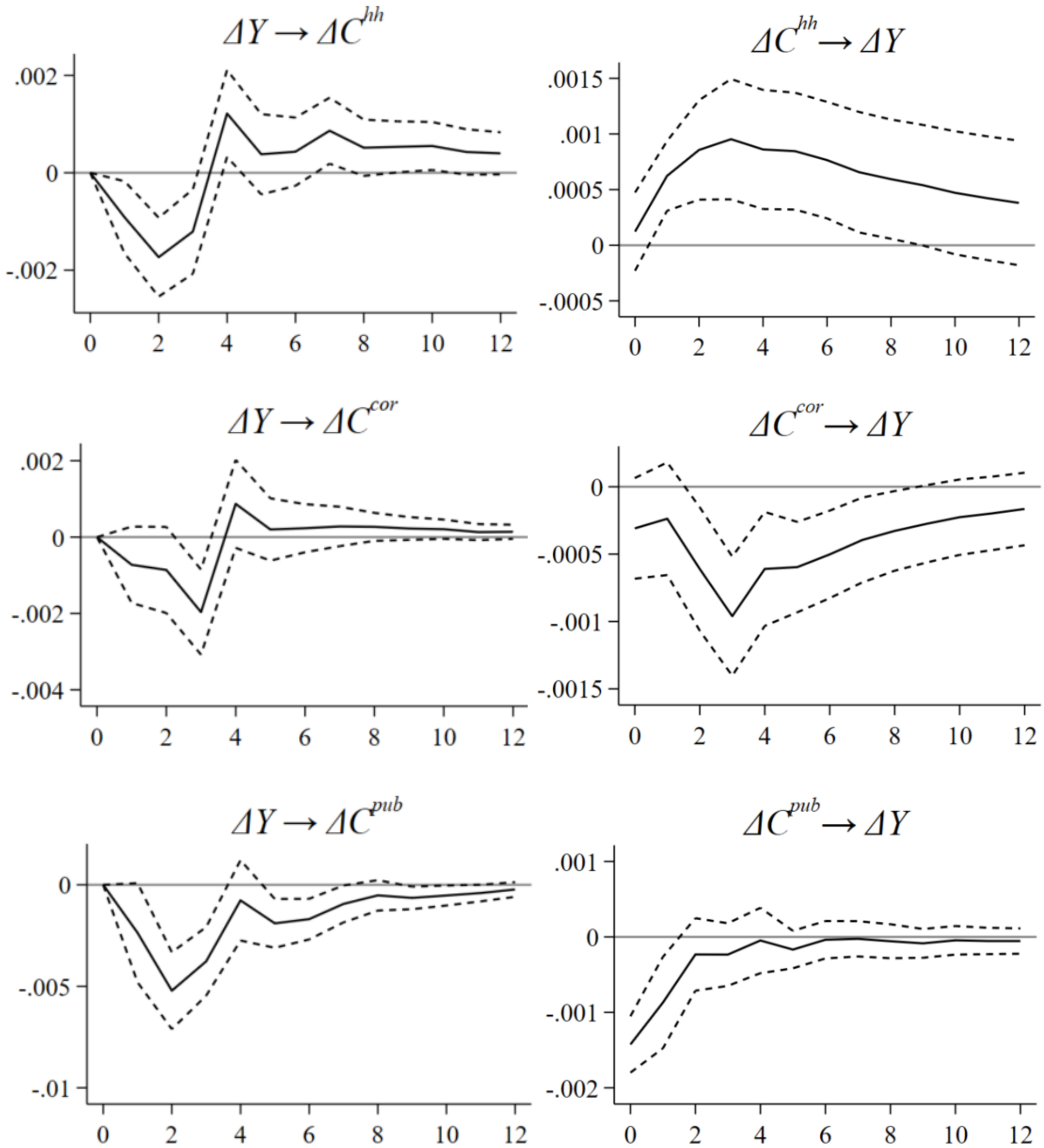

Figure 4.7. Household, corporate, and public debt (left) IRFs (solid lines) following a one-standard-deviation shock in output growth. Output growth (right) IRFs following a one-standard-deviation shock in credit variables. The dashed lines denote the upper and lower bounds of the 95% confidence intervals. All variables are not de-factored. IRFs obtained from PVAR model where output growth ordered before credit and estimated on the panel data of 22 countries over the period 2000Q1-2019Q4 for 22 countries (*N*=22, *T*=80).

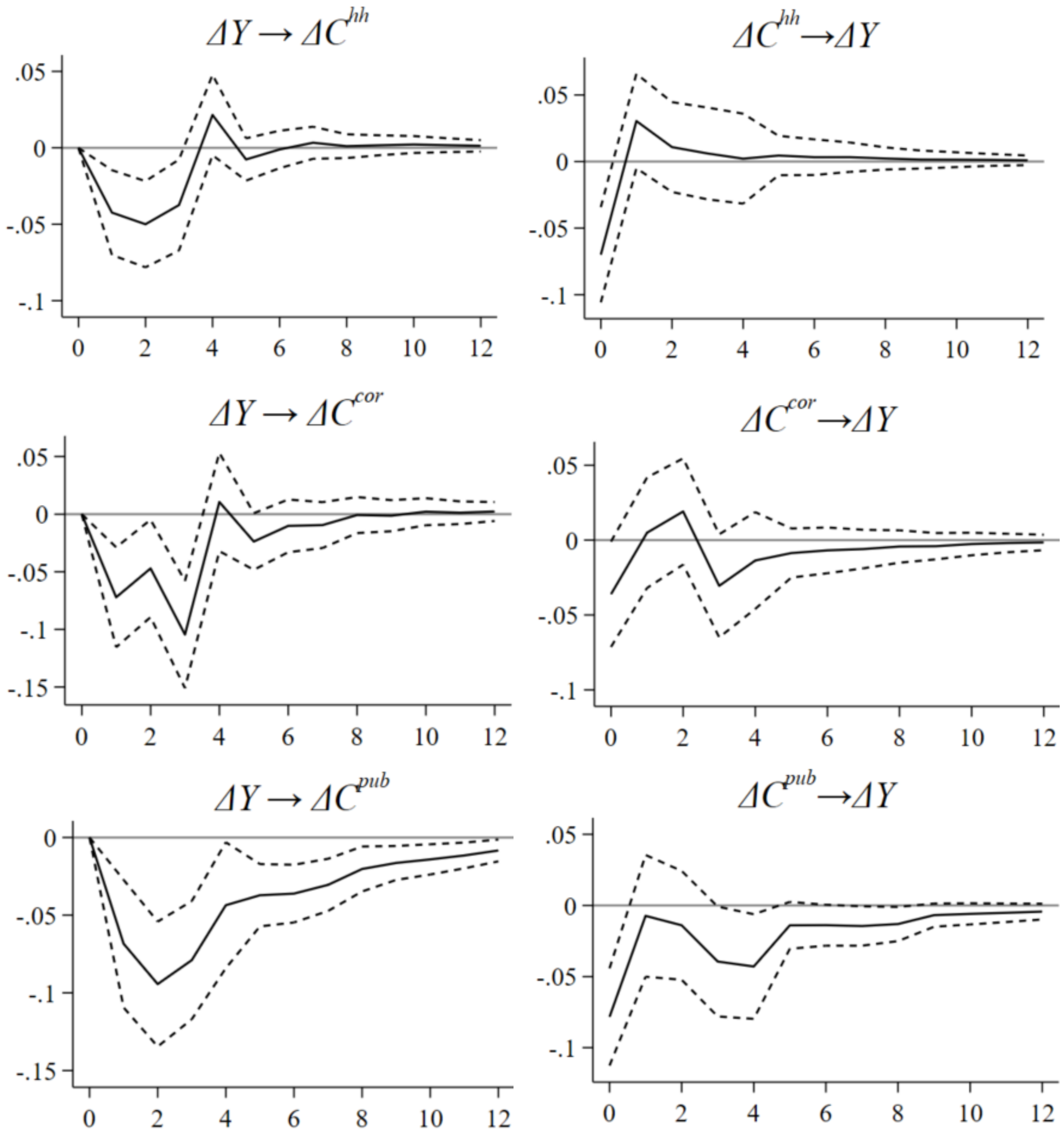

Figure 4.8. Household, corporate, and public debt (left) IRFs (solid lines) following a one-standard-deviation shock in output growth. Output growth (right) IRFs following a one-standard-deviation shock in credit variables. The dashed lines denote the upper and lower bounds of the 95% confidence intervals. All variables are de-factored using Equation (4.1). IRFs obtained from PVAR model where output growth ordered before credit and estimated on the panel data of 22 countries over the period 2000Q1-2019Q4 for 22 countries (N=22, T=80).

Chapter 5. Thesis conclusions

In this thesis, we present three interrelated studies on the role of banking shocks and credit in the real economy and aim to improve the understanding of the endogenous nexus between finance and growth. We do so by using traditional and advanced econometric methods that are novel and innovative for the research questions raised and are able to address some long-standing issues in the empirical literature on banking and the macroeconomy. This section summarizes the findings and contributions of this thesis and outlines relevant policy implications, research limitations and possible avenues for future research.

In Chapter Two, we investigate the impact of banking granular shocks – based on the Granularity Hypothesis – on financial stability, the latter being measured by the credit-to-GDP gap as a proxy for aggregate leverage risk. We contribute to the existing literature in three ways. First, we assume that large banking shocks are endogenously determined in respect to the real economy. We motivate this assumption by noticing that banks' balance sheets are affected by regulatory changes, interest and inflation rates, and in parallel, banks' intermediation contributes to economic growth or recession through investment and consumption channels. Second, we associate banking granular shocks with the credit-to-GDP gap as an indicator for financial distress, and thereby we put into question the suitability of the banking shocks measure to convey information about the build-up of financial vulnerabilities, i.e., extreme events of credit booms and busts. Third, we make use of methods that account for endogeneity and feedback effects between the financial and real sectors to deliver a more robust estimation process.

The empirical findings show that large positive banking shocks are associated with a sizable deviation of the credit-to-GDP ratio from its long-term trend which signals that the private sector is borrowing at levels that are not justified by the producing capabilities of the economy. Subsequently, in response to such excessive credit growth, the banking system becomes fragile and tends to precede crises. Further, the results show a reverse causality between banking granular shocks and output growth, for example, positive banking shocks increase economic growth, however, such positive relationship, again, reflects the build-up of macro-financial risks that may undermine the financial system. A bi-directional and casual relationship is also evident in our results between banking shocks and house prices. We argue that housing wealth and collateral effects are the origins of this relationship where banks pass the housing markets shocks onto the real economy, see, e.g., Goodhart and Hofmann (2008).

The insights in Chapter Two entail several policy implications in the context of financial stability.

First, banking granular shocks measure matters for policymakers and forecasters as it contains useful information about real economic activity. We argue that this is prima-facie evidence that such granular shocks could replace the yield spread, as the latter lost its predictive power over the last decade. Second, policymakers need to monitor the practices and standards of lending by large banking institutions because their shocks signal the building-up of financial risks. Macroprudential policies, such as lender- and borrower-based tools, are often believed to mitigate excessive risk-taking and adverse macroeconomic development by curbing credit supply. These policies are more likely to be successful when enforced during stable periods to allow banks adjusting their lending standards, hence the timing of monitoring banking shocks is crucial for policy implementation in this framework. Third, our views draw attention to policies that monitor banking market concentration because higher concertation tends to exacerbate large banking shocks, and subsequently, induce more severe fluctuations of macroeconomic aggregates. This strategy aims to enhance banking resilience and avoid costly government interventions in the form of bailouts of large banks.

Despite carrying out an extensive sensitivity analysis of our empirical work – our analysis suffers from a number of limitations due to the availability of the data in use. First, the BGS measure does not include a comprehensive and complete sample of large banks in each country due to data availability. As mentioned in section 2.3, if one bank has missing observations, we had to replace it with the next large bank available from *Datastream* database. Second, one of the robustness tests is to split the sample into a pre- and post-crisis subsample. A limitation here is that the resulting subsamples pose problems for a meaningful result, especially in the case of the short post-crisis subsample. Second, we use a broad measure of banks' loans (total loans). This implies that we are unable to learn about the exact sources of the calculated banking shocks, for example, whether or not large banking shocks differ or vary based on the type of loan, i.e., mortgage loans, personal or commercial and industrial loans. Moreover, the availability of banking data at a quarterly frequency would enable a potentially more refined estimation of the credit-to-GDP gap, a variable that is central for our analysis.

The literature on large banking shocks is new and still developing, therefore, the topic and findings in Chapter Two have several potential extensions. One possibility is to study the micro determinants of banking shocks by integrating bank-specific variables and characteristics, for example, profitability and efficiency measures. Another aspect of the literature that would deserve attention is the effect of unconventional monetary policy stance on banking shocks and financial stability. Further, it could be fruitful to investigate the nexus between the granular banking shocks and other financial and macro indicators such as global liquidity and risk measures or study the effects of mergers and acquisitions on banking shocks. Finally, it could be interesting to expand the dataset to include and compare banking shocks from another set of countries, for example, developing countries and emerging market economies. Another suggestion would be to compare and contrast shocks to other banks' sizes, i.e., medium and small banks, in relation to the macroeconomy. This direction would depart from the granularity hypothesis; however, it could address the banking sector in economies with a lower banking concentration and different banks' sizes.

These suggestions aim at understanding the dynamics of large banking shocks in different economic settings and therefore provide better guidance to policymakers operating in different country contexts.

In Chapter Three, we contribute to the recent literature concerning the macroeconomic effects of unconventional monetary policy (UMP) by studying the effects of ECB's UMP on private credit. Our approach consists of three steps. First, we investigate the time series properties of private credit in Europe. Second, we examine the long-run relationship between aggregate credit and ECB's policy measures. Third, we consider a short-run analysis and study the macroeconomic effects of UMP shocks identified using a structural Bayesian VAR.

Two findings emerge from the preliminary analysis in this chapter. We find a strong cross-correlation between countries in the panel data of private credit, and such interdependent is due to persistent common factors. Moreover, credit seems to display convergence properties over the full sample.

The main result of the long-run analysis carried out in both time series and panel data cointegration setting shows that credit comoves with the policy variables, and such results are robust when the analysis accounts for multiple structural breaks occurring in the data. Focusing on the short-run, we find that UMP shocks positively affect the common factor of credit. We take this result as evidence of the transmission mechanism of ECB's UMP, hence the policy actions by the ECB have been operative by allowing banks to convert the extra liquidity into further lending. Moreover, we find that an expansionary UMP shock is effective in reviving the economy by increasing output and prices and decreasing interest rates and levels of financial distress, whereas the effect on prices is weakly significant. Finally, the empirical results support the idea of using the shadow rate to identify monetary policy shocks, especially in the ongoing context of the zero lower bound where the conventional policy rates are unable to reflect policy actions by central banks.

Such findings inspire relevant policy discussions and implications. On this note, ECB should continue to maintain convergence in credit – which is needed to foster monetary policy in the EMU – by eliminating, or at least reducing, structural differences across financial institutions and lending standards of the Eurozone countries. These structural differences in fact might be at the origin of asymmetric shocks that eventually hamper the transmission mechanism of monetary policy. One suggestion to reduce asymmetric shocks and maintain convergence in credit is to have a common deposit insurance mechanism at the Euro level instead of the current insurance scheme at the national level. A Euro-based deposit insurance scheme might enable the resolution of crises centrally at the Eurozone level, and it is an urgent step towards creating an EU-banking union.

Moreover, because the response of prices to UMP shocks is weaker and less persistent compared to output, the ECB might need to find an effective solution to stabilizing prices other than, or beside, UMP. We argue that the ECB should still pursue other targets using UMP, for example, increase banks' liquidity, as long as they do not interfere with price stability. In response to this challenge, harmonized budgetary policies across the Member States along with a formation of a fiscal union will complement the EMU to secure price stability over a well-defined action and an agreed-on time-horizon.

The fact that credit in the non-Euro zone countries responds to ECB's policy measures, raises concerns about policy spillover from ECB to these economies. As a consequence, the ECB and its key counterparts need to acknowledge potential and adverse policy spillover effects. Central banks should arrange and communicate towards specific, and yet appropriate, UMP actions in terms of objectives, timing and target markets in their jurisdictions. We argue that such an agenda in times of economic turmoil and fallouts from the recent pandemic may become the norm for a monetary orientation to support lending in the context of economic stimulus, thereby creating incentives for international policy coordination. This also pleads in favour of coordination between polices, for example, monetary and macroprudential policies, to avoid adverse effects on the economy.

There are several limitations related to the analysis of this chapter. First, we do not control for banks' capital ratios in the Eurozone because such regulatory data is confidential and not available. Thus, one cannot rule out the hypothesis that the increase in private credit is driven by adjustments in regulatory capital requirements rather than UMPs actions. Second, we aggregate the monthly observations of ECB policy measures to match the quarterly data of credit. Such step poses challenges to the identification strategy of UMP shocks using zero and sign restrictions based on quarterly data. The possible applicability of these limitations does not, however, alter our approach, which focuses on the effect of UMP on private credit.

Finally, the findings in Chapter Three offer fruitful extensions for future research. First, it would be interesting to partition the aggregate credit series used in our analysis into household, corporate and public debt. Such approach will enable us to better gauge if UMP affects each type of credit in a different fashion, and identify which sector needs more attention from the central bank. Second, using disaggregated data at the country level might enable the researchers to better understand the response of each economy to UMP, and question whether asymmetry in policy shocks are in place across countries. Third, heterogeneity in response to UMP might be as well present across individual banks in different countries, to that end, a possible extension is to use micro-data on banks and study how they react to policy measures while controlling for bank-specific characteristics.

In Chapter Four, we study the nexus between finance and growth using a panel set of countries in the long- and short-run through the lens of a factor structure. The contributions of this chapter, besides using recent data on the last two decades, is the focusing on three types of finance, namely, household credit, corporate credit and public debt, and hence, the questioning as to whether the nexus between finance and growth depends on each type of credit. Another novelty of this chapter is the econometric framework we employ to model cross-sectional dependence which is a common issue in macroeconomic panel data. Notably, we rely on the principal component (PC) approach to de-factor the data and remove cross-sectional dependence. Unlike nonparametric methods used in the literature, for example, Chudik et al. (2017) on public debt and Lombardi et al. (2017) on household credit, the PC approach has the desirable feature of remaining robust to multiple factors structure in the data. To the best of our knowledge, the PC approach has not been employed in the literature to treat cross-sectional dependence when studying the finance and growth nexus.

The empirical findings of this chapter can be classified along three different orders. First, when modelling the factor structure of credit, the results show that household credit and public debt are strongly tied with the global unobserved common factors, while corporate credit exhibits mostly idiosyncratic behaviour. Albeit this commonality, credit development in individual countries presents a remarkable heterogeneity in their common factor and country-specific structures. Put differently, some countries are strongly tied with the global common factors compared to others. We take this as evidence of asymmetric transmission of common shocks in credit between the countries in our sample. Second, our empirical exercise using the de-factored data shows that growth is a drag on credit variables with considerable differences, depending on the type of credit. Public debt seems to be substantially affected by growth, followed by household credit. Subsequently, the negative long-run association between credit and economic growth is mainly driven by the negative effect of growth on credit in the short-run. Third, we find significant evidence on the link that goes from credit to growth using the same empirical methods, however, without filtering out the common factors from the data, i.e., with the presence of cross-sectional dependence. This finding signals that developments in the global financial system and the patterns of structural global common factors in credit are responsible for the propagation of shocks from the financial sector to the real economy in individual countries in our sample.

The findings of Chapter Four offer several insights. Three points stand out. First, academics and policy practitioners should explore the hypothesis that credit should, at least to some extent, be modelled as a global rather than a local phenomenon. This framework is plausible to solve the issue of dependence, ensure consistent estimation and hence find the appropriate policy measures that aim to promote sustainable development levels in private and public debt that are consistent with output. Second, in the presence of common factors – which can be accommodative of monetary policy stance as seen in Chapter Three of this thesis – reverse causality becomes apparent. Therefore, methods to account for endogeneity should be used when investigating the finance and growth nexus. Third, due to the international connectedness in credit, central banks may want to re-consider a new prudential policy tool that is tailored to a specific borrowing sector. This sort of policy is relevant because household credit – compared to corporate credit – is more tied with the global common factors, and hence, it is prone to global shocks beyond the control of one country which could weaken conventional policies taken at the local level. A complement to this suggestion is a global policy aiming at stabilising household credit at the global level, which again requires policy coordination between national central banks from different countries.

Some caveats to the results of this chapter are in order. First, our sample period is recent and focuses only on the last two decades, a period that has seen financial deepening, a build-up of financial imbalances and implementation of new monetary policies and reforms. As a result, our conclusion does not necessarily speak about finance and growth nexus before the year 2000. Second, and in a similar vein, our relatively short data sample does not allow us to study non-linearities and threshold effects between the finance and growth nexus. A natural question that arises here is what the normal and sustainable levels of credit would be to maintain economic welfare. Although such a question remains beyond the scope of this chapter, any assessment in this direction must consider the global difference between three types of credit that we highlight in this chapter.

Modelling the finance and growth nexus using PC approach allows for promising avenues for future research. First, more investigation is needed to understand the sources of heterogeneity between each type of credit concerning the global common factors and the asymmetric transmission of common factors across countries. Incorporating country-specific variables, for example, key characteristics of the financial system and behavioural or institutional factors would be useful to observe if the finance and growth nexus varies with these factors. Second, our findings only utilize private and public debt as measures of finance in this chapter. However, equity finance is also important in channelling funds to the real economy. Investigating the role of common factors in the stock market in relation to growth can be a fertile topic for future research. Third, one may develop a user-friendly statistical package that integrates the PC approach to model cross-sectional dependence which can be useful for many applications in the macro-financial literature.

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