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Essays on Applied Macroeconomics, Banking and Financial Stability

Nicolas Reigl

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Essays on Applied Macroeconomics, Banking and Financial Stability

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Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology, has not been submitted for any academic degree elsewhere.

Nicolas Reigl ________________________________
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List of Publications

- I Nicolas Reigl (2017). "Forecasting the Estonian Rate of Inflation Using Factor Models". *Baltic Journal of Economics* 17.2, pp. 152–189
- II Nicolas Reigl (2022). "Noise Shocks and Business Cycle Fluctuations in Three Major European Economies". *Empirical Economics* (forthcoming) (*forthcoming*)
- III Nicolas Reigl and Lenno Uusküla (2021). "Alternative Frameworks for Measuring Credit Gaps and Setting Countercyclical Capital Buffers". *Journal of Financial Economic Policy* 13.2, pp. 161–179
- IV Juan Carlos Cuestas, Yannick Lucotte, and Nicolas Reigl (2020). "Banking Sector Concentration, Competition and Financial Stability: The Case of the Baltic Countries". *Post-Communist Economies* 32.2, pp. 215–249
- V Juan Carlos Cuestas, Yannick Lucotte, and Nicolas Reigl (2022). "The Evolution and Heterogeneity of Credit Procyclicality in Central and Eastern Europe". *International Journal of Finance & Economics* 27.1, pp. 911–942

Author’s Contributions to the Publications

I The author of the thesis is the sole author of the article.

II The author of the thesis is the sole author of the article.

III The author of the thesis had a leading role in systematising the literature review, preparing the dataset and drafting the paper

IV The author of the thesis had a leading role in systematising the literature, preparing the dataset, conducting the first part of the empirical analysis and drafting the paper. The author of the thesis acted as the corresponding author in the later phases of the publishing process.

V The author of this thesis had a leading role in systemising the literate, preparing the dataset, conducting the first part of the empirical analysis and writing the paper. The author of the thesis acted as corresponding author in the later phase of the publishing process.

Introduction

During the run up to the financial crisis in 2008 and the subsequent economic crisis, many countries saw economic booms, high inflation, fast credit growth, and changes in the structure of the financial sector, such as increasing concentration between banks. The global financial crisis shone light on some blind spots in economic thinking and the models used, particularly in the area of how macroeconomic and financial conditions are linked. The crisis sparked discussions about how expectations form in the economy in general, including how expectations about inflation, output and future productivity are formed. Furthermore, the crisis provoked a re-evaluation of how macro-financial linkages affect the financial system and the economy as a whole.

This thesis consists of five studies in applied macroeconomics that consider various aspects of financial cycles, business cycles, and the link between the structure of the financial sector and financial risk. In broad terms, this thesis looks at the relationship between the macroeconomic aggregates and price dynamics and the links between finance and the macro-economy. The publications in this thesis analyse inflation dynamics in Estonia, financial stability in the three Baltic countries, and credit dynamics in Central and Eastern European countries. In addition, the thesis provides comparative evidence for the role of expectational error shocks or noise shocks in business cycle fluctuations in France, Germany and Italy. Finally, one study in the thesis analyses measures of financial cycles for a wide set of countries in Europe.

Business cycle analysis looks at questions that relate to overall macroeconomic developments at a global, country or sectoral level, while studies that concentrate on the financial sector deal with the movement of various aspects of the financial system. The core interest of business cycle research lies in understanding the dynamics of output, employment and inflation; the cyclicality of the components of aggregate demand, meaning consumption, investment, government spending and exports; and the persistence of movements of aggregate activity. Research into the financial sector mostly focuses on understanding the factors that influence financial variables, and understanding the potential relationship between economic and financial fluctuations.

Cyclical analysis of the economy is nothing new. The first systemic set of empirical results on measuring business cycles was produced as early as 1946 by the seminal work of Burns and Mitchell (1946). Over the decades the literature has established several stylised facts. One is that consumption, investment, exports and imports on average show procyclical behaviour with output (Uribe and Schmitt-Grohé 2017, p.6), with their own lead and lag structure. Another important question is whether business cycles in poor, emerging and rich countries look different, and whether the stylised facts of the developed world also hold for other parts of the globe. Although certain models and empirical findings are well established for rich countries, alternative models might be required to explain business cycle fluctuations in emerging or transition economies (Rand and Tarp 2002; García-Cicco et al. 2010). Emerging economies tend to have more volatile business cycles than developed ones (Neumeyer and Perri 2005).

There is a growing literature analysing how developments in the financial cycle might affect business cycle fluctuations. General equilibrium models that include a financial sector predominantly tend to model the interaction between financial factors and macroeconomic aggregates with two assumptions. First, it is assumed that the financial system acts as an amplifier of shocks, and second, the financial system is assumed to be the source of shocks that triggers business cycle fluctuations (Kiyotaki and Moore 1997; Gertler and Karadi 2011; Iacoviello 2005). The balance sheet of households gives rise for example to various procyclical mechanisms, since the value of collateral such as residential property affects borrowing constraints and the dynamics of consumption.

The empirical relationship between economic activity and inflation may have weakened over time (Koop and Korobilis 2012; Constancio 2015; Del Negro et al. 2020), but inflation is still considered to be a cyclical variable as it reacts to disturbances in demand and supply. Inflation rates incorporate the price changes of a wide range of goods and services. Some of those rates respond more to economic conditions, implying stronger cyclical behaviour, while others can be quite acyclical. The varying degrees of subcomponent cyclicality have led researchers to examine whether the weakening observed in the Phillips curve relationship is driven by changes in the composition of components and sectoral factors. Stock and Watson (2020) for example use 14 core personal consumer expenditure price index inflation subcomponents from the US and analyse the degree of cyclicality by looking at the relationship between each subcomponent and economic activity.

Potential drivers of an economic upturn come from an increase in demand, but structural shifts such as changes in the sectoral preferences of the labour force after the Covid-19 pandemic can also induce cyclical dynamics. Shocks that appear transitory in nature, such as the increase in energy prices following the Russian invasion of Ukraine, might become entrenched in inflation expectations. On a theoretical level, inertia in inflation dynamics can be linked to business cycle fluctuations by the cyclical behaviour observed in marginal costs, and the two main components of that behaviour, labour productivity and real wages (Gali et al. 2001).

In the run up to the global financial crisis, Estonia for example experienced high levels of inflation, which peaked at around 11% in April 2008. The subsequent severe economic downturn was accompanied by inflation falling into negative territory in May 2009. After a brief period of deflation that lasted until February 2010, inflation accelerated again to levels that should not have been reached given the length and severity of the global financial crisis. This phenomenon, termed the "twin puzzle", was not unique to Estonia but affected the euro area as a whole. The first part of the twin puzzle was that inflation was higher than expected, while the second part of the puzzle arose after 2012 when the inflation rate was lower than expected given the speed of the economic recovery (Ciccarelli et al. 2017; Kulikov and Reigl 2019).

Even though inflation in Estonia was more subdued in the years following the global financial crisis, forecasting it has proved challenging. At the time of writing in August 2022, Estonian headline inflation stood at over 20%. Even though an important component of the rise in the inflation rate has come from energy and food price shocks (Eesti Pank 2022), there are other factors such as structural shifts from changes in the sectoral preferences of the labour force after the Covid-19 pandemic, and expectations of inflation that play a role. The new hikes in inflation have clearly made inflation forecasting using simple autoregressive models difficult, and structural approaches might be of more use. Simple Phillips-curve models, which are used in research into the business cycle, have not been able to explain satisfactorily the dynamics of euro area inflation after 2012 (Kulikov and Reigl 2019). Publication I studies how to augment inflation forecasting models with methods that can accommodate high-dimensional data. The large dataset covers a wide range of domestic and foreign indicators that is subsequently used to extract information to produce forecasts for a low inflation environment. The publication contributes to the literature by showing that factor model forecasts can improve upon simple univariate forecasts of Estonian headline and core inflation, but the forecasting gains are small and not systematic. The publication also adds to the existing literature by showing that subgroup factors that are extracted from a homogeneous set of variables can be included in forecasting models to sharpen forecast performance. While factor model forecasts seem to perform well in a low inflation environment where there are no structural breaks, Philips curves or even broader models might be of more use in the current climate.

Total factor productivity is a central variable in explaining long-run economic growth. TFP is generally seen as a technological multiplier that makes capital and labour more productive. One important source of long-term economic growth is changes in technology (Bean and Pissarides 1993; Rogerson 2006; Reif et al. 2021). Technology also plays an important role in the analysis of short-run business cycle fluctuations (Galí 1999). In the early stages of business cycle analysis, technology was reduced to exogenous disturbances that impacted the economy as random innovations that made people more productive. In a neoclassical workhorse model like the Real Business Cycle Model (Kydland and Prescott 1982), shocks to technology are the main factor affecting economic growth. Those models synthesise business cycle fluctuations by interpreting total factor productivity (TFP) as a measure of technology that is subject to trend growth and exogenous, stochastic deviations from the trend. Technology shocks played a lesser role in subsequent models for explaining business cycle fluctuations, like that popularised by (Galí 1999) for example. [1]

Frameworks within New Keynesian models have been developed in the recent literature that combine expectations about technology and prices (Eusepi and Preston 2011; Benhima and Poilly 2021). Different drivers of expectations have been discussed in the literature, among them psychological wave (Akerlof and Shiller 2010) or self-fulfilling animal spirits (Farmer 1999; Farmer 2012a; Farmer 2012b; Benhabib et al. 2016). The driving force of any expectation is a diverse set that contains news about future demand patterns, future technologies and future demographic trends. The news view argues that the sources of information that firms and households have access to are imperfect. As the agents are imperfectly informed, any expectations they form might be subject to misperceptions. Agents might be overoptimistic about future technology or opportunities for consumption, thus driving an economic expansion. When the expectations driving the expansion are revised downwards, economic activity drops and the economy enters a recession. This is the mechanism through which news can influence business cycles. Publication II uses existing nowcasts to analyse how misperceptions of output and prices may influence business cycle dynamics in France, Germany and Italy. The publication adds to the literature on multiple fronts. First, it is to the best of my knowledge the first comparative study of supply noise and demand noise shocks covering countries outside the United States. Second, the results shows that demand noise shocks can have expansionary effects on output and inflation in France and Germany. Third, the publication contributes to the understanding of how much variation in output is explained by fundamental shocks and how much by noise shocks.

The dominant view in the pre-crisis world was that finance largely played a sideshow role in macroeconomic fluctuations. It was assumed that the only link between the financial and non-financial sides of the economy was through interest rates. At least in simple models, setting the real policy rate in line with the natural rate (Wicksell 1936)means that monetary policy will accommodate fluctuations in the economy to bring output into line with potential output. [2]This presumption may have been misguided. Juselius et al. (2016) criticise the predominant view as having been too narrowly focused on inflation and the output gap while omitting factors that affect the financial cycle. Even models that incorporated the financial side were inadequate when it came to creating and replicating the fluctuations in credit and output, as was later seen in the crisis.

[1]These models are often labelled as New Keynesian (NK) models. Prototypical stochastic general equilibrium NK models build upon the grounding of neoclassical models but allow for nominal frictions in both the goods and labour markets (Christiano et al. 2018).

[2]For a representative discussion see for example Woodford (2003).

The origins of the financial crisis of 2008-2009 can be traced back to a plethora of factors, most of them linked to the nexus of financial deregulation, international capital flows and monetary policy. While the specific factors varied from country to country, there were two overarching themes of financial vulnerability and credit shocks. The global financial crisis also triggered a re-evaluation of financial supervisory and macroprudential policy. Systemic risk was put under the focus of the policy makers alongside bank-level risk. Understanding systemic risk first requires analysis of cycles and the factors that affect them. Cyclical financial movements such as credit booms or credit busts carry risks that impede the functioning not only of the financial system but also of the real economy as whole.

The banking crisis also led to a large increase in public debt (Reinhart and Rogoff 2009; Reinhart et al. 2012; Laeven and Valencia 2013; Laeven and Valencia 2018; Furceri and Zdzienicka 2012). The increase in public debt stemmed from two main sources. First, fiscal resources were used to recapitalise failed financial institutions in the form of bailouts, or to fund restructuring measures. Second, the decline in economic activity led to surges in public debt as countercyclical policies were enacted to stabilise economies.

This makes understanding the drivers of financial risk crucial for awareness of the actual phase of the financial cycle (Borio 2014). The activation of macroprudential policy measures like capital buffers makes it especially important that policy makers recognise and understand the position of the financial cycle.

Research into the financial cycle involves documenting the relationship between credit, asset prices, and real economic activity (Borio et al. 1994; Detken and Smets 2004; Goodhart and Hofmann 2008; Schularick and Taylor 2012). The procyclicality of the financial system in particular has drawn considerable interest, as financial boom and bust cycles are costly for the banks involved and for the economy at large. The experience of the global financial crisis added impetus to the efforts of policymakers to develop a set of tools to identify and mitigate the effects of procyclicality in the financial system. One such tool is time-varying regulatory capital buffers for banks. These capital requirements should act countercyclically by setting buffers to restrain risk-taking in the financial sector during booms, and by releasing the buffers to cushion the effects during busts.[3] In that way, countercyclical capital buffers aim to smooth the business cycle through active demand management, where demand is influenced by credit supplied to households and firms in the economy. This ambitious goal is indirectly targeted by aiming for a broad macroprudential goal. This macroprudential goal consists of broadly smoothing the financial cycle by steering the provision of credit, and narrowly doing so by protecting banks from the build-up of system-wide vulnerabilities.

Other researchers have developed indicators of financial stress (Borio and Lowe 2004; Alessi and Detken 2011; Gerdesmeier et al. 2010). Research into which financial indicators other than the interest rate affect economic activity has also received considerable attention (English et al. 2005; Borio and Lowe 2004; Ng 2011; Hatzius et al. 2010). One particularly important area of research concerns the analysis of cyclical positions and turning points. Claessens et al. (2011) and Claessens et al. (2012) employ traditional methods for dating the business cycle for a large number of countries to identify peaks and troughs in credit and asset prices. Methods for dating the financial cycle can also use filters based on frequency or spectral density to identify the length and amplitude of financial cycles (Aikman et al. 2014).

Post-crisis reforms of the Basel III framework led to guidelines for the implementation of

[3]Risk-taking behaviour has been identified as a key-channel that transforms supportive financial conditions into boom-bust cycles (Borio 2013).

a regulatory leverage ratio in addition to the risk-weighted capital ratios. The countercyclical capital buffer is an integral part of the standards for risk-based capital. The countercyclical capital buffers themselves respond to the credit-to-GDP gap, which is an indicator of periods of excess credit growth (Basel Committee 2011). The baseline estimation for the credit-to-GDP gap is provided by the Basel III regulations, but alternative measures can be used to inform the policy maker about the stance of the financial cycle. Publication III delves into the question of how alternative credit-gap measures relate to financial developments in Europe, how they compare to the benchmark Basel III credit-to-GDP gap, or the Basel gap, and how countercyclical capital buffers would relate to the new measures of credit gaps. The paper suggests additional capital buffers that can complement the standard Basel buffers framework. The publication contributes to the existing literature by showing that simple credit cycle measures are well suited to complement the Basel gap measure. In addition, it shows that the alternative measures can also be used even if the available data are more limited than those for the Basel gap.

The financial sector of many countries experienced a consolidation of the banking industry in the decade following the global financial crisis. The number of banks declined in large advanced economies especially, though for some countries the consolidations appear to have continued from processes that had already started before 2007. Systemic risk, which is the risk of the entire financial system collapsing, also increased before the financial crisis in Europe, with the build-up more pronounced in Central and Eastern European countries. Furthermore, the banking sector structure was different in CEE and Western Europe (Uhde and Heimeshoff 2009). In the beginning of the 1990s, CEE countries started out with highly concentrated banking sectors, which remained more concentrated than those in WE countries despite the entry of foreign banks. The Baltic states, and Estonia in particular, stand out for their high levels of banking sector concentration, and they were also hit hard by the global financial crisis. Another feature of the banking structure in the three Baltic countries is the strong presence of foreign-owned banks.

The study of the relationship between systemic risk and banking sector structure builds on the literature analysing bank-level competition data and bank-specific risk taking. The competition-fragility and competition-stability views provide two competing hypotheses. The theoretical competition-fragility view, which dates back at least to Keeley (1990), Marcus (1984), and Smith (1984), argues that high levels of competition lead to incentives to take larger risks and reduce lending standards in order to gain market share. During recessions, however, the surviving numerous but small banks are affected negatively by procyclical credit patterns as they have not accumulated sufficient capital buffers, and therefore lending becomes curtailed, suppressing the economic recovery. The competing competition-stability view claims that high levels of market competition reduce moral hazard incentives, which may arise from by allowing banks to become too big to fail for instance, and improve the screening of potential borrowers as banks try to create long-term relationships with their customers (Boot and Thakor 2000).

The extensive literature on banking sector structure and risk does not yield conclusive results. A metastudy of 31 articles published between 2003 and 2014 found no evidence for any robust relationship between banking sector concentration and financial stability (Zigraiova and Havranek 2016). The results of the metastudy indicate that the choice of countries, measures of financial stability and bank competition, and the estimation method can influence the results. Publication IV analyses the relationship between banking sector concentration and financial stability from a micro-level perspective. The analysis is conducted for commercial banks in the three Baltic countries and covers a sample that spans the pre-crisis build-up of financial risk, and also the post-crisis consolidation period. Rather than estimating a simple linear relationship, the paper builds on newer theoretical predications by Martinez-Miera and Repullo (2010) and allows for a non-linear relationship between banking sector concentration and financial stability. The publication contributes to the literature on banking sector structure and bank-level risk taking by providing the first empirical evidence on the relationship for the three Baltic countries, which are prime examples of highly concentrated banking sectors. In addition the paper adds to the literature by incorporating the theoretical predications of Martinez-Miera and Repullo (2010) and modelling a U-shaped relationship between different proxies of competition and proxies of bank-risk.

Research into financial cycles has also aimed to identify factors that may contribute to the procyclicality of credit. The procyclicality of credit needs to be understood and possibly counteracted because it can exacerbate the economic cycle. In other words, credit procyclicality is a dominant factor deciding the peaks and the troughs of the economic cycle. Credit fuels investment and consumption during the expansionary phase, but it can also contribute to the creation of unsustainable booms, by creating a housing bubble for example. When the bubble bursts, the reduced creditworthiness of borrowers, falls in asset prices and a drop in economic activity are pushed further by the procyclicality of credit as credit institutions reduce their lending. The reduction in the credit released in turn affects consumption and investment negatively, thereby deepening and prolonging the recession. Publication V ties together the previous research by combining research on banking sector concentration in Central and Eastern Europe with analysis of credit cycle dynamics. The article presents evidence of credit procyclicality in CEE countries, where the degree of procyclicality is influenced by the competition structure of the banking sector in each country.

The main contribution of the publication is that it documents the heterogeneity of credit procyclicality between the Baltic countries and other Central and Eastern European countries. This publication also contributes to the understanding that banking sector competition also has effects on credit provision. The findings indicate that bank competition not only affects credit procyclicality in CEE but also explains differences in credit dynamics across the CEE countries.

This thesis is organised as follows. Section 1 describes the results for an inflation forecasting exercise for Estonia and shows how high-dimensional datasets can be used to improve the relative forecasting performance of a multivariate forecasting model. Section 2 shows how supply noise and demand noise shocks can drive business cycle fluctuations in France, Germany and Italy. In Section 3, alternative measures for measuring the financial cycle are discussed. Section 4 discusses the effects of banking sector concentration on financial stability in the three Baltic countries. Section 5 gives an overview of the connection between banking sector concentration and credit cycles. Finally, Section 6 concludes by outlining the contributions of the thesis and discussing potential future research areas. The Appendix contains the five publications of this thesis.

1 Economic indicators and high-dimensional forecasting models

Forecasting inflation dynamics is an important part of macroeconomic policymaking. In small open economies, the prices of imports affect domestic inflation while export prices determine export performance. During their initial integration into global trade and the deepening of their financial networks and supply chains, small open economies are exposed to global shocks. Such global shocks are an important source of domestic inflation. A combination of those factors can explain why forecasts based on simple Philips curve models tend to perform less well than Philips curve forecasts for larger economies (Matheson 2008). The relatively poor forecasting performance of simple Phillips curve models is often attributed to the lack of incorporating variables that capture the dynamics of energy price shocks and import price shocks (Batini et al. 2005), or a wider range of explanatory variables such as variables that capture inflation expectations (Kulikov and Reigl 2019).

Publication I, "Forecasting the Estonian rate of inflation using factor models", presents forecasts for the Estonian headline and core inflation rates using factor models. Producing accurate inflation forecasts has proven to be a challenge as numerous factors can influence the dynamics of inflation. Forecasters often rely on models that are able to incorporate only a few predictors. However, as increasing amounts of macroeconomic, microeconomic and financial data are becoming available, new models for forecasting can be used. The focus of Publication I is on forecasting the inflation rate during a period when the core and headline inflation rates are relatively low and persistent and there are no structural shifts.

Factor models can be used to summarise the information contained in the individual macroeconomic and financial time series. This paper uses the static principal component method as in Stock and Watson (2002) to extract the first six factors from a large dataset. This dataset contains macro data from Estonia and price data from its trading partners. In total it covers 388 domestic and foreign time series at 42 quarterly observations, ranging from the first quarter of 2004 until the second quarter of 2014. Although forward-looking inflation expectations were not available for the sample under observation, the dataset includes business sentiment and composite leading indicators that can proxy forward-looking business dynamics. To test for panel size and target predictor effects, the panel is split in the later parts of the analysis.

The forecasting equation follows the factor-augmented vector autoregressive (FAVAR) approach of Bernanke et al. (2005). The FAVAR consists of the headline or core inflation rate and a pre-specified number of factors that are extracted using the methodology by Stock and Watson (2002). This allows the joint dynamics of the inflation rate and a set of factors to be modelled, and also allows lagged dynamics to be controlled for. The forecasts are made at one-quarter to six-quarter-ahead horizons in a recursive pseudo out-of-sample forecasting framework. The variables to be forecast are the Estonian headline inflation rate and the Estonian core inflation rate. The forecasts are compared to a range of competing forecasting models with an autoregressive model forecast as the benchmark.[4]

The first part of the paper shows the result of a factor analysis that provides a picture of the dynamics in the large-scale dataset. The first extracted factor explains around 22% of the total variance in the large dataset. The cumulative share of the total variation of

[4] At the time that Publication I was written in spring 2016, methods for comparing the forecast performance of nested models in small samples were not well developed. Consequently no tests of comparative forecast performance were conducted. At the time of writing of this introduction in summer 2022, researchers have developed methods of testing for equal forecasting accuracy for the nested factor model (Stauskas and Westerlund 2021).

all the macroeconomic variables for the first three factors is around 47%. Visual analysis of the first three factors also shows that they tend either to comove with or to lead the headline inflation rate. In the large dataset with 388 variables, the producer prices of Estonia's trading partners generally contribute most to the first factor.

The main results of the analysis offer several interesting findings. First, even though factor models can improve upon the forecasting performance of autoregressive forecast models in most cases, the forecasting gain is limited. This means that forecasting the Estonian headline and core inflation rates remains a challenge even in a modelling framework that can accommodate large amounts of data.

Second, the size and composition of the dataset that is used to extract the factors matters for the forecasting performance. When the factors are extracted from the big dataset of 388 variables, models that include only the first of these factors tend to have forecasting performance that exceeds the forecasting performance of the benchmark autoregressive model.

Reducing the size of the dataset by excluding price-related variables creates a different set of factors. In this case the first three factors have to be included in the FAVAR model to achieve forecasts that outperform a FAVAR with one factor and the autoregressive benchmark forecasts. Reducing the size of the dataset by excluding price variables creates a different set of factors. To achieve forecasts that perform well, the first three factors have to be included in the FAVAR model. One potential reason for this is that the information content in the smaller dataset is lower and therefore more factors have to be included in the forecasting equation.

In addition, models that tend to show good forecasting performance for the headline inflation rate do not necessarily show good forecasting performance for the core inflation rate. Subgroup forecasts can help to sharpen the forecasting performance when the volatility of the headline inflation rate differs from the volatility of the core inflation rate.

The paper contributes to the growing literature on the use of FAVAR models for forecasting inflation in small open economies. The paper shows how the information contained in large datasets can be summarised through a small number of factors; the paper does not show that it is better to use the factors than the full dataset. It provides insights into what common dynamics drive the variation in a large set of predictors. The results of the paper also show that it remains a challenge to forecast the headline and core inflation rates in Estonia and outperform a simple autoregressive model or a random walk forecast. It is difficult to determine the exact size and composition of the dataset needed to extract useful factors, at least for the Estonian data, but some rules of thumb might be derived from the paper. While many FAVAR models offer small forecast accuracy gains, pronounced forecast gains can only be reaped from distinct specifications.

2 Expectational errors and business cycles

News about future technologies can create waves of optimism, causing firms to increase investment immediately, to meet future demand for example. Economic news also affects consumers, who form expectations about future prices and opportunities for consumption. One core premise in the news view literature is that agents receive imperfect information. If the amount of imperfect information is small and market opportunities actually materialise in the future, expectations do not majorly diverge from what is realised, and so the increase in current investment and consumption will not result in a crash in the future. However, if agents make errors, and become overly optimistic for example, the resulting boom will be followed by a crash. Therefore, if there are no changes in fundamentals, misperceptions can drive short-run fluctuations in the business cycle.

Publication II, "Noise shocks and business cycle fluctuations in three major European Economies", analyses the effects of supply noise and demand noise shocks on business cycle fluctuations. The study builds on the idea that news about future policies, demographics or technologies, and uncertainties about them, affects current macroeconomic conditions even when there are no material changes in the current underlying economic conditions.

The literature has mostly focused on fundamental supply shocks and supply noise shocks. Lorenzoni (2009) demonstrated that a supply noise shock is observationally indistinguishable from a fundamental demand shock. This means that an uninformed observer cannot distinguish whether the positive comovement observed between GDP growth and inflation stems from a positive supply noise shock or from a fundamental demand shock. This implies that small mis-specified models do not account for fundamental demand and demand noise shocks. Benhima and Poilly (2021) pick up that idea and develop a theoretical model for assessing the effects of supply and demand shocks, fundamental and noise alike. Their Dynamic Stochastic General Equilibrium (DSGE) model extends the classical New Keynesian model of Galí (1999) with information-related frictions. The decision-making agents in the model are households and firms that have an information set that consists of public signals, which are hit by noise shocks, and private signals about demand and supply shocks. The dynamics of the model arise from the asymmetry of the information available to firms and households. The authors then use their theoretical models to provide a general framework for identifying the supply and demand shocks, and use survey data in their empirical model to test their theoretical predictions on the US economy.

This paper builds an identification scheme on the idea that misperceptions can be approximated by nowcast errors of economic fundamentals. The empirical model is estimated with a structural vector autoregressive model that includes GDP growth, the inflation rate, the nowcast error for GDP growth, and the nowcast error for the inflation rate. The benchmark identification scheme builds on the idea that nowcast errors made by rational forecasters need to be internally consistent. This means for example that a demand shock that drives a positive correlation between GDP growth and the inflation rate should also cause a positive correlation between the nowcaster's error in output and the nowcast error for inflation. Sign restrictions on the impulse responses of the nowcast errors make it possible to identify fundamental shocks and noise shocks.

While Benhima and Poilly (2021) provide evidence of the effects of demand noise shocks for the US, no analysis exists for other large economies. A motivation for producing a comparative analysis of supply noise and demand noise shocks could be that the magnitude and speed with which key business cycle variables adjust varies in different countries. In addition, different countries have different monetary policy regimes, which could affect expectation formation, and they react differently to shocks affecting output, employment and inflation. Therefore, Publication II collects data for France, German and Italy, three large and integrated European economies whose monetary policy is conducted by the European Central Bank in Frankfurt. The model is estimated individually for each country. The sample starts from 2003Q1 for France and Germany and from 2003Q2 for Italy. The sample ends in 2019Q4 to avoid the large distortionary impacts that the Covid-19 pandemic had on macroeconomic indicators. The nowcast errors are calculated as the difference between the nowcast for GDP growth and the inflation rate from the professional forecasters participating in the Consensus Economics survey, and the first release estimates for the same variables from the national statistical offices.

The main model results are in line with the existing literature on fundamental supply and demand shocks. Positive supply shocks and positive demand shocks both have expansionary effects on output. As found in the general literature, a positive fundamental demand shock also drives a positive correlation between output and inflation. More interestingly, the expansionary response of GDP and inflation to supply noise shocks is visible for all three countries but the magnitude differs across countries. The expansionary effect of positive supply noise shocks is in line with the findings of Benhima and Poilly (2021). The reverse conclusion from the theoretical model should be that positive demand noise shocks should resemble an inverse fundamental supply shock. However, the results for France, Germany and Italy are at odds with the theoretical predications and the empirical findings of Benhima and Poilly (2021). A positive demand noise shock has an expansionary effect on output in France and Germany, though the impulse responses for Italy fall short of being significant. One potential reason for the difference in the results might be that there are differences in the monetary policy transmission across the three countries.

The main contribution of the paper is that it provides empirical evidence of the importance of supply noise and demand noise shocks in the three largest European economies. I quantify the contribution to business cycles made by both supply noise and demand noise shocks. The paper also shows that while supply noise shocks seem to have similar effects on output growth and inflation in the three European countries and in the US, as indicated by the results of Benhima and Poilly (2021), the effects of demand noise shocks in the three European countries are distinctly different to those from the US. The findings of my paper indicate there is an expansionary effect from demand noise shocks to output growth but the contribution of the shocks to fluctuations in the business cycle is less pronounced. While the benchmark model does not allow for analysis of the monetary policy channel, one potential factor explaining why the results in the US and in Europe are different might be that the effects of monetary policy are heterogeneous.

3 Financial cycles and countercyclical capital buffers

Interest in financial cycles increased markedly after the global financial crisis, with financial developments being viewed as an integral part of business cycle fluctuations. Financial crises can often lead to deep economic recessions with rising unemployment, triggering an increase in public debt levels and, potentially, expensive bailouts or countercyclical policies passed to stabilise the economy. Regulators increasingly seek to put in place polices that would address the question of how to determine the position of the financial cycle, and instruments that could counter adverse macro-financial developments. While it is not straightforward to measure what could be called excessive credit developments in the economy, many attempts have been made to provide frameworks for ways of capturing unbalanced credit provisioning in the economy. One such attempt is the Basel III international regulatory framework for banks, which has been developed by the Basel Committee on Banking Supervision. The main aim of the framework is to strength the regulation, supervision and risk management of banks (Basel Committee 2011).

Two core components of the Basel III framework are determining the state of the financial cycle and then calibrating the countercyclical capital buffers that are designed to reduce countercyclical financial dynamics by allowing for there to be enough capital in potential downturns. To set the countercyclical capital buffer, the underlying credit gap needs to be calculated. The main Basel III framework uses the debt-to-GDP ratio at quarterly values. The gap is then derived as the difference between the current ratio of total credit to GDP and the long-run statistical trend of that ratio. A positive gap opens when the actual value of the Basel gap is higher than the trend value, where the trend is calculated using a one-sided Hodrick-Prescott (HP) filtered debt-to-GDP ratio. If the actual debt-to-GDP value is higher than the long-term value, it is considered a sign of macrofinancial imbalance and a potential threat to the economy. The Basel framework suggests that countercyclical capital buffers be applied when the credit gap exceeds 2 percentage points. The buffer rate is then increased linearly to 2.5% of bank capital when the credit gap hits 10 percentage points.

The original framework for calculating the Basel gap has been the subject of much debate (Drehmann and Tsatsaronis 2014; Drehmann and Yetman 2018; Edge and Meisenzahl 2011; Lang et al. 2019). One major weakness of the original framework arose from the statistical properties of the HP filter, in particular its need to use long data-series to pick up a trend. Another point of criticism is that the deleveraging cycle in the aftermath of a period of excessive credit growth, in the wake of a financial crisis say, often comes with an implausibly large negative Basel gap. The mechanisms behind this phenomenon can be traced back to the statistical trend estimate, which is highly persistent. The longer a credit boom lasts, the more the trend inherits part of the excess credit growth, which may lead to a statistical trend estimate that is far above the one that would be justified by economic fundamentals. In the deleveraging phase, this weakness would lead to long-standing large negative gaps that might delay the activation of macroprudential policies if new and rapidly growing financial imbalances emerge.

While the Basel gap is considered the benchmark buffer guide for the countercyclical capital buffer, the European Systemic Risk Board recommends that national supervisory authorities should develop alternative measures of credit provisioning misalignments in order to address the potential shortcomings of the Basel gap.

The publication "Alternative frameworks for measuring credit gaps and setting countercyclical capital buffers" co-authored with Lenno Uusküla suggests a number of additional measures for calculating credit-to-GDP gaps. These additional measures can be used to validate the original Basel credit-to-GDP gap and to provide policy makers with tools that are better suited for shorter time series data. Some alternative measures also allow for an easier interpretation as they do not rely on statistical filtering techniques to calculate the credit-to-GDP gap.

The rules are calculated for countries in Central Europe for which longer data are available, and for a set of Central and Eastern European countries where shorter data are available. While the Basel gap shows negative gaps for some years after the global financial crisis, the new measures show few to no negative gaps for the countries with shorter time series. Overall, the new measures show similar results for the middle of the sample, which is where the Basel gap performs well in capturing the financial cycle. The new measures also show the financial boom of 2004 to 2007 much more strongly, and the gaps open at the right time before the financial crisis hits. The paper also estimates the buffer rate for the alternative credit gaps. Except for the 5% gap rule, which differs in the earlier parts of the sample, most gaps show similar dynamics. Therefore, the buffer rates also behave fairly similarly for many countries in the sample.

The first measure that the paper suggests is a change in the debt-to-GDP ratio over a two year period to allow the type of credit cycle to be picked up where credit growth is stronger than nominal GDP in shorter horizons. This measure of the gap is a compromise that can measure the depth of long-past episodes of financial deepening and early warning indicators of fast credit expansion. While somewhat longer periods would capture longer cycles better, they would fail to signal the rapid credit expansion that could set off rapidly emerging imbalances.

The second approach the paper suggests compares the nominal credit growth over two years with the average GDP growth rate over eight years. The eight-year average of GDP growth covers a sufficiently large window to account for business cycle dynamics. Furthermore, the method does not depend on long time-series, and it can also recognise shorter credit booms that the change in the debt-to-GDP ratio cannot pick up.

The third method uses the nominal growth in debt relative to a nominal growth rate of 5% to construct the gap. This rule could be interpreted as the annual real GDP growth rate of 2% and the annual growth rate of the GDP deflator of 2%. The remaining 1% is an extra margin to compensate for potential adjustments after the global financial crisis. Unlike the eight-year period rule, this method is not sensitive to credit-driven booms that result in either strong real GDP growth or high GDP inflation rates.

The fourth rule the paper assesses compares the level of debt to a trend value for GDP. This measure is close to the first alternative approach, which measured the change in the debt-to-GDP ratio over a two-year period. The fourth measure takes the debt-to-GDP ratio, but calculates it relative to the GDP trend value. The advantage of this approach over the Basel approach is that a positive gap opens when credit booms are accompanied by GDP booms.[5]

Finally, the paper also estimates the buffer rate for the alternative credit gaps. Most of the gaps except the 5% gap rule, which differs in earlier parts of the sample, show similar dynamics. The buffer rates consequently behave fairly similarly for many of the countries in the sample.

Overall, this paper shows that alternative measures of the credit gap can be used to support and improve upon the standard measure of the Basel gap. This follows the policy recommendation by the European Systemic Risk Board that suggests that information derived from alternative measures should be incorporated in discussions about whether

[5] The fourth rule also relies on an HP-filter to estimate a trend component. However, instead of estimating the credit-to-GDP gap, the fourth rule uses the HP-filter to estimate the trend component of GDP.

the Basel gap signals correctly the opening of a credit gap and where the countercyclical buffer rate should be set.

This publication contributes to the body of literature by suggesting measures that can be used in countries with relatively short time series. As a consequence, this publication also allows for an extended cross-country analysis of credit-cycle dynamics by including countries that have been neglected in previous studies.

4 Banking sector concentration and financial stability

Many Eastern European countries were already experiencing a marked increase in financial risks before the global financial crisis (Enoch 2007). Even when the convergence process towards Western European financial integration and country-specific financial states of development is controlled for, the deviations of credit from its long-term trend equilibrium could be observed (Zdzienicka 2011).

After the collapse of Lehman Brothers in the US in 2008 and the ensuing global financial crisis, a number of European banks were bailed out, while others merged or left individual markets in Central and Eastern Europe. These events led to an increased interest in understanding how changes in the structure of the market affect banking sector risks, including possible links between banking sector competition and banking sector stability.

There are two dominant, but contradictory, views. The first is the competition-fragility view, which argues that a high level of banking sector concentration can improve the stability of the financial sector. In a highly competitive market managers are incentivised to take large risks in order to meet short-term objectives. This may lead to riskier portfolios of assets, which might be impaired during times of financial distress. In the opposite case, a less competitive environment allows banks to afford higher capital buffers, thereby increasing their ability to absorb financial shocks.

The second view is the competition-stability view, which argues the opposite, proposing that the few available banks in a weakly competitive environment will dictate borrowing conditions, thereby increasing the cost of borrowing, which may make non-performing loans more likely to increase in number. The most important argument in favour of the competition-stability view is the "too big to fail" hazard. This moral hazard effect arises when the authorities are forced to provide bailouts when problems arise in large banks because the collapse of one large institution would endanger the financial system as a whole (Mishkin 1999).

Publication IV, "Banking Sector Concentration, Competition and Financial Stability: The Case of the Baltic Countries", co-authored with Juan Carlos Cuestas and Yannick Lucotte, contributes to the existing literature by providing evidence for the existence of a non-linear relationship between different measures of market concentration and proxies of bank risk in each of the three Baltic states. The banking sector in the three states, Estonia, Latvia and Lithuania, has a high degree of banking sector concentration, with a large number of mostly foreign commercial banks.[6]

Rather than analysing a simple linear relationship between market concentration and proxies of banking sector stability, the paper follows the theoretical predictions of Martinez-Miera and Repullo (2010), and allows for the possibility of non-linear relationships. The model of Martinez-Miera and Repullo (2010) reflects the view that both the competition-stability and competition-fragility views are appropriate, depending on the level of banking sector concentration.

The empirical estimation strategy considers all the commercial banks in the Baltic countries for which balance sheet data over the period 2004-2014 are available, giving an unbalanced panel of 40 banks. Both the Lerner index and market share are used as proxies of banking sector concentration. Financial stability at the firm level is evaluated by considering two different proxies of bank risk. The first is the Z-score, which measures the

[6] While the presence of foreign banks is one important characteristic of the banking sector structure in the three Baltic states, Publication IV does not find a statistically significant and economically meaningful relationship between the ownership structure and banking sector stability.

probability of a bank becoming insolvent. A higher Z-score implies a lower probability of default. For the second, the study also estimates models using the loan loss reserves as a percentage of gross loans.

A fixed effects model is estimated to give the baseline specification by regressing the proxy of risk on different measures of market concentration, a financial crisis dummy and a vector of controls. In order to analyse any potential non-linear relationship, the paper not only includes a squared term in the regression but also tests for the U-shape using the methodology developed by Lind and Mehlum (2010).

The empirical results show an inverse U-shaped relationship between the Lerner index and the Z-score, and a U-shaped relationship between the Lerner index, market share and the loan loss reserves. This means that both low levels of competition and high levels of competition are associated with an increase in the risk of insolvency for the banks. The optimal result for financial stability has on average been 0.606 for the Lerner index. This implies that the probability of insolvency is lowest at this level of market competition.

The results suggest that policy makers in charge of monitoring and regulating the banking industry should place greater emphasis on mergers and acquisitions. In highly competitive environments, mergers and acquisitions could be encouraged, as this would improve financial stability. At the same time, in countries like the Baltic states with a high degree of concentration, mergers and acquisitions would contribute to a build-up of financial risk.

This publication contributes to the empirical literature by providing an analysis of what relationship between banking sector concentration and banking sector stability holds empirically in a set of countries with very high levels of banking sector concentration. It also adds to the existing literature by showing that the Lerner index and the market share act as proxies of competition but are not necessarily highly correlated, and that they seem to capture different aspects of competition in the three Baltic countries.

5 Banking sector concentration and credit cycles

Credit is one the main drivers of the financial cycle. Procyclical credit dynamics can exacerbate the financial cycle, which then affects the dynamics of the business cycle. Procyclical credit provisioning makes economic boom phases faster. A rise in asset prices and easy access to credit drive consumption and investment. However, during periods of economic downturns, the procyclicality leads to restricted access to credit and a drop in economic activity.

Several studies have shown that Central and Eastern European countries have experienced deviations in credit above the long-term equilibrium, which cannot be accounted for by simple country-specific factors (Zdzienicka 2011). Furthermore, the banking sector structure in the Baltic region in particular is highly concentrated (Cuestas et al. 2020).

The focus of Publication V, "The evolution and heterogeneity of credit procyclicality in Central and Eastern Europe", co-authored with Juan Carlos Cuestas and Yannick Lucotte, is on the relationship between banking sector competition and the procyclicality of credit in the Central and Eastern European countries (CEECs).

The empirical analysis consists of two parts. First, the paper estimates a panel vector autoregressive model to assess the evolution of credit procyclicality. Next, the analysis is extended by estimating an interacted panel vector autoregressive model (IPVAR), following the example of Leroy and Lucotte (2019). The IPVAR model makes it possible to test whether differences in credit procyclicality across Central and Eastern European could potentially by explained by differences in the levels of banking sector competition.

The panel VAR includes four macroeconomic variables, which are real GDP, the consumer price index (CPI), the real outstanding amount of credit to the private non-financial sector, and the nominal short-term interest rate. The data cover the period 2000Q1–2016Q4 for a sample of 11 CEECs, which are Bulgaria, Croatia, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia. The Cholesky ordering of the variables in the VAR is determined by the question of how credit reacts to business cycle shocks. Alternative orderings are tested in the robustness section.

The first outcome is that the results from the PVAR analysis indicate that credit does indeed behave procyclically in the CEECs. A positive shock to the output gap has a positive and significant effect on bank credit. More importantly, the effect of an output gap shock is more pronounced during economic boom periods. The impulse responses also suggest that credit procyclicality was higher before the great financial crisis than after it.

To assess the differences in cross-country credit procyclicality, the paper estimates a country-specific VAR model for each country in our sample. In most countries, a GDP cycle shock affects credit procyclicality contemporaneously and positively. Procyclicality seems to be strongest in Bulgaria, Poland and Czechia, while procyclicality is low, albeit positive, for Estonia.

Finally, the analysis investigates whether concentration in the banking sector relates to different levels of credit procyclicality and whether it could explain the cross-country heterogeneity observed in credit procyclicality highlighted above.

The IPVAR framework makes it possible to incorporate a proxy for the level of banking sector concentration as a cross-country time-varying parameter into an extended VAR model. The analysis evaluates the impulse response functions of bank credit to a one-unit shock in the output gap evaluated at different percentiles of the Lerner index sample distribution. The Lerner index is an inverse proxy of banking sector competition so at the 80th percentile of the distribution, it is possible to evaluate the effect on bank credit for banking systems that have imperfect competition. The results obtained confirm the previous findings. Bank competition affects credit procyclicality and therefore different levels of banking sector competition can also explain the differences in credit dynamics across the CEECs.

The comparison of credit dynamics at different percentiles shows that increases and decreases in credit are weaker when bank competition is stronger, and the procyclicality is stronger when competition is weak. This means that banking systems with more competition show less procyclicality and can absorb shocks more easily.

The paper contributes to the existing literature by analysing whether the structure of the banking sector could affect the procyclicality of credit and whether differences can be observed in credit procyclicality across the CEECs, before and after the crisis. These findings hold important implications for further research. One important question for future research regards the role of foreign banks in explaining credit dynamics. Furthermore, future research should aim to determine whether the estimation of the Lerner index competition measure could be affected by the cost and revenue structure of foreign banks.

6 Conclusion

The five publications included in this thesis study the drivers of macroeconomic and financial aggregates, their cyclical behaviour, and financial stability. The publications focus specifically on factors that contribute to business cycle fluctuations, measures of the stance of the financial cycle, and the dynamics of banking sector concentration, credit provisioning and banking sector stability. Three of the publications centre their attention on the Central and Eastern European countries and have a particular focus on the three Baltic countries, Estonia, Latvia and Lithuania. Publications II and III take a wider scope and analyse measures of the financial cycle and factors that contribute to the business cycle in other European countries.

The topics investigated in this thesis raise numerous important questions. Publication I seeks to understand whether models that are able to incorporate a wider range of variables can improve upon classic Philips-curve models or simple theory-agnostic econometric models at forecasting the Estonian inflation rate. Even though an ever increasing amount of data is available to policy makers and the general public alike, achieving a high level of forecasting accuracy remains a challenge. Observing the first signs of structural shocks and then incorporating them into economic models in time seems to remain particularly difficult. Publication I focuses on short-term forecasts in a relatively stable low inflation environment. In the current, volatile environment of high inflation, a different class of forecast models might be warranted. In addition, future research might focus on forecasts that can predict the turning point from an environment of low inflation to one with high inflation.

The policy maker benefits from models that summarise a lot of information by compressing the data through statistical techniques, as such models often provide good forecasting performance. However, such forecasts remain unable to provide an intuitive economic story behind the projected paths of variables, and this can make communicating the forecast scenarios to the public a challenge. Forecasters and econometricians should work on making forecasts from high-dimensional models traceable, which means providing an underlying economic reasoning for the factors that drive the forecasting results so that the policy maker can give the public more intuitive explanations about the potential future paths of macroeconomic aggregates.

Publication II contributes to the understanding of business cycle fluctuations in France, Germany and Italy. The model studied in this publication takes a fresh look at the old question of belief-driven business cycle fluctuations. While the contribution of supply and demand shocks stemming from misperceptions about macroeconomic fundamentals is small, the results still show that factors other than fundamentals can drive fluctuations in the macroeconomy. Surprisingly, the effects observed for the three European countries differ from the results described in a study for the US.

A number of observers have argued that the differences in the policies and mandates of central banks can have marked effects on the speed and decisiveness of the reaction to shocks that affect important macroeconomic variables. The first question is whether differences in the transmission channels of monetary policy or the country-specific dynamics of supply and demand could explain the differences between the US and the three European countries. A second issue is that while it is not studied implicitly in the model, there is a monetary policy channel in the general theoretical framework that could affect the results, particularly those for the impulse responses to the ambiguous demand noise shocks. Finally, it would be beneficial to analyse whether, given the economic integration in Europe, expectations from one country can affect expectations and therefore business cycle fluctuations in another country. Publication II also holds important lessons for the policy maker. Communication and building expectations are important components in the toolbox of modern central banking. By communicating the future path of interest rates and reacting to inflation in accordance with their mandates, central banks might be able to buffer the effects of noise shocks that would otherwise lead to inflation being above or below its target.

Publications III, IV and V analyse questions related to financial risk, the structure of the market, and ultimately the dynamics of credit provisioning. All three related areas of study, are important factors for learning about financial cycles, financial risk and banking sector structure. As financial factors can amplify business fluctuations or can even be the cause of fluctuations, all three publications are of importance for the policy maker and the regulatory authorities. Publication III shows that the policy maker would benefit from using alternative measures of credit gaps on top of the mandated Basel III calculation method. These findings are of importance for policy makers like central banks or financial supervisory authorities, as the proposed alternative measures are easy to calculate and allow them to validate the Basel gap findings. For policy makers with access only to shorter time series, the alternative measures offer a particular improvement on the conventional Basel III method, which requires longer time series.

Publication IV uses micro data from banks in the three Baltic countries, Estonia, Latvia and Lithuania, to analyse the relationship between bank risk and the market structure in the banking sector. The study finds that a non-linear relationship exists between individual bank risk and the degree of competition or concentration in the banking sector.

This research is also of interest for the policy maker. First, it provides empirical evidence that neither very high nor very low concentration is beneficial for financial stability, but that an optimal degree of concentration exists in approximately the centre of the scale. This means that policy makers should try to target this optimal level of banking sector concentration by regulating potential mergers and acquisitions, or the entry of new banks. Future research might extend the model specification with measures that relate not only to bank risk but also to measures that relate the risks of individual banks to systemic risk. This would link the research area of market structure and risk taking by banks to the research area of systemic risk, which is more focused on macro-stability. While the preliminary estimates in Publication IV did not show a statistically significant and economically meaningful relationship between the ownership structure of the banks in the three Baltic countries and risk taking by individual banks, it cannot be ruled out that the interaction between market power and ownership structure may have effects on systemic risk. In addition, the measure of competition could be influenced by the presence of foreign banks. The Lerner index relies on an approximation of the marginal costs of the banks. The cost structure itself could depend on whether certain services are performed at the subsidiary or at the parent-company level. Future research should therefore also analyse whether the ownership structure affects country-specific risk and also region-specific systemic risk. Academic research could analyse how the ownership structure might affect different measures of competition.

Finally, Publication V synthesises some key insights from Publication III on credit cycles and Publication IV on banking sector concentration in the three Baltic countries by analysing the relationship between banking sector competition and the procyclicality of credit in the Central and Eastern European countries. As credit is the main driver of the financial cycle, understanding how the banking structure affects credit provisioning is of the utmost importance for the policy maker. The main result of Publication V shows that when banking sector competition is strong, procyclicality is reduced. However, when banking sector competition is weak, the increases and decreases in credit are larger in magnitude. This raises many challenging questions for the policy maker, particularly about the extent to which the policy maker should worry about financial cycles, and how those concerns should be balanced against the mandated macroeconomic objectives. Three areas should be investigated by future research. The first concerns whether it is possible to quantify the effects of financial cycle smoothing, which means regulating the financial sector to reduce the degree of procyclical dynamics. The second question relates once more to how to move from a well-established bank-level analysis of banking sector concentration and credit provisioning to a macrofinancial analysis that is orientated to a system risk view. The third area is that as more macroprudential policy actions have been recorded in recent years than before, researchers could analyse whether the introduction of such policies has had any effect on credit procyclicality. Researchers should particularly aim to answer the question of whether country-specific differences in credit procyclicality are related to different macroprudential policies across countries. Such analysis would provide useful insights for the policy maker who is interested in calibrating macroprudential measures, and regulating bank entry and bank mergers or acquisitions in the economy.

Research providing a holistic view on the macroeconomic and financial cycle nexus will remain highly important in the future. The five studies presented in this thesis provide grounds for future debates and give a starting point for further research into these topics.

Abbreviations

CEE	Central and Eastern Europe
CEECs	Central and Eastern European Countries
CPI	Consumer Price Index
FAVAR	Factor-Augmented Vector Autoregressive
GFC	Great Financial Crisis
GDP	Gross Domestic Product
VAR	Vector Autoregressive
PVAR	Panel Vector Autoregressive
IPVAR	Interacted Panel Vector Autoregressive
NK	New Keynesian
TFP	Total Factor Productivity

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Abstract
Essays on Applied Macroeconomics, Banking and Financial Stability

The thesis "Essays on Applied Macroeconomics, Banking and Financial Stability" presents studies in the research areas of the business cycle, the financial cycle research, banking sector concentration, and financial stability. This thesis seeks to extend an understanding of the factors that drive macroeconomic aggregates, and then continues by analysing how market structure affects financial stability and financial cycles.

This thesis consists of five empirical studies. Publication I is titled "Forecasting the Estonian rate of inflation using factor models". The purpose of this paper is to investigate the forecasting performance of time series models in which large amounts of information are summarised in a smaller set of factors. These factors are then incorporated into a vector autoregressive model in order to forecast the Estonian headline and core inflation rates. The results from factor analysis first show that the producer price variables of Estonia's trading partners contribute most to the first factor. The results of the forecasting exercise then show that while including a few factors from a large dataset can sometimes improve the forecasting performance, achieving consistent forecast improvement is hard across alternative model specifications. Finally, the paper shows that even though factor extraction is based on a theory-agnostic procedure, the factor structure can be sharpened by pre-selecting variables into subgroups and then using the subgroup factors to forecast the rate of headline or core inflation.

Publication I contributes to the literature on factor-augmented time series models in small open economies and provides insights into the common factors affecting the Estonian rate of inflation. The publication also relates to the literature on factor block structures by showing that subgroup forecasts can help to sharpen the forecasting performance.

Publication II "Noise shocks and business cycle fluctuations in three major European Economies" studies how supply and demand noise shocks contribute to business cycle fluctuations in France, Germany and Italy. Building on a model where non-fundamental shocks can affect business fluctuations, the model studied in this paper also allows shocks stemming from misperceptions about economic fundamentals to influence output and inflation. The empirical estimation strategy builds on extracting nowcast errors from survey data and then identifying the structural shocks using sign-restrictions in a vector autoregressive framework. The main results show that positive shocks to both supply and demand have an expansionary effect on output. In contrast to the results from the related literature, the findings of the paper are that a positive demand noise shock has an expansionary effect on output in Germany and France, while the results are insignificant for Italy.

Publication II contributes to the discussion on the effects of non-fundamental shocks on business cycle fluctuations by providing results for three major European economies. The comparative analysis shows that the response of output to a positive demand noise shock in the 3 European economies is markedly different from the response of output obtained by studies that focused on the United States.

Publication III "Alternative frameworks for measuring credit gaps and setting countercyclical capital buffers" explores whether alternative measures of credit-to-GDP gaps can be used to inform the policy maker about the stance of the financial cycle. The four alternative measures are designed to resolve some of the possible issues with the traditional Basel credit-to-GDP gap formula. The results indicate that most of the alternative measures show few to no negative credit-to-GDP gaps after the great financial crisis. Additionally, the new

measures exhibit good early warning properties when they are estimated on shorter time series data. Finally, the paper also estimates the capital buffer rates found when the four alternative measures are used to calculate the credit-to-GDP gap. Those results indicate that the buffer rates behave fairly similar for many countries in the sample.

The main value of Publication III is that it suggests alternative measures of the credit cycle that also show good signalling properties in short data samples and that are robust in resisting structural changes. The publication also contributes to the literature by showing that alternative measures of the credit cycle can also be employed when only shorter time series are available.

Publication IV "Banking Sector Concentration, Competition and Financial Stability: The Case of the Baltic Countries" analyses the relationship between different measures of banking sector concentration and different measures of banking sector risk in Estonia, Latvia and Lithuania. The empirical model uses bank-level data from all commercial banks in the Baltic countries over the period 2004-2014. The main results show that there is a inverse U-shaped relationship between the Lerner index and the Z-score. This means that both low levels of competition and high levels of competition are associated with a higher risk of bank-specific insolvency. The results are robust to alternative measures of banking sector concentration and competition, and alternative bank-risk measures.

Publication IV contributes to the existing literature on banking sector concentration and financial stability. The publication provides empirical evidence for the existence of a non-linear relationship between proxies of banking sector concentration and proxies of banking sector risk in the three Baltic countries. These results are of great importance for the policy maker and academics alike, as the three Baltic states are a textbook example of a highly concentrated banking sector.

Publication V "The evolution and heterogeneity of credit procyclicality in Central and Eastern Europe" focuses on the relationship between banking sector competition and the procyclicality of credit in Central and Eastern Europe. In the first part of the analysis, the paper estimates a panel autoregressive model to assess the evolution of credit procyclicality. The results confirm the existence of credit procyclicality in the six CEE countries and show that credit behaves procyclically with the business cycle. In the second part of the analysis, an interacted panel VAR model is estimated to analyse whether bank-level competition is a force driving the credit procyclicality. The results show that credit provisioning is higher in less concentrated banking markets.

Publication V complements the existing literature with an analysis of how the structure of the banking sector may affect the observed procyclicality of credit. The main contribution of this publication is that it shows that different levels of banking sector concentration might affect credit provisioning differently and have heterogeneous effects on credit dynamics in the CEE countries. This contributes to the understanding that banking sector competition also has effects on credit provision. The findings indicate that bank competition not only affects credit procyclicality in CEE but also explains differences in credit dynamics across the CEE countries.

Kokkuvõte
Esseed rakenduslikust makroökonoomikast, pangandusest ja finantsstabiilsusest

Esseed rakenduslikust makroökonoomikast, pangandusest ja finantsstabiilsusest Doktoritöö "Esseed rakenduslikust makroökonoomikast, pangandusest ja finantsstabiilsusest" sisaldab uurimusi majandustsüklite, finantstsüklite, pangandussektori kontsentratsiooni ja finantsstabiilsuse vallast. Doktoritöö eesmärgiks on laiendada teadmisi sellest, millised tegurid määravad makromajanduslikke arenguid, ning analüüsida, mil viisil on seotud pangandusturu struktuur, finantsstabiilsus ja finantstsüklid.

Doktoritöö koosneb viiest empiirilisest uurimusest. Neist esimese pealkiri on „Eesti inflatsioonimäära prognoosimine faktormudelite abil". Selle artikli eesmärgiks on uurida selliste aegridade mudelite prognoosivõimet, milles suur hulk informatsiooni on koondatud üksikutesse faktoritesse. Neid faktoreid lisatakse vektor autoregressiivsetesse mudelitesse, et prognoosida tarbijahindade inflatsiooni ja alusinflatsiooni Eestis. Prognoosiharjutus näitab, et kuigi üksikuid suurel andmehulgal põhinevaid faktoreid prognoosimudelisse kaasates õnnestub mõnel juhul mudeli prognoosivõimet parandada, on ühtlast prognoosi paranemist üle erinevate mudelispetsifikatsioonide siiski raske saavutada. Kuigi faktori-te koostamine ei tugine teoreetilisele alusele, siis faktorite struktuuri saab täpsemaks teha muutujad esmalt alagruppidesse jaotades ning seejärel alagruppide põhjal loodud faktoreid tarbijahindade inflatsiooni ja alusinflatsiooni prognoosimiseks kasutades. See artikkel panustab väikeste avatud majanduste faktoritega rikastatud aegridade mudelite kirjandusse ja pakub uut teavet Eesti inflatsiooni mõjutavate tegurite kohta. Samuti panus-tab artikkel oma faktorite kirjandusse, näidates, et faktorite koostamine alagruppidesse jaotatud tunnuste põhjal aitab parandada mudeli prognoosivõimet.

Teine artikkel pealkirjaga "Mürašokid ja äritsükli dünaamika kolmes Euroopa suures majanduses" käsitleb seda, kuidas infomüra pakkumise ja nõudluse osas panustavad majanduse tsüklilisusesse Prantsusmaal, Saksamaal ja Itaalias. Tuginedes teoreetilisele mudelile, milles mitte-fundamentaalsed mürašokid võivad mõjutada majandust, lubatakse artiklis kasutatud empiirilises mudelis mõjutada majanduse lisandväärtust ja inflatsiooni šokkidel, mis tulenevad majanduse fundamentaalnäitajate vigasest tajumisest. Empiiriline hindamisstrateegia hõlmab reaalaja kohta tehtud prognooside vigade kasutamist struktuursete šokkide identifitseerimist vektor-autoregressiivses raamistikus. Tulemused näitavad, et nii nõudluse kui ka pakkumise positiivsed mürašokid suurendavad majanduses toodetud lisandväärtust. Uuringu peamised tulemused näitavad, et erinevalt varasemalt teistes töödes leitust, omasid positiivsed nõudluse mürašokid majanduse kogutoodangule suurendavat mõju Saksamaal ja Prantsusmaal, kuid Itaalia puhul polnud hinnatud mõju oluline.

Teine artikkel panustab mitte-fundamentaalsete mürašokkide äritsüklile avaldatavat mõju käsitlevasse diskussiooni läbi selle, et pakub mõjuhinnanguid kolme peamise Euroopa majanduse kohta. Võrdlev analüüs näitab, et kogutoodang reageerib kolmes peamises Euroopa majanduses positiivsetele nõudluse mürašokkidele väga erinevalt võrreldes sellega, mida on leitud varasemates uurimustes Ameerika Ühendriikide kohta.

Kolmandas artiklis, mille pealkiri on "Alternatiivsed võimalused krediidilõhe mõõtmiseks ja vastutsüklilise kapitalipuhvri nõude määramiseks", uuritakse seda, milliseid võla-SKP suhte näidikuid saaks kasutada poliitikakujundaja teavitamiseks finantstsükli seisust ja majanduspoliitiliste otsuste vastuvõtmiseks. Artiklis pakutakse neli alternatiivset mõõdikut lahendamaks võimalikke probleeme, mis seonduvad traditsioonilise Baseli võla-SKP suhte lõhe leidmise reegliga. Uurimuse tulemused näitavad, et enamik alternatiivseid mõõdikuid viitavad sellele, et finantskriisi järgselt esines negatiivset võla-SKP suhte lõhet vähe või üldse mitte. Lisaks on uutel mõõdikutel head varajase hoiatuse omadused ka siis, kui neid hinnatakse lühemaid aegridu kasutades. Viimaks hinnatakse artiklis nelja alternatiivse võla-SKP suhte lõhe näidiku alusel ka uued kapitalipuhvri määrad. Tulemused näitavad, et erinevad kapitalipuhvri määrad käituvad mitmete valimis olnud riikide puhul küllaltki sarnaselt.

Kolmanda artikli peamine lisandväärtus seisneb uutes väljapakutud krediiditsükli seisu hindamise alternatiivsetes mõõdikutes, millel on head signaliseerivad omadused lühikes-te aegridade korral ja mille omadused säilivad ka struktuursete muutuste puhul. Lisaks panustab artikkel kirjandusse näidates, et alternatiivseid krediiditsükli mõõdikuid saab kasutada ka siis, kui kasutada on vaid lühikesed aegread, mis on Baseli põhiraamistiku rakendamisel tõsiseks probleemiks. Neljandas artiklis, mille pealkirjaks on "Pangandussektori kontsentratsioon, konkurents ja finantsstabiilsus: Balti riikides", analüüsitakse seost pangandussektori kontsentratsiooni näitajate ja pangandussektori riski mõõdikute vahel Eestis, Lätis ja Leedus. Empiirilises mudelis kasutatakse panga tasandi andmeid kõigi Balti riikides aastatel 2004 kuni 2014 tegutsenud kommertspankade kohta. Tulemused näitavad, et Lerneri indeksi ja Z-skoori vahel on U-kujuline seos. See tähendab, et nii väga madal kui ka väga kõrge pangandussektori kontsentratsioon on seotud kõrgema panga-spetsiifilise maksejõuetuse riskiga. Tulemused jäävad muutumatuks erinevate pangandussektori kontsentratsiooni, konkurentsi tugevuse ja panga tasandi riskimäära mõõdikute kasutamise korral.

Neljas artikkel panustab pangandussektori kontsentratsiooni ja finantsstabiilsust käsitlevasse kirjandusse. Selles esitletakse uusi empiirilisi tulemusi selle kohta, et pangandussektori kontsentratsiooni ja panga tasandi maksejõuetuse riskimäära näitajate vahel eksisteerib mittelineaarne seos. Need tulemused on olulised nii poliitikakujundajatele, sest Balti riigid kujutavad endast kõrge pangandussektori kontsentratsiooniga riikide õpikunäidet. Viies artikkel, mille pealkirjaks on "Laenutegevuse päritsüklilisuse areng ja riikidevahelised erinevused Kesk- ja Ida-Euroopas" keskendub pangandussektori konkurentsiolukorra ja laenutegevuse päritsüklilisuse suhtele Kesk- ja Ida-Euroopa riikides. Uurimuse esimeses osas hinnatakse paneelandmete autoregressiivset mudelit, et analüüsida laenutegevuse päritsüklilisust. Tulemused kinnitavad, et kuues Kesk- ja Ida-Euroopa riigis on laenutegevus käib äritsükliga samasuunaliselt koos. Uurimuse teises osas hinnatakse paneelandmete vektor-autoregressiivset mudelit, et analüüsida, kas pangandussektori konkurentsi tugevus mõjutab võlataseme päritsüklilise kõikumise ulatust. Tulemused näitavad, et laenupakkumine on suurem pangandusturgudel, mille kontsentratsioon on madalam.

Viies artikkel täiendab olemasolevat kirjandust analüüsiga selle kohta, kuidas pangandussektori struktuur võib mõjutada laenutegevuse vaadeldud päritsüklilisust. Uurimuse peamiseks panuseks väide, et erinev kontsentratsioon pangandusturul mõjutada laenupakkumist erinevalt ja põhjustada Kesk- ja Ida-Euroopa riikide vahel erinevusi laenutegevuse dünaamikas. Artikkel kinnitab ka arusaama, et pangandussektori konkurents mõjutab laenupakkumist. Analüüsi tulemused viitavad sellele, et pangandussektori konkurents mitte ainult ei mõjuta võla päritsüklilisust Kesk- ja Ida-Euroopas, vaid ka aitab selgitada Kesk- ja Ida-Euroopa riikide vahelisi erinevusi laenupakkumise dünaamikas.

Appendix 1

Publication I
Nicolas Reigl (2017). “Forecasting the Estonian Rate of Inflation Using Factor Models”. *Baltic Journal of Economics* 17.2, pp. 152–189

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Forecasting the Estonian rate of inflation using factor models

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ABSTRACT
The paper presents forecasts of headline and core inflation in Estonia with factor models in a recursive pseudo out-of-sample framework. The factors are constructed with a principal component analysis and are then incorporated into vector autoregressive (VAR) forecasting models. The analyses show that certain factor-augmented VAR models improve upon a simple univariate autoregressive model but the forecasting gains are small and not systematic. Models with a small number of factors extracted from a large dataset are best suited for forecasting headline inflation. The results also show that models with a larger number of factors extracted from a small dataset outperform the benchmark model in the forecast of Estonian headline and, especially, core inflation.

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Factor models; factor-augmented vector autoregressive models; factor analysis; principal components; inflation forecasting; Estonia

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1. Introduction

Inflation and changes in inflation are key measures of macroeconomic performance, so it follows that forecasting inflation is important in countries around the world, including Estonia. Volatile dynamics such as the pre-crisis rise in inflation, which has been largely attributed to the supply-side shocks that hit the small open economy (Benkovskis, Kulikov, Paula, & Ruud 2009), have challenged the forecasting skills of central bankers and policy-makers.[1]

Forecasters earlier relied on models with only a few predictors, until increasing amounts of data became available at high levels of sectoral, regional and temporal disaggregation. Those macroeconomic, microeconomic and financial time series hold information that may be useful for economic forecasting and empirical analysis of monetary policy (Ibarra-Ramírez 2010). Bernanke & Boivin (2003) point out, however, that researchers who use a small number of variables in their analysis can exploit only a limited amount of information. Small-scale models have some advantages in their simplicity and tractability, but they are prone to omitted variable bias (Gavin & Kliesen 2008).

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Factor models in which the individual macroeconomic and financial time series are driven by a small number of factors can be used to address the shortfalls of small-scale models. First, factor models summarize the information contained in a big dataset, which allows a richer information set to be incorporated in the analysis. Second, factor models are flexible in the way that they can simultaneously accommodate data released at different times, frequencies and areas. Finally, their methods for extracting driving factors are statistically rigorous, as they are agnostic about the structure of the economy (Bernanke & Boivin 2003).

This paper investigates the properties of the factor model forecast of Estonian headline and core inflation for the period from the second quarter of 2011 to the second quarter of 2014. Factors are constructed using a principal component analysis and are then incorporated into different parametrized forecasting models. To evaluate the relative performance of the forecasting methods, the forecasting errors of the factor-augmented models are compared to a univariate benchmark model to assess their predictive abilities.

This paper contributes to the growing literature on forecasting in a data-rich environment in three ways.[2] It is the first systematic study to analyse the applicability of a factor-augmented vector autoregressive (VAR) model for forecasting inflation in Estonia. Second, it examines the importance of the number of factors in the inflation forecasting model, when the factors are extracted from datasets where consumer price indicators are excluded or from subgroups of variables. Third, the paper analyses the impact of small changes in the dataset on the forecast error distributions of different factor-augmented forecasting models.

This paper is organized as follows. Section 2 reviews briefly the existing literature. Section 3 discusses the econometric framework. Section 4 presents the data used in the econometric model. Section 5 presents the empirical results. The final section concludes. Tables 1–4 are displayed in the main text. Appendix 1 presents the factor analysis result tables and graphs and Appendix 2 presents the robustness test results. The Online Appendix displays the data used in the benchmark model.

2. Literature review

Forecasting using factor models has received a considerable amount of attention in recent years. Various studies have provided compelling evidence in support of the factor model forecast methodology. However, the literature is less conclusive in answering questions of how many factors to use in the model, the size of the dataset and the forecasting horizon.

Table 1. Headline inflation out-of-sample forecasting results one to six quarters horizon.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
VAR	1.083	1.090	1.089	1.091	1.103	1.118
RW	1.147	1.024	0.872	0.817	0.804	0.824
FAVAR 1F. 1 Lag	0.992	1.030	1.020	1.022	1.057	1.101
FAVAR 1F. 2 Lags	0.902	**0.953**	**0.951**	**0.944**	0.980	**1.025**
FAVAR 1F. 3 Lags	**0.901**	0.997	1.012	1.018	1.049	1.088
FAVAR 12F. 1 Lag	1.043	0.990	0.992	1.004	1.048	1.098
FAVAR 12F. 2 Lags	1.043	0.969	0.991	1.011	**0.977**	1.061
FAVAR 12F. 3 Lags	1.148	0.999	1.023	1.037	1.013	1.086
FAVAR 123F. 1 Lag	1.047	0.995	0.988	0.993	1.027	1.066
Benchmark AR, abs. RMSE	0.474	1.004	1.666	2.256	2.698	3.000

Note: RMSEs in percentage points.

Table 2. Core inflation out-of-sample forecasting results benchmark dataset.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
VAR	1.017	1.106	1.354	1.480	1.739	1.744
RW	1.387	1.625	1.846	1.869	2.357	2.252
FAVAR 1F. 1 Lag	0.908	**0.890**	**1.058**	1.151	1.435	1.475
FAVAR 1F. 2 Lags	0.923	1.000	1.198	1.231	1.481	1.569
FAVAR 1F. 3 Lags	0.934	1.091	1.447	1.566	1.876	1.930
FAVAR 12F. 1 Lag	0.919	0.943	1.145	1.236	1.501	1.449
FAVAR 12F. 2 Lags	0.993	1.177	1.509	1.628	2.003	2.090
FAVAR 12F. 3 Lags	1.034	1.154	1.464	1.546	1.959	1.932
FAVAR 123F. 1 Lag	**0.906**	0.903	1.076	**1.150**	**1.387**	**1.285**
Benchmark AR, abs. RMSE	0.339	0.516	0.635	0.807	0.797	1.003

Note: RMSE in percentage points.

Stock & Watson (2002b) review the forecast performance of factors, which they call diffusion indexes. The authors extract those factors from large datasets and estimate the consistency of models with time variation. They show that their diffusion index models, or factor models, offer substantial improvements over univariate autoregressive models, leading indicator and VAR models in an out-of-sample forecast of the Federal Reserve Board's Index of Industrial Production.

Lin & Tsay (2005) compare the forecasts of simple factor models with those produced by advanced large predictor models such as partial least squares, BMA and combination forecasts models. Their findings indicate that partial least squares outperform other models in short-horizon forecasts using a dataset of 141 predictors. The factor model provides good forecast accuracy when the number of common components is between three and five.

Gosselin & Tkacz (2001) compare the forecasting performance of four different factor models with that of univariate models. They conclude that the factor models are as accurate as more advanced models in forecasting the Canadian inflation rate. They include 344 Canadian variables together with 110 U.S. macroeconomic and financial variables. Small factor models that contain one, two or three factors yield the best forecast accuracy. The researchers provide evidence that gains in forecast efficiency can be obtained for a small open economy by combining foreign macroeconomic and domestic time series.

Angelini, Henry, & Mestre (2001) extract up to 4 factors from large cross-sectional datasets comprising 278 variables for 11 EMU countries. They conclude that factor models have relatively good forecasting performance in four and eight quarter-ahead forecasts. Their

Table 3. Headline inflation out-of-sample forecasting results one to six quarters horizon.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
VAR	1.110	1.101	1.094	1.1095	1.100	1.118
RW	1.147	1.024	0.872	0.817	0.804	0.824
FAVAR 1F. 1 Lag	1.031	1.069	1.050	1.056	1.069	1.079
FAVAR 1F. 2 Lags	0.952	1.010	0.981	0.988	1.019	1.031
FAVAR 1F. 3 Lags	**0.949**	1.063	1.047	1.049	1.074	1.076
FAVAR 12F. 1 Lag	1.041	1.071	1.052	1.063	1.090	1.085
FAVAR 12F. 2 Lags	0.963	1.023	0.978	0.971	1.018	1.050
FAVAR 12F. 3 Lags	1.017	1.088	1.075	1.125	1.161	1.198
FAVAR 123F. 1 Lag	1.075	**1.006**	**0.955**	**0.920**	**0.919**	**0.991**
Benchmark AR, abs. RMSE	0.474	1.004	1.666	2.256	2.698	3.000

Note: RMSE in percentage points.

Table 4. Core inflation out-of-sample forecasting results one to six quarters horizon.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
VAR	1.025	1.095	1.334	1.457	1.705	1.730
RW	1.387	1.625	1.846	1.869	2.357	2.252
FAVAR 1F. 1 Lag	0.928	0.903	1.051	1.136	1.385	1.375
FAVAR 1F. 2 Lags	0.939	1.029	1.220	1.253	1.522	1.579
FAVAR 1F. 3 Lags	0.909	1.059	1.419	1.534	1.872	1.896
FAVAR 12F. 1 Lag	0.897	0.884	1.046	1.134	1.382	1.36
FAVAR 12F. 2 Lags	0.925	1.020	1.227	1.250	1.531	1.583
FAVAR 12F. 3 Lags	1.078	1.224	1.671	1.888	2.126	2.129
FAVAR 123F. 1 Lag	**0.833**	**0.728**	**0.881**	**0.935**	**1.104**	**1.175**
Benchmark AR, abs. RMSE	0.339	0.516	0.635	0.807	0.797	1.003

Note: RMSE in percentage points.

findings indicate that small models with two or three factors match the best alternative forecast models in an out-of-sample forecasting framework, especially if those factors are related to nominal developments.

Bruneau, De Bandt, Flageollet, & Michaux (2007) investigate the forecasting performance of dynamic factors, which are extracted from 200 macroeconomic variables for France. Their results indicate that the dynamic factor model has good forecasting properties, especially when forecasting the core inflation rate. Factors extracted from datasets with blocks of homogeneous variables, particularly variables related to labour markets, improve their forecasts considerably. They also provide small-horizon factor-augmented VAR forecasts, finding that the FAVAR forecasts outperform the standard dynamic linear regression forecasting equation models at times of rising core inflation.

Schumacher & Dreger (2004) study the performance of large-scale factor models for economic activity in Germany. They extract the factors from a dataset of 121 time series and calculate the prediction errors in out-of-sample forecasts, and they find that factor models outperform simpler univariate benchmark models. However, their forecasting gains prove to be limited and not systematic.

Artis, Banerjee, & Marcellino (2005) construct a dynamic factor model from a U.K. dataset consisting of 81 variables. They consider forecasting models with between 4 and 12 factors and up to 3 lags. Their results are in line with those of previous studies for the U.S.A., such as Stock & Watson (2002b), who find that factor-based forecasts outperform standard benchmark models for price developments at both short and longer horizons.

The literature on factor model forecasts is less extensive for countries in Central and Eastern Europe (CEE), particularly for inflation forecasting. Ajevskis & Davidsons (2008) compare the forecasting performance of a diffusion index model with a generalized dynamic factor model for Latvia's gross domestic product (GDP). They use 126 quarterly time series to extract up to 12 factors. Both models outperform simpler models but the differences are not statistically significant. For short horizons, a model with four factors and two lags provides the best forecasting performance, but models with more factors and zero lags lead to better forecasting results for longer horizons.

Stakenas (2012) focuses on Lithuanian GDP forecasting and uses simple and advanced principal component analysis to extract factors from a dataset of 52 monthly variables. He finds that factor models outperform naive univariate benchmark models. The most suitable models for the Lithuanian case encompass two factors irrespective of whether the factors are extracted by a generalized or static principal component method. In addition, the forecasts produced by a state-space model give similar results to those from forecasting using the principal component method.

For Estonia, Schulz (2007) derives common factors with a small-scale state-space model and with a large-scale diffusion index model, and subsequently forecasts real economic growth. The factor models show a better forecasting performance for most forecasting periods than univariate and multivariate benchmark models do. Schulz (2007) emphasizes that even though many data series are available for the Baltic states, those series are not very long and this makes it difficult to compare the results with those from mature Western countries.

3. Empirical model

The forecasting model uses a two-step approach. First, the factors are extracted and then they are incorporated in a forecasting model. This paper closely follows the static principal component approach of Stock & Watson (2002b) for the factor extraction. The forecasting equation is based on the approach proposed by Bernanke, Boivin, & Eliasz (2005).

3.1. Econometric framework

For the formal setup, assume X_t to be an $N \times 1$ vector of time series with $t = 1, \ldots, T$. It is assumed that both N and T are large. Those time series are driven by a few (q unobserved common factors. In the general formulation of a dynamic factor model, each element of the vector$X_t = [x_{1t} \ldots x_{it} \ldots x_{Nt}]'$, for $i = 1,2, \ldots, N$ can be represented as follows:

$$X_{it} = \lambda_i(L) f_t + e_{it}, \tag{1}$$

where f_t is the $q \times 1$ vector of common factors, $\lambda_i(L)$ is a lag polynomial in non-negative powers of L and e_{it} is the idiosyncratic error term.

The lag polynomial adds dynamics to the factor loadings λ_i, which are the weights that form a linear combination of the original variable when multiplied with the latent component. It is assumed that the innovation of the common factor f_t has an autoregressive structure and that the idiosyncratic error term and the common factor are mutually orthogonal at all leads and lags. Moreover, in the so-called exact dynamic factor model, it is assumed that $\mathbb{E} e_{it} e_{js} = 0$ for all s if $i \neq j$, meaning that the idiosyncratic errors are mutually uncorrelated at any leads and lags (Stock & Watson 2011). Equation (1) has an alternative formulation in finite lag form:

$$X_t = \Lambda F_t + e_t, \tag{2}$$

where $F_t = (f_t', \ldots, f_{t-p}')'$ is an $r \times 1$ vector, where $r = (p + 1) \times q$ factors drive the variables. Λ is the factor loading matrix that relates the common factor to the unobserved series. It can be seen that the high-dimensional time series variable vector, X_t is driven by a vector of latent factors, F_t and a vector of mean-zero idiosyncratic disturbances, e_t.

The static representation of the dynamic factor model yields the advantage that the factors can be estimated using principal components. It should be noted that since X_t can contain lagged values, F_t can be understood as containing arbitrary lags of factors. When the number of predictors N and the number of observations T grow large, the factors can consistently be estimated by the principal components of the $T \times T$ covariance matrix of X_t.[3]

Stock & Watson (2002b) show that consistency is even preserved in an approximate factor model with factor loadings and idiosyncratic errors that are serially and weakly cross-sectionally correlated (Soares 2013).

The intuition behind this property is that only the linear combination of factors will remain after the weighted averages of the idiosyncratic disturbances have converged to zero because of the law of large numbers (Stock & Watson 2011).

The forecasting equation is based on the approach proposed by Bernanke et al. (2005), who extract the factors in a similar manner to Stock & Watson (2002b) and then proceed by estimating a factor-augmented VAR. Though the variable of interest is the inflation rate, more economic variables could be incorporated in the VAR model. Let Y_t denote an $M \times 1$ vector of observable macroeconomic variables. Along with the vector of observable time series, additional economic information is contained in a $k \times 1$ vector of unobserved factors, F_t. Given a vector Y_t of important macroeconomic variables and a vector F_t of unobserved driving factors, it is reasonable to assume joint dynamics for(F_t,Y_t).

The joint dynamics are given by

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \epsilon_t, \tag{3}$$

where $\Phi(L)$ is a conformable lag polynomial of finite order d in the lag operator L and ϵ_h is an error term with a mean of zero and a covariance matrix Q.

If at least one of the terms of $\Phi(L)$ that relate Y_t to F_{t-1} is non-zero, Equation (3) is referred to as a factor-augmented vector autoregression, or FAVAR; otherwise, this system reduces to a standard VAR in Y_t. Since it is assumed that $M + k \ll N$, the FAVAR model can handle more information than standard small-scale VAR models, as the informational content of the large N size dataset is summarized in a small set of k factors.

The h-step ahead forecast for $\begin{bmatrix} F_t \\ Y_t \end{bmatrix}$ is obtained recursively.

The point estimate obtained is compared to the actual observed value, forming the forecast error ϵ^t_{t+h} to calculate the root-mean-square errors (RMSE) (Hamilton 1994).

3.2. Number of factors and lag structure

Factor forecast applications differ not only in the factor estimation method employed but also in the number of factors used. The basic factor approach suffers from an important shortcoming as the factors that are extracted are ordered by how they express the common movement in the whole dataset, but this does not take account of the specific variables being forecast. Nor is the forecast horizon considered, thought this could be of significance when targeted predictors co-move with the variable to be forecast more in certain periods than in others. Periods of stronger co-movement can be expected to yield better forecast performance (Eickmeier & Ziegler 2008). Dias, Pinheiro, & Rua (2010) point out that including only the first few factors in the forecasting equation might exclude other factors that have a high correlation with the target variable or the forecast horizon.

One important determinant of the predictive power of the factors and the number of them to be included in the forecasting equation is the size and composition of the dataset. Studies have shown the relevance of targeted predictors (Bai & Ng 2008; Boivin & Ng 2006). Somewhat in contradiction to the principle that large datasets are beneficial, oversampling problems are reported when arbitrary variables that are irrelevant for the time series to be forecast are added. Boivin & Ng (2006) point out that reducing the sample size can help sharpen the factor structure, and that as a result forecast efficiency improves when certain series show idiosyncratic error cross-correlations.[4] A second argument in favour of pre-selecting variables is that economic considerations might mean subgroups of variables related to the variable of interest would enhance the forecasting abilities of the factors extracted. For example, Bruneau et al. (2007) extract the first factor from a block of homogeneous sets of variables such as the Survey Block or the Employment Block to compare the forecasting performance of pre-selected subgroups with the ungrouped dataset forecasts. The assumption that removing or grouping targeted predictors should affect the forecasting performance is tested in two ways. First, I extract the same number of factors from a benchmark sample set and a reduced size one. The reduced size dataset excludes time series of domestic and foreign consumer prices, which should constitute targeted predictors of the headline and core inflation rates, therefore potentially worsening the predictive abilities of the extracted factors. Second, I construct sets of homogeneous variables and extract the factors from those subgroups. In the next step, I compare the forecasting performance of subgroup factor model forecasts. In addition, I also combine the first factor from each of the subgroups, which is usually considered to contribute most to the forecast, and compare the forecasting performance of that factor with the performance of the individual subgroup forecasts.

While some studies base the number of factors on formal restrictions, others choose the number of factors heuristically. Following Bernanke et al. (2005), I use a heuristic approach and construct various FAVAR models with different numbers of factors and lag structures from different sized datasets, and use performance measures to assess their forecasting abilities. The reason for doing this is to allow the lag length and the number of statistically significant factors to be re-estimated in recursive out-of-sample forecasts for each period when the in-sample window is extended. However, assessing the impact of the number of factors and their lags on the forecasting performance is more difficult when these are re-estimated for each period, making it challenging to draw conclusions if models with fewer factors and lags have higher predictive abilities than models with more factors.

3.3. Forecasting procedure and evaluation

Multistep ahead forecasts are made at one-quarter to six-quarter-ahead horizons, so $h = 1, \ldots, 6$. I use a recursive pseudo out-of-sample forecasting method. The forecast performance is evaluated on the out-of-sample set. The in-sample set is used to initialize the methods of factor estimation, model estimation and lag order selection. The dataset starts in the first quarter of 2004 and ends in the second quarter of 2014. The choice of the starting date reflects the aim of incorporating a large number of balanced time series in the analysis. For every quarter, the forecast h-steps-ahead is obtained recursively.

From $y^h_{2011/2Q+h}$ to $y^h_{2014/2Q+h}$, the forecast mechanism reoccurs 12 times. The iterative forecasts at the end of the out-of-sample set produce forecast values that are not used for further analysis as the actual observed inflation and core inflation values were not available at the point of analysis. Therefore, fewer observations enter the forecast performance evaluation for larger *h*-steps-ahead forecasts.

To compare the forecast accuracy of the models, the RMSEs are calculated for each model from the differences in the values for the quarter-on-quarter inflation rate.

So that the forecast results are comparable, the RMSEs of all the forecast models are also computed relative to the RMSE of the benchmark autoregressive (AR) forecasts. Therefore, the relative RMSE of the benchmark AR is 1.00 % or 100%.

I abstain from using the Diebold–Mariano test (Diebold & Mariano 1995) to test formally the statistically significant difference between the models in their predictive abilities.[5] Researchers tend to conduct forecasting exercises on different time periods but testing the model on different time periods proves difficult in the Estonian case, as the length of the data sample for the factor estimation is limited. Instead, I test for the impact of removing one observation by excluding the second quarter of 2014 from the calculation of the RMSE for every forecast horizon. The new RMSE are calculated using data from the second quarter of 2011 to the first quarter of 2014. If the RMSE do not deviate by significant margins between the two time periods, the results obtained are considered to be robust for small changes. In addition to testing for the impact of small changes to the forecasting period, I draw 2000 random samples from the benchmark dataset of 388 variables (see Section 4) and create datasets of 329 variables. The same principle is applied to the reduced dataset, with the number of variables in each random draw cut by 37, or about 15%. Those 2000 different datasets are used to extract the factors and forecast the headline and core inflation rates in the way described earlier. In the next step, the distributional properties of the 2000 consecutive individual model forecast errors are analysed. Specifically, I plot the frequency distribution of the FAVAR models and analyse their shape, centre, spread and position relative to the benchmark AR model. I also test for the impact of different stationarity-inducing transformation schemes on the forecast performance.

3.4. Factor-augmented VAR forecast models

The FAVAR forecasts are constructed by choosing the number of factors to be included and the lag order. I estimate 13 FAVAR models, the results for 7 of which are reported in detail.[6] All the 13 FAVAR forecasts share the same properties for the *M* vector. The *M* vector is a one-variable vector that contains either the headline inflation rate or the core inflation rate, depending on the forecasting exercise.

For the models with a fixed lag length, I start testing from small dimensional FAVAR models and then add more factors and lags. 'FAVAR 1F.1 Lag' contains the first factor (1F.) and has a lag length of one (1 Lag). 'FAVAR 12F. 1 Lag' is a three-variable vector, containing the inflation rate plus the first two factors (12F.). The model 'FAVAR 123F. 1 Lag' contains the third factor as well. Equal size *k*-factor models were also tested for lag lengths of two and three.

The forecast results of the FAVAR models are compared to the results of the benchmark model. Following Stock & Watson (2002b), a univariate autoregressive model of order *p* is used as the benchmark. The benchmark AR is based on the headline inflation rate and the core inflation rate. The lag length of the estimated lag polynomial is iteratively estimated by BIC, and is allowed to vary between one and three ($1 \leq p \leq 3$).[7] Given that the ARMA model forecasts do not improve upon the AR model forecasts, they are not reported in Section 5.[8]

In the spirit of Rünstler et al. (2009), the forecasting abilities of the FAVAR models are also tested against the averages of N varying-length bivariate VARs. For each time series, the VAR is $z_{i,t} = \mu_i + \sum_{s=1}^{p_i} A_s z_{i,t-s} + \epsilon_{i,t}$, with $z_{i,t} = (y_t, x_{i,t})'$, where y_t is the inflation rate and $x_{i,t}$ is a quarterly indicator. The average of the N forecasts are then $y_{t+h|h} = N^{-1} \sum_{i=1}^{N} y_{i,t+h|t}$.

Stock & Watson (2010) also posit that since the financial crisis, it has become increasingly difficult to improve systematically upon simple univariate forecasting modes like the random walk model (RWM) by Atkeson & Ohanian (2001). Therefore, a RWM constitutes the last alternative benchmark model.

4. Data

The data section contains two parts. Section 4.1 briefly presents the variables and their treatment in the dataset and Section 4.2 reports the results of the factor analysis.

4.1. Variables

The series chosen for the panel used in the analysis are similar to the variables used by Stock & Watson (2002b). First, credit aggregates such as credit to firms and households are included along with data for different credit maturities, such as long-term and short-term credit. Similarly, series such as deposits from companies and deposits from individuals have been included. State budget revenues and state budget expenditures series are used in addition.

Various interest rates such as the 6-month Euribor rate and short-term interest rates are included in the dataset as money supply aggregates such as the M3 rate and key data on the balance of payments. Further statistics on trade in consumer and capital goods are used so as to account for Estonia's open economy structure. The series of the composite leading indicators (CLI) may help to predict the future economic climate and are also included.

Labour market dynamics can play a significant role in the development of wages and prices, and I include the unemployment and job vacancy rates among other statistics. Next, I took in data on the output of total, intermediate and capital goods, and data on new orders such as new orders for manufacturing goods. Like the CLI, business survey statistics give information on economic expectations, so turnover and sales are included in the dataset as they can be seen as indicators of consumer sentiment.

Following the findings of Gosselin & Tkacz (2001), who conclude that the macroeconomic dynamics of trading partners are of importance for factor modelling of inflation and output in open economies, I also consider price aggregates and the composite leading indicator series of Estonia's biggest trading partners. The aggregate PPI index for the whole euro area enters the panel as, alongside the individual PPI indexes for Finland, Lithuania, Latvia, Germany and other main trading partners. In addition, the indexes are split up into sub-categories such as producer prices for energy, and food and beverages.

Another major group of variables is the harmonized consumer price indexes (HICP) of Estonia and Estonia's trading partners. The foreign consumer price indexes can be interpreted as foreign inflation proxies. First, the HICP series from trading partners in the European Union are included in the dataset and second, the sub-indexes such as the HICP energy series or HICP food and beverages series also enter the dataset. In total, more than 140 different harmonized consumer prices indexes are included in the dataset.

Financial market dynamics should also be considered, so I include stock price data from the Helsinki stock exchange (OMXH) and the Russian RTS index. The effects of productivity changes are captured by incorporating data on the number of hours worked, average wages by employment and nominal and real unit labour costs. The last major items included in the dataset are various economic deflators.

Only a few variables on personal consumption are available for Estonia and the same applies to detailed payroll and housing sales statistics. There are no Estonian sovereign debt securities or Estonian inflation-protected securities. This is unfortunate as inflation-protected securities may be used to compute measures of inflation expectations (Shen & Corning 2001).

The variables to be forecast are the Estonian headline inflation rate and the Estonian core inflation rate. Headline inflation is defined as the official measure of consumer price inflation in Estonia for goods and services. Core inflation is a sub-category of headline inflation that excludes energy, food, alcohol and tobacco items.

The first panel used in this paper consists of 388 domestic and foreign time series at 42 quarterly observations, ranging from the first quarter of 2004 until the second quarter of 2014. This panel is labelled the 'benchmark dataset'.

To test for panel size effects and targeted predictor effects, the second panel with 246 time series was created. Its basis is the benchmark dataset, with all domestic and foreign HICP excluded. First, those series have been excluded as the factor analysis in Section 4.2 has indicated their importance for the first factor, and as a possible consequence their forecasting performance. Thereby, I can also test how a reduced-size dataset which is based on the idea that removing targeted predictors should limit the predictive abilities of the extracted factors compares to a reduced-size dataset where the series to be removed from the dataset are determined by random sampling. This procedure is explained in more detail in Section 5.4. The panel excluding all domestic and foreign HICP was labelled the 'reduced dataset', or for clarity, the 'reduced-size dataset'. A complete list of the variables used in the benchmark dataset is reported in the Online Appendix (see Table C1).

The untreated dataset contained monthly and quarterly time series, so the monthly series were transformed into quarterly series. First, this yields the advantage that the quarterly series do not have to undergo a linear interpolation procedure to generate monthly series. Second, Eickmeier & Ziegler (2008) point to evidence that quarterly data are better suited to factor forecasts than monthly data. The process of transformation involved averaging the monthly values as quarterly values, summing up the monthly values, or taking the value for the end of the last month as the quarterly value.

Missing observations were treated with a regularized iterative missing principal component analysis algorithm to avoid the overfitting problems associated with using an expected-maximization algorithm (Josse & Husson 2012). In the next step, the seasonal effects were removed from the set of variables. Time series that were already seasonally adjusted according to the issuing source were still put through this stage to remove any residual seasonality. The augmented Dickey–Fuller test was performed on all the seasonally adjusted time series. Non-stationary series were marked and then subjected to the stationarity-inducing transformation. The transformations involved taking the log differences for series that included non-negative values. For series that included positive and negative values, the first difference was taken. The exact treatment of every time series can be found in the Online Appendix C.1. In the last step, all the series were standardized to have sample mean zero and unit sample variance.

4.2. Factor analysis

I start the analysis of the factors with the benchmark dataset ($N = 388$). As described in Section 3.4, a maximum of five factors is used in the vector autoregressive models. The principal components summarize the variance in a dataset. The first component explains 21.94%, the second 16.68%, the third 7.99%, the fourth 5.65%, and the last one 3.82% of the total variance in the dataset. The cumulative share of the total variation of the macroeconomic variables explained by the first three factors is 46.61% and that explained by the first five factors is 56.08%.

For the reduced-size dataset, the variance explained by the first principal component is almost six percentage points more than the variance explained by the first principal component in the big dataset. The cumulative explained variance of the first three common components is 46.24% and that for the first five components is 56.44%, which is about the same as in the big dataset.

In the next step, the latent common components are extracted. The dynamics over the span of the dataset of these factor indexes are captured in the time series plot of Figure A1 in the appendix. To make the presentation clearer, only the first three factors are depicted. The initially unobserved factor dynamics are plotted together with the observed headline inflation rate. The visual analysis indicates that all three factors show either strong co-movements or converse movements with the inflation rate. Those movements seem either to coincide with or to lead the inflation rate, which should give them predictive abilities. For the smaller dataset ($N = 246$), co-movements of the factors and the inflation rate are visible but not as conspicuous.

The correlation between the observed variables and the unobserved common component can be analysed by extracting the variables that are most characteristic for each dimension obtained by principal component analysis. This means that the statistically significant variables are identified and ranked by their correlation coefficient for the particular factors. The significance threshold at which a variable characterizes the dimension is set at 0.05. Only the variables with the 10 highest positive and negative correlation coefficients are extracted and analysed.

An example of the correlation between the observed variables and the unobserved common component is given in Table A1 in the appendix. The table reports the correlation of variables with the direction of the first factor. The producer price indexes (PPI) of Estonia's trading partners contribute most to the first factor, with the Finnish PPI excluding construction being the most important. PPI Industry Lithuania (ex construction) and PPI Intermediate goods of the European Union 15 are ranked as the fourth and fifth most important variables in terms of correlation. The turnover and sales of intermediate goods and the output of intermediate goods are also strongly positively correlated with the first factor.

5. Results

5.1. Benchmark dataset forecasting results

The results for the forecast errors from the benchmark dataset are reported in Table 1. First, the relative root-mean-square errors (RMSE) of the benchmark AR, the alternative forecasts and the FAVAR forecasts are reported. The RMSE of each of the forecasting models are shown relative to the RMSE of the benchmark AR model (so the autoregressive forecast has a relative RMSE of 1.00). The six columns show the relative forecast error for one- to six-quarter-ahead forecasts. To give an example, the forecast error of the simulated alternative RWM is 114.7% of the forecast error of the autoregressive forecast at the one-quarter horizon. Obviously, low values of RMSE indicate smaller forecast errors. The results for the lowest relative RMSE, which indicates the highest predictive abilities of the factor models, are given in bold.

The last row in the table shows the RMSE of the autoregressive benchmark for the given forecast horizon. The RMSE of the benchmark AR model can be interpreted as the percentage deviation of the forecast point estimates from the actual observed values over the full forecast window.

First, in many cases, the performances of the FAVAR forecasts are better than those of the benchmark forecasts, but the differences are generally quite small. For example, from the results of the one-quarter-ahead forecasts in the first column, it can be observed that factor-augmented VAR forecasts including only the first factor show an improvement in forecasting performance over the AR benchmark and the other alternative models.

In line with the results of Stock & Watson (2002b), models with a low lag order tend to perform better for all horizons. In most cases, the FAVAR models with two lags show the best forecasting performance, and they show a tendency to improve on the benchmark at short horizons. The smallest forecast errors are usually obtained for forecasts two quarters ahead. Forecasting one-year ahead, only the FAVAR model with the first factor and two lags offers an improvement of 5% over the benchmark. For the forecasts six quarters ahead, no FAVAR model is able to outperform the benchmark AR model. In contrast, the RWM seems to capture the inflation dynamics appropriately on longer horizons, outperforming the benchmark AR model by almost 20%.

Turning to the results for the core inflation in Table 2, it can be seen that the RMSE of the benchmark model are smaller than those for the headline inflation forecasts. This is in line with the theoretical arguments; given that the core inflation rate is less volatile than the headline inflation rate, it should be easier to forecast and therefore should yield smaller forecasting errors.

The FAVAR models tend to have slightly higher predictive abilities for headline inflation than for core inflation and this is especially true at longer forecast horizons. The forecasts from the FAVAR models outperform the benchmark AR forecasts only on the one- and two-quarter forecast horizon for core inflation.

5.2. Forecasting results for the reduced dataset

The forecasting results for headline inflation using the reduced size dataset are shown in Table 3. It may be presumed that domestic and foreign consumer price indexes constitute important predictors of the Estonian headline and the core inflation rates. Removing those targeted predictors may change the factor structure and consequently the forecasting performance of the FAVAR model. Decreasing the size of the dataset and removing the targeted predictors may thus produce higher RMSE, indicating lower predictive abilities. It is, however, also possible that decreasing the sample size from 388 to 246 variables will lead to the removal of less important predictors that dilute the extracted factors, resulting in a set of factors which can be used to calculate FAVAR forecasts that have lower RMSE than the FAVAR forecast with factors extracted from the benchmark dataset. As the underlying time series of the benchmark model have not changed, and so neither have their RMSE, the absolute and relative forecasting errors of the FAVAR models can be directly compared between the two different sized datasets.

Stock & Watson (2002b) found that the performance of comparable models is usually better when factors from a full dataset are used than when those from a reduced size subset are used. However, the assumption that removing predictors from the dataset would lead to worse RMSE values cannot be confirmed by the results obtained for Estonia. First, the best performing headline FAVAR models from the benchmark dataset contain fewer factors than the best performing headline FAVAR models from the reduced dataset. Second, for forecasts within one to three quarters, the FAVAR model with the first factor shows the lowest RMSE in the benchmark dataset, whereas the FAVAR model with the first three factors shows lower forecasting errors in the reduced size dataset for the four to six quarters horizon. Comparing these different models, I see the forecasting performance is quite similar and most models outperform the benchmark by small margins.

Table 4 shows the forecasting results for core inflation when the reduced dataset is used. I already know that the benchmark AR model is the main competitor to the FAVAR forecasts, as the RWM does not seem to capture very well the less volatile dynamics of the core inflation rate.

Notable differences appear when the headline and the core inflation forecasts are compared within each of the two datasets and are also apparent between the benchmark and the reduced-size datasets. The best headline FAVAR forecasts show lower forecasting errors than the benchmark AR for the forecasts one, three, four, five and six quarters ahead even though the performance improvement is partly weak in economic terms. The best core FAVAR model forecasts improve upon the benchmark AR in all the one- to four-quarter-ahead forecasts. However, the forecast improvement gains are much higher, especially for the forecasts one, two and three quarters ahead. To give an example, for the forecasts one to four quarters ahead, the core FAVAR models improve on average upon the headline FAVAR forecasts by 11%.

Comparing the headline inflation forecasts of the benchmark dataset with the headline inflation forecasts of the reduced dataset, it can be seen that FAVAR models with one factor have the lowest forecasting errors in the benchmark dataset, whereas FAVAR models with the first three factors have the lowest RMSE in the reduced dataset. The differences in forecasting errors between these two forecasting models are, however, small and not systematic.

The results for the core inflation forecasts are more conclusive. Not only can a tendency for multi-factor models to have better forecasting abilities than models with only the first factor be observed, but the best performing core FAVAR forecasts are obtained when the factors are extracted from the reduced size dataset. In addition, those forecast errors are the smallest of any model at any for all forecasting horizons.

The results from Tables 1 to 4 indicate that the forecasting performance of the FAVAR models is directly related to the number of factors included in the model. There is a clear tendency for FAVAR models with the first three factors to have higher predictive abilities than models containing only the first factor when those factors are extracted from a reduced size dataset. The forecasting performance also depends on the number of factors and the inflation measure to be forecast. These dynamics are interesting and deserve some discussion.

One possible explanation why models including the first three factors have a similar forecasting performance to that of models with only the first factor, depending on the size of the dataset, is that the information content of the benchmark dataset is higher than the information content of the reduced size dataset. When the factors are extracted and included in an FAVAR model, the number of factors needed in the model for it to exhibit good predictive abilities reflects the additional information content of the dataset. An FAVAR model with only the first factor from the benchmark dataset seems to capture an appropriate amount of additional predictive information. In contrast, the first three factors have to be included in an FAVAR model to obtain similar predictive abilities when those factors are extracted from a reduced size dataset with presumably lower information content. One explanation might be that the benchmark dataset contains more targeted predictors. For that reason, the first factor shows good predictive abilities, whereas more than just the first factor is needed to achieve similar predictive abilities when the size of the dataset is reduced and thereby possible targeted predictors are excluded.

The second question that arises is why the core inflation forecasts with factors extracted from the reduced-size dataset improve upon the benchmark dataset and headline inflation forecasts by significant margins. One possible reason underlying this observation may be derived from the factor analysis in Section 4.2. When the factors are extracted from the small dataset, their dynamics are less pronounced. It may be conjectured that the interdependencies of these three factors and the inflation rate in the VAR system are more accurate in capturing the less volatile dynamics of the core inflation rate.

Finally, the results for the random walk forecasts deserve attention. The only model which consistently outperforms the benchmark AR by economically meaningful margins is a unit-root-based forecast, which is arguably a surprise. Comparing the results of the random walk forecasts for headline inflation and for core inflation, it is clearly observable that random walk forecasts have substantially better forecasting abilities than all other models when headline inflation is forecast three to six quarters ahead. No such pattern is visible for core inflation, and the random walk forecast tends to worsen with increasing forecast horizon.

The results for headline inflation are in line with the findings in Atkeson & Ohanian (2001) who found that backward-looking Philips curve forecasts cannot improve upon naive RWMs. Even though it has been shown that those findings are sensitive to the sample period and the parametrization of the Philips curve model, Stock & Watson (2007) admit that on average, it is difficult for multivariate models to beat simple univariate models. Stock & Watson (2007) argue therefore that the value added of more complex multivariate models compared to simple univariate models is limited.

5.3. Forecasting results for the subgroups

So that homogeneous subgroups are obtained, only the monthly data series are used. To give an example of the series construction, consider the composition of the money and price indexes subgroups. The money subgroup groups together credit, deposits, finance, interest rates and money supply variables. The price indexes subgroup brings together PPI trade partners, domestic PPI, HICP trade partners, and import and export prices are joined. Forecasts are conducted for each subgroup.[9] In addition, the first factor from each of the six subgroups is estimated. In the next step, all six factors enter a separate factor-augmented VAR and the forecasting procedure is repeated. Last, only the first factor from the three best performing subgroups (money, price indexes and real factors) are combined to form an FAVAR model that include three factors.

Table 5 shows the forecasting results for headline inflation for the subgroup price indexes. An FAVAR model where all three factors are included shows impressive forecasting performance, outperforming not only the benchmark model but also the random walk forecasts.

On the four-quarter horizon, the subgroup model shows forecast errors that are less than half those of the benchmark model.[10] Even the worst three-factor forecast improves upon the benchmark model by almost 20%.

However, the price indexes subgroup forecasts do not have the same predictive power when the core inflation rate is forecast, showing forecast improvements only at short horizons (Table A18 in the appendix). Similarly, the headline inflation forecasts of the subgroup money show good predictive abilities on longer horizons, outperforming the benchmark model by approximately 30% when the first factor is used for forecasting (Table A12 in the appendix). Also, the one-factor forecasts of the subgroup including real variables show lower prediction errors than the benchmark model at short horizons.[11]

In the last step, I combine the first extracted factor from each subgroup and include them in the forecasting equation (Table 6). The forecasts fail to improve upon the benchmark forecasts under most specifications and show higher forecasting errors than models where the factors are extracted from a single dataset. This dismal forecasting behaviour might be a consequence of factors that have proven their forecasting abilities being put together in some subgroups such as price indexes or money with factors that do not improve forecasts when they are used to augment the VAR model. Surprisingly, an FAVAR that includes the first factor from the price indexes, money and real subgroups does not improve solidly over the model with all six subgroup factors at short horizons. At longer horizons in contrast, grouping only

Table 5. Headline inflation out-of-sample forecasting results one to six quarters horizon: price indexes.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
VAR	1.083	1.090	1.089	1.091	1.103	1.118
RW	0.929	0.909	0.847	0.874	0.912	0.851
FAVAR 1F. 1 Lag	1.014	0.984	1.029	1.065	1.118	1.221
FAVAR 1F. 2 Lags	1.142	1.015	1.009	0.988	0.922	0.986
FAVAR 1F. 3 Lags	1.269	1.276	1.284	1.209	1.145	1.202
FAVAR 12F. 1 Lag	0.931	0.923	0.977	0.990	1.083	1.202
FAVAR 12F. 2 Lags	1.049	0.985	0.999	0.955	0.903	0.967
FAVAR 12F. 3 Lags	1.451	1.510	1.535	1.493	1.458	1.548
FAVAR 123F. 1 Lag	**0.810**	**0.653**	**0.606**	**0.485**	**0.597**	**0.681**
Absolute RMSE, AR model	0.474	1.004	1.666	2.256	2.698	3.000

Note: RMSE in percentage points.

Table 6. Headline inflation out-of-sample forecasting results one to six quarters combination of the first factor from the subgroups.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
FAVAR 6 subgroups 1 Lag	1.220	1.153	1.048	0.998	**0.987**	1.013
FAVAR 6 subgroups 2 Lags	1.895	1.947	1.903	1.69	**1.621**	1.723
FAVAR 6 subgroups 3 Lags	**2.375**	2.542	2.654	2.785	2.827	3.058
FAVAR 3 subgroups 1 Lag	1.171	1.127	1.018	0.892	0.726	**0.554**
FAVAR 3 subgroups 2 Lags	**1.778**	1.908	1.919	1.814	1.833	1.796
FAVAR 3 subgroups 3 Lags	**1.947**	2.029	2.004	2.032	2.136	2.164
Absolute RMSE, AR model	0.474	1.004	1.666	2.256	2.698	3.000

Notes: RMSE in percentage points. The six subgroups are Price Indexes, External Balance, Money, Real, Forward Looking Indexes and External Indexes. From every subgroup, the first factor is extracted. The reduced FAVAR model includes Price Indexes, Money and Real factors.

the three subgroup factors yields considerable forecasting gains. On the six-quarter horizon, a model composed of the first factor from the price indexes, money and real subgroups shows forecasting errors that are almost 50% lower than those of the benchmark AR model. However, these forecasting gains vanish with core inflation and no model shows stronger predictive abilities than the benchmark model.

The results of the subgroup forecasts indicate that factors extracted from homogeneous blocks of nominal variables, in particular those derived from consumer and producer prices, show superior forecasting abilities at most horizons when headline inflation is forecast. I also find good forecasting properties from the money subgroup, especially at longer horizons. These encouraging results are in line with the results obtained by other authors who use similar subgroups of nominal variables to extract factors to forecast nominal economic variables (Banerjee, Marcellino, & Masten 2014; Bruneau et al. 2007). Nevertheless, the question remains whether the strong forecasting performance stems from removing series with highly cross-correlated errors in the factor model or from linking nominal price series to the variable to be forecast or a combination of both.[12]

5.4. Robustness analysis

First, I check if the transformation procedure impacts the forecast performance of the models. Following Stock & Watson (2002a), I use a group-wise stationarity-inducing transformation scheme on the benchmark dataset. To do this, I take, for example, the first difference of time series in the finance class and the second difference of time series in the credit class.[13] After the transformation, I test again for stationarity of the variables, then I repeat the complete forecasting exercise for headline and core inflation. The results indicate that the group-wise transformation scheme leads to inferior forecasts under all specifications (headline, core, reduced-sized and subgroup forecasts).[14] This might indicate that group-wise transformation excessively differentiates the variables in the dataset, diminishing their predictive power even before their information content is summarized by the factors.

Analysing the sensitivity of the forecasts to small changes in the time period reveals that the results obtained for both datasets tend to be quite robust; see Tables A7–A10 in Appendix 2. When one-quarter is removed from each period for which the forecast errors are calculated, the RMSEs change only a little in most cases. The models with the best forecasting abilities in the full datasets also tend to have the highest predictive abilities in the datasets where one period was removed. Overall, the robust forecasting performance can be attributed to the models obtained from the benchmarked and the reduced size datasets. The results for the core inflation forecasts indicate even less sensitivity to changes in the time sample.

Next, I analyse whether small changes in the composition of the dataset affect the forecasting results. The frequency distribution for the headline inflation forecasts with factors extracted from the benchmark dataset can be seen in Figure A3. The vertical line represents the AR benchmark, while the frequency plots report the distribution of the forecasting errors of the FAVAR models. Model distributions that are to the left of the vertical line have lower forecasting errors than the benchmark AR model does.

The distribution of the forecast errors supports the hypothesis that FAVAR models with the first factor and two lags (FAVAR 1F. 2 Lags) outperform the benchmark model. Up to the forecast horizon five quarters ahead, the mass of the distribution is centred clearly to the left of the benchmark AR model with a low spread. On the five-quarter-ahead horizon, the mass is still centred to the left of the benchmark, although for some samples the RMSE are larger than for the benchmark. Forecasting six quarters ahead, the FAVAR models do not manage to outperform the benchmark in the majority of the sample cases.

The sampling distribution for core inflation (see Figure A4) shows that five FAVAR models have lower forecast errors than the benchmark AR model has at the one- and two-quarter forecasting horizons. In particular, the RMSE of the samples from the FAVAR models with the first factor and one lag (FAVAR 1F. 1 Lag) and the first three factors and one lag (FAVAR 123F. 1 Lag) clearly outperform the benchmark AR. Analysing the graphs over longer forecasting horizons leads to the same conclusions as those in the analysis of Table 2, as all the FAVAR model forecasts fail to outperform the benchmark AR forecasts in most cases.

When the number of variables in the reduced size dataset is decreased by 15%, the forecasting error frequency distribution for headline inflation (see Figure A5) shows less stable behaviour. At the one-quarter forecasting horizon, the distribution of the forecasting errors of the FAVAR model with the first factor and two lags (FAVAR 1F. 2 Lags) and the FAVAR models with the first factor and three lags (FAVAR 1F. 3 Lags) are clearly to the left of the benchmark AR model. At the two-quarter forecasting horizon, the mean of the FAVAR model with the first factor and two lags (FAVAR 1F. 2 Lags) is centred slightly to the right of the benchmark. More interestingly, the FAVAR model with the first three factors and one lag (FAVAR 123F. 1 Lag) has a spread distribution with a mean slightly to the left of the benchmark AR. For the one-factor two lags or one-factor three lags FAVAR models, the distributions tend to be to the left of the benchmark value for the three- and four-quarter-ahead forecasts. The distributions of the first three factors model (FAVAR 123F. 1 Lag) are spread between a range of approximately 0.9 and 1.1, with a tendency to be centred slightly to the left of the benchmark AR.

For core inflation, the distributional properties (see Figure A6) of the forecasting errors of the FAVAR models are similar to those of the headline inflation forecasts. At short forecasting horizons of one and two quarters, the FAVAR model including the first factor and one lag (FAVAR 1F. 1 Lag), the model with the first and the second factor and one lag (FAVAR 12F. 1 Lag) and the model with the first three factors (FAVAR 123F. 1 Lag) clearly outperform the benchmark AR, even when the reduced size dataset is shrunk in size by 15%. At the three- and four-quarter forecasting horizon, only the model with the first three factors (FAVAR 123F. 1 Lag) tends to outperform the benchmark AR.

However, the distribution is spread out and asymmetric. Similarly, for the five- and six-quarter forecast horizon, some samples from the same model (FAVAR 123F. 1 Lag) show lower forecasting errors than those of the benchmark, but most values lie at the right side of the spread-out distribution.

In summary, the results show that small arbitrary changes to the number of variables in the two datasets have only a small impact on the forecast performance of FAVAR models that include only the first factor. For the reduced size dataset, however, a different dataset composition has substantial effects on the FAVAR model with the first three factors and one lag (FAVAR 123F. 1 Lag). At the three- to four-quarter forecasting horizon in particular, the slightly asymmetric spread of the distribution around the benchmark AR value of one makes it difficult to draw a conclusion as to whether the FAVAR 123F. 1 Lag model forecasts outperform the benchmark model or not. This indicates that arbitrary changes to the number of predictors have a stronger impact on the reduced-size dataset than on the larger benchmark dataset.

6. Final comments

This paper investigates the performance of factor-augmented VAR models when they are used to predict the Estonian headline and core inflation rates. The factors are extracted by a principal component method from a big benchmark dataset with 388 quarterly economic and financial time series, and a reduced size dataset consisting of 246 series. In addition, factors are extracted from subgroups of variables that are formed by economic intuition. The FAVAR forecasts range from the second quarter of 2011 to the second quarter of 2014 and their forecasting errors are compared to naive benchmarks, such as an autoregressive forecast.

The analysis of the forecasts of Estonian headline and core inflation at various forecast horizons and using different sample sets yields interesting and arguably surprising results. Five findings can be highlighted. First, factor model forecasts can improve upon an autoregressive forecast but in most cases the forecasting gain is limited. Second, some models with one factor have smaller forecasting errors when the factors are extracted from a big benchmark dataset. Third, certain big factor models that contain three factors perform better than models with fewer factors when the factors are taken from a smaller dataset where the consumer price indicators have been excluded. This indicates that the dataset size and dataset composition matter for forecasting performance. Fourth, factors extracted from homogeneous subgroups of nominal variables show the best performance for projecting headline inflation but have less predictive power for core inflation forecasts. Fifth, the forecasting performance is less contingent upon small arbitrary changes in the dataset composition when the factors are extracted from a large dataset than is the case with small arbitrary changes in a small dataset.

Surprisingly, essentially similar forecasting results for the Estonian inflation rate, and even better ones in certain cases, emerge when the factors are extracted from a reduced-size dataset that excludes domestic and foreign consumer price indicators. These effective forecasts can be obtained from FAVAR models with the first three factors and one lag. However, the robustness analysis for this model indicates that small changes in the composition of the reduced-size dataset might have a substantial impact on the first three factors and therefore also on the forecasting performance.

Extracting factors from subgroups of nominal variables, in particular those derived from price and money data yield substantial forecasting improvements under all horizons, whereas forecasts from other subgroups show dismal forecasting performance. Combinations of the first three factors from the subgroup prices improve upon the benchmark model by almost 50%. However, combinations of the first factor from all six subgroups or the best performing three subgroups do not improve substantially upon the benchmark model.

Even though the results point to notable differences between the headline and core inflation forecasts, a clear statement of whether FAVAR models are better suited to forecasting one or the other is difficult to derive. Headline inflation forecasts show a tendency to perform better at longer horizons, whereas core inflation forecasts have slightly better predictive abilities at short horizons when the factors are extracted from the benchmark dataset. However, for the FAVAR models with more factors, when the factors are extracted from the reduced-size dataset, the core inflation results clearly outperform the headline inflation results in the first four quarters. Restricting the dataset size further by constructing homogeneous subgroups of variables fails to improve forecast accuracy upon the benchmark model where core inflation is concerned.

The findings provide evidence that simple factor model forecasts such as factor-augmented VAR models can improve upon naive forecasts under certain circumstances. The forecast performance depends greatly on the number of factors included in the model, the size of the dataset from which the factors are extracted, the time series to be forecast, and lastly, the forecasting horizons.

Forecasting inflation still remains a challenge and this also applies to Estonian inflation. Among the models examined, substantial forecasting gains can only be reaped from two distinct models. Even from the perspective of an experienced forecaster, it is still difficult to assess a priory how many factors should be incorporated in the model in relation to the size of the dataset. Forecasting with factors extracted from subgroups built on economic intuition can improve upon forecasts with factors extracted from a single dataset. However, categorizing variables into subgroups and combing the correct number of factors from different subgroups is non-trivial, especially compared to constructing an FAVAR model from a single large dataset. For Estonia, the results indicate that using an FAVAR model with the first factor extracted from a large dataset provides good forecasting performance, even when the exact size and composition of the dataset are unknown.

Notes

1. Detailed discussions of the dynamics of inflation in Estonia are also provided in Dabušinskas (2005), Dabušinskas & Kulikov (2007), Arratibel, Kamps, & Leiner-Killinger (2009) and Errit & Uusküla (2014).
2. In addition to those discussed in the literature review, other methods have been used for summarizing and extracting information from high-dimensional datasets. Forni, Hallin, Lippi, & Reichlin (2000, 2005) popularized generalized dynamic models where the factors are estimated in the frequency domain. Bai & Ng (2009) use boosting as a method of selecting the predictors in factor-augmented autoregressions. A factor-augmented VARMA model was introduced by Dufour & Stevanović (2013). Stock & Watson (2012) propose a general shrinkage model based on pretests such as Bayesian Model Averaging (BMA), empirical Bayes or bagging. Banerjee et al. (2014) present forecasts using a factor-augmented error correction model. Comparisons and reviews of various factor forecasting models can be found in Eickmeier & Ziegler (2008) and Kim & Swanson (2013).

3. The objective function for the estimation of the factors F_t is given by

$$V(F, \Lambda) = \min_{\Lambda, F} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (X_{it} - \Lambda_i F_t)^2,$$

where $F = [F_1, \ldots, F_t, \ldots F_T]'$ and Λ_i is the ith row of Λ. F and Λ are subject to the constraint $F'F/T = I_r$, where I_r is the $r \times r$ identity matrix. Hence, applying the principal components method means that the residual sum of squares is minimized subject to the normalization that $F'F/T = I_r$.
4. One formal way to separate targeted predictors from uninformative time series is proposed by Bai & Ng (2008). They suggest partitioning the panel of predictors into two subsets. The first subset should include all time series (targeted predictors) that are relevant for the specific variable to be forecast and the other subset should include all series that are non-informative. The partitioning is done with thresholds defined by the least absolute shrinkage and selection operator (LASSO) and the elastic net rules. While those shrinkage models are interesting from a technical perspective and most researchers in the field acknowledge the importance of targeted predictors, practitioners tend to rely on heuristics to determine which time series to include in their dataset.
5. The Diebold–Mariano test suffers from two shortcomings when the forecasting approach of Bernanke et al. (2005) is followed. First, the finite sample properties of the estimators on which the forecasts may depend are not preserved asymptotically. Second, the DM test is prone to nested model bias (Giacomini & White 2006). That presents a problem under the out-of-sample extending window forecasting procedure when the competing forecasts are obtained from autoregressive and factor-augmented VAR models.
6. The six models not reported include an FAVAR forecast where the lag order is allowed to vary, a model including the first five factors, and models including only the second factor at different lag lengths. The forecasting results for those models are available upon request.
7. To ensure that the AR model constitutes a competitive benchmark model, the RMSE of different lag length intervals were compared. Neither a fixed lag order of one, two or three lags nor intervals ranging from $1 \leq p \leq 2$ up to $1 \leq p \leq 12$ show lower forecasting errors for the benchmark model than the forecasts obtained from AR models where p is allowed to vary between one and three.
8. The results for the autoregressive moving average (ARMA) are identical to the results from the AR benchmark forecasts. Within the order constraints given, which are a maximum of three lags for any autoregressive component and a maximum of three lags for any moving average component, the Bayesian information criterion (BIC) determined unanimously that the given process does not include any moving average terms. Therefore, the lag structure is equal to the lag structure of the benchmark AR process, and the forecasting results are identical.
9. The exact grouping scheme can be found in Table A11.
10. Adding the third factor from the subgroup price indexes improves substantially upon the benchmark model. A factor analysis reveals that the HICP components of Estonia's Central and Northern European trading partners, namely the U.K., Germany and Finland, contribute most to the third factor. The most important HICP components are non-energy industrial goods (NEIG), industrial goods and goods (ox services). In contrast, the HICP components of Estonia's Baltic trading partner Latvia dominate the variables that are negatively correlated with the third factor. The most important HICP component is once more non-energy industrial goods (NEIG).
11. The forecasting results for the additional subgroups for headline and core inflation are shown in Tables A12–A24 in the appendix.
12. To test whether the good forecasting performance is driven by a sharpened factor structure, I use the LASSO on the benchmark dataset. The LASSO operator is constructed in a similar fashion to that used in Bai & Ng (2008), the difference being that the LASSO tuning parameter λ is chosen by cross-validation. The LASSO model indicates that the reduced panel should only

contain seven variables from the given benchmark dataset. Six of those variables are nominal price indicators, with the seventh being the survey of consumer price trends over the last 12 months. This means that the selection operator chooses a majority of the variables that are included in the subgroup prices, albeit in smaller numbers. One interpretation of this finding is that the variables to be included in a model suggested by the LASSO operator are similar to those variables grouped by economic intuition. This might indicate that the good results are driven in part by a sharpened factor structure and in part by a close link between the nominal variables the factors are extracted from and the nominal variable to be forecast.
13. The detailed transformation scheme can be found in the appendix Table 11
14. The results are available upon request.

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Disclosure statement

No potential conflict of interest was reported by the authors.

Notes on contributor

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Appendix 1

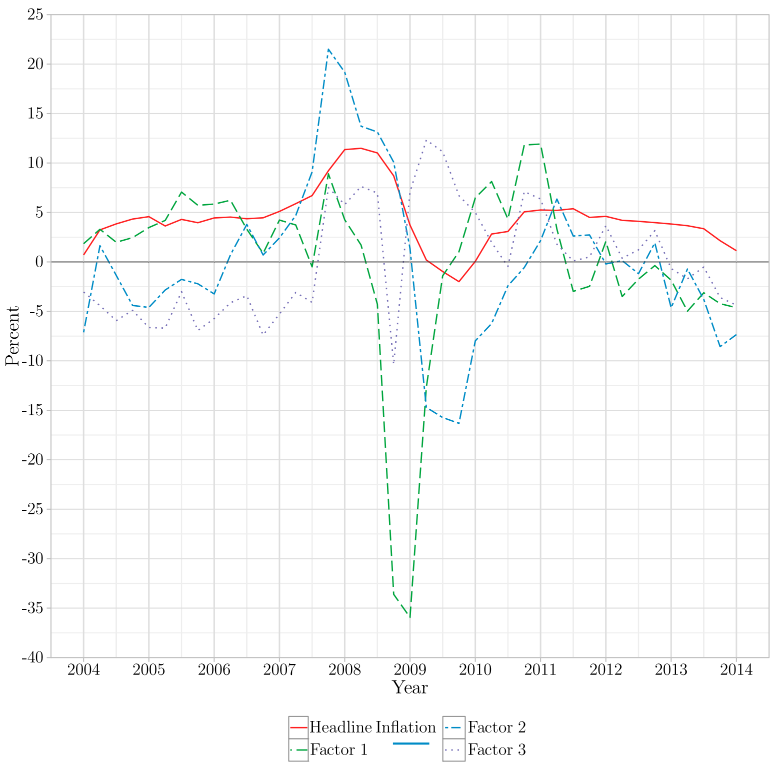

Figure A1. Estimated common factors and Estonian headline inflation rate – benchmark dataset.

Table A1. Correlation of the variables with the first factor.

Variable code	Variable full name	Correlation	p-Value
ppi_ind_finla_sa_no	PPI tradep: PPI Industry Finland	0.920	.00000
tv_intermgood_sa_no	Turnover and Sales: Intermediate Goods	0.881	.00000
tv_total_sa_no	Turnover and Sales: Total categories	0.880	.00000
ppi_ind_lithu_sa_no	PPI tradep: PPI Industry Lithuania	0.876	.00000
ppi_ind_eu15_sa_no	PPI tradep: PPI Intermediate Goods EU 15	0.860	.00000
op_intermgood_sa_no	Output: Intermediate Goods	0.859	.00000
hicp_nrg_wa_sa_no	HICP Estonia: Energy Estonia	0.856	.00000
op_total_sa_no	Output: Total categories	0.852	.00000
ppi_ind_eu28_sa_no	PPI tradep: PPI Industry EU 28	0.847	.00000
price_import_sa_no	Import ex prices: Export price index	0.846	.00000
spread_eur_e_sa_no	Interest margins 6-month Euribor NFC	0.592	.00004
spread_eur_h_sa_no	Interest margins 6-month Euribor House loans	0.568	.00009
xunempl_sa_no	Total unemployment	0.499	.00077
neer_br_sa_no	Import ex prices: BIS, Nom. Broad Effective Exch.	0.437	.00384
ca_total_sa_no	BOP: Current Account Total	0.417	.00602
hicp_i_nd_se_sa_no	HICP partners: NEIG non-dur only Sweden	0.411	.00679
hicp_i_nd_de_sa_no	HICP partners: NEIG non-dur only Germany	0.405	.00785
empl_u_tkh_av_sa_no	Labor: The average unemployment insurance benefit	0.397	.00917
ca_goods_net_sa_no	BOP: Estonia, Current Account, Goods, Net	0.354	.02151
hicp_i_nd_wa_sa_no	HICP partners: NEIG non-dur only Euro area	0.338	.02842

Notes: Benchmark dataset ($N = 388$). p-Value = .05.

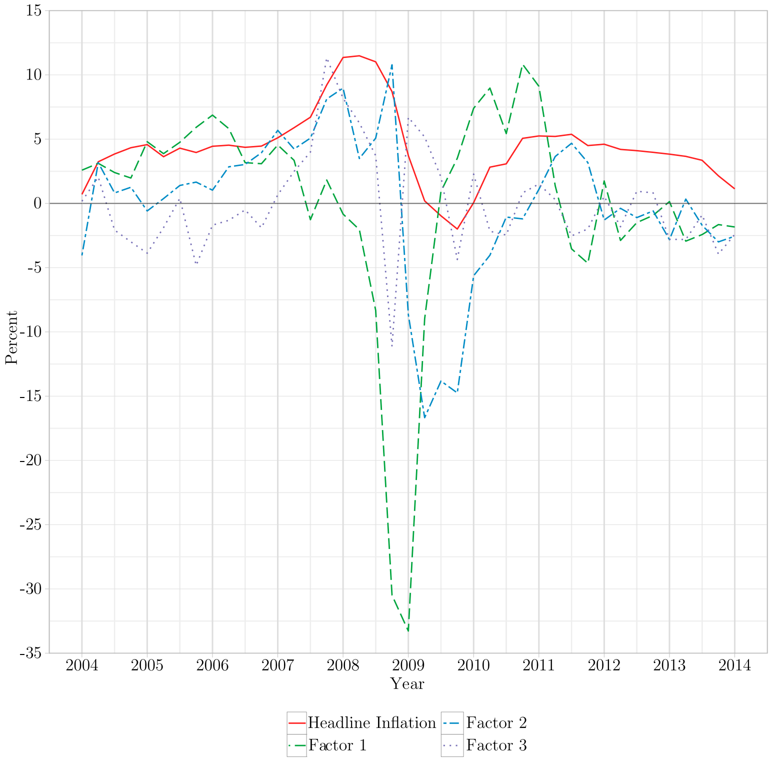

Figure A2. Estimated common factors and Estonian core inflation rate – reduced-size dataset.

Appendix 2

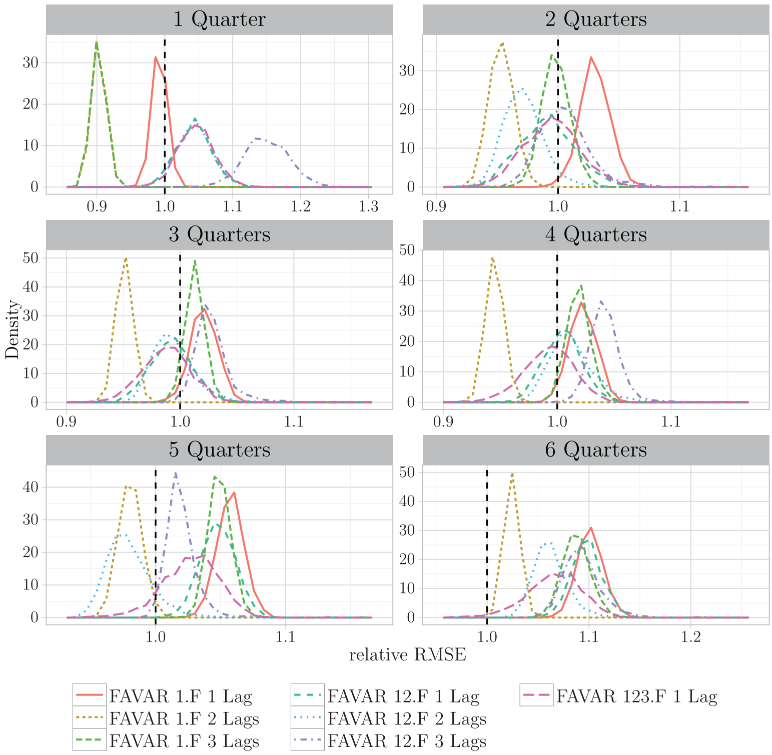

Figure A3. Frequency distribution Estonian headline inflation – benchmark dataset.

Table A2. Correlation of the variables with the second factor.

Variable code	Variable full name	Correlation	p-Value
hicp_cp00_lt_sa_no	HICP partners: All-items HICP Lithuania	0.883	.00000
hicp_serv_lt_sa_no	HICP partners: Services (ex goods) Lithuania	0.856	.00000
hicp_x_nrg_f_sa_no	HICP partners: ex energy EU	0.850	.00000
hicp_cp01_lt_sa_no	HICP partners: Food and non-alcoholic beverages Lithuania	0.839	.00000
hicp_cp011_lt_sa_no	HICP partners: Food Lithuania	0.837	.00000
hicp_gd_lt_sa_no	HICP partners: Goods (ex services) Lithuania	0.829	.00000
hicp_cp01_wu_sa_no	HICP partners: Food and non-alcoholic beverages EU	0.821	.00000
hicp_food_lt_sa_no	HICP partners: Food including alcohol and tobacco Lithuania	0.816	.00000
hicp_cp00_lv_sa_no	HICP partners: All-items HICP Latvia	0.816	.00000
hicp_food_wu_sa_no	HICP partners: Food including alcohol and tobacco EU	0.814	.00000
cli_finl_a_sa_no	CLI: Finland, CLI, amplitude adjusted	−0.806	.00000
cli_finl_t_sa_no	CLI: Finland, CLI, tr	−0.756	.00000
cli_ez_amp_sa_no	CLI: EuroZone, CLI, amplitude adjusted	−0.707	.00000
cs_conf_sa_no	Surveys: CS, Confidence indicator	−0.706	.00000
sent_sa_no	Surveys: Economic Sentiment, Economic sentiment indicator	−0.706	.00000
cli_oecd_t_sa_no	CLI: OECD, CLI, amplitude adjusted	−0.704	.00000
cli_oecd_a_sa_no	CLI: OECD, CLI, amplitude adjusted	−0.697	.00000
ex_omx_sto_pr_sa_no	OMXS30 Index, Price Return, EUR	−0.687	.00000
cli_ger_t_sa_no	CLI: Germany, CLI, tr	−0.667	.00000
cli_ger_a_sa_no	CLI: Germany, CLI, amplitude adjusted	−0.667	.00000

Notes: Benchmark dataset ($N = 388$). p-Value = 0.05.

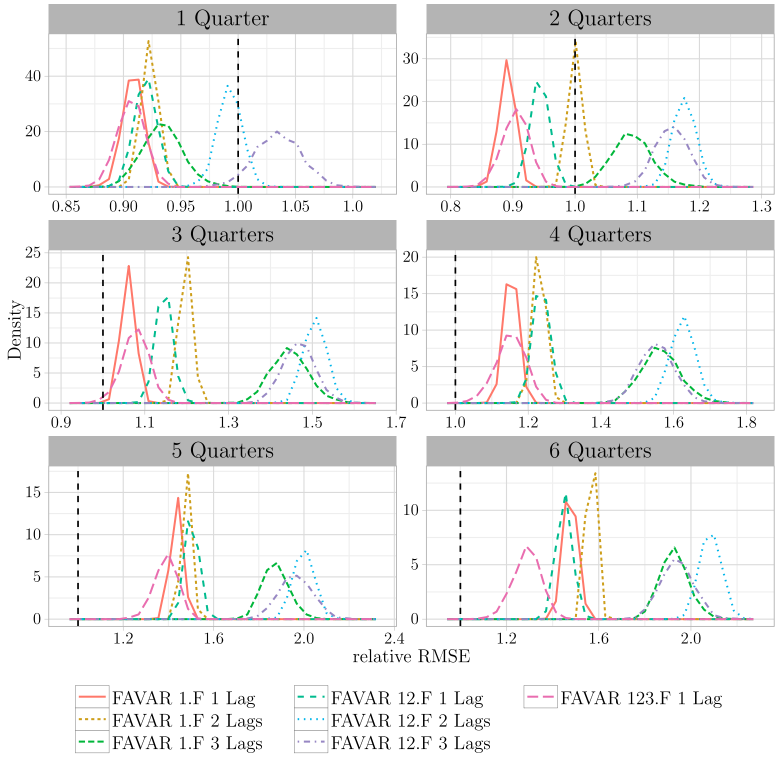

Figure A4. Frequency distribution Estonian core inflation – benchmark dataset.

Table A3. Correlation of the variables with the third factor.

Variable code	Variable full name	Correlation	*p*-Value
hicp_igd_uk_sa_no	HICP partners: Industrial goods UK	0.696	.00000
hicp_i_uk_sa_no	HICP partners: NEIG UK	0.685	.00000
hicp_gd_uk_sa_no	HICP partners: Goods (ex services) UK	0.641	.00000
hicp_i_d_uk_sa_no	HICP partners: NEIG dur only UK	0.611	.00002
hicp_cp00_se_sa_no	HICP partners: All-items HICP Sweden	0.598	.00003
hicp_gd_se_sa_no	HICP partners: Goods (ex services) Sweden	0.591	.00004
hicp_i_nd_uk_sa_no	HICP partners: NEIG non-dur only UK	0.553	.00015
hicp_cp00_fi_sa_no	HICP partners: All-items HICP Finland	0.544	.00020
hicp_cp00_uk_sa_no	HICP partners: All-items HICP UK	0.538	.00024
hicp_igd_se_sa_no	HICP partners: Industrial goods Sweden	0.531	.00030
hicp_i_d_lv_sa_no	HICP partners: NEIG dur only Latvia	−0.677	.00000
st_it_usd_nfc_sa_no	Short-term interest (1 < year) rates USD NFC	−0.646	.00000
cred_st_ind_sa_no	Credit: Individuals	−0.619	.00001
ret_rt_food_sa_no	Retail Sales: Food, beverages and tobacco in non-specialized stores	−0.607	.00002
cred_st_lt_10_sa_no	Credit: Long-term	−0.583	.00005
cred_st_cu_sa_no	Credit: Cooperations	−0.582	.00005
xkgd_sa_no	Deflator: GDP total	−0.577	.00006
fin_tg_soc_pe_sa_no	State budget tax revenues, soc. security, pension	−0.570	.00008
fin_tg_soc_sa_no	State budget tax revenues, soc. security	−0.566	.00010
xkpr_sa_no	Deflator: Private	−0.560	.00011

Notes: Benchmark dataset ($N = 388$). *p*-Value = .05.

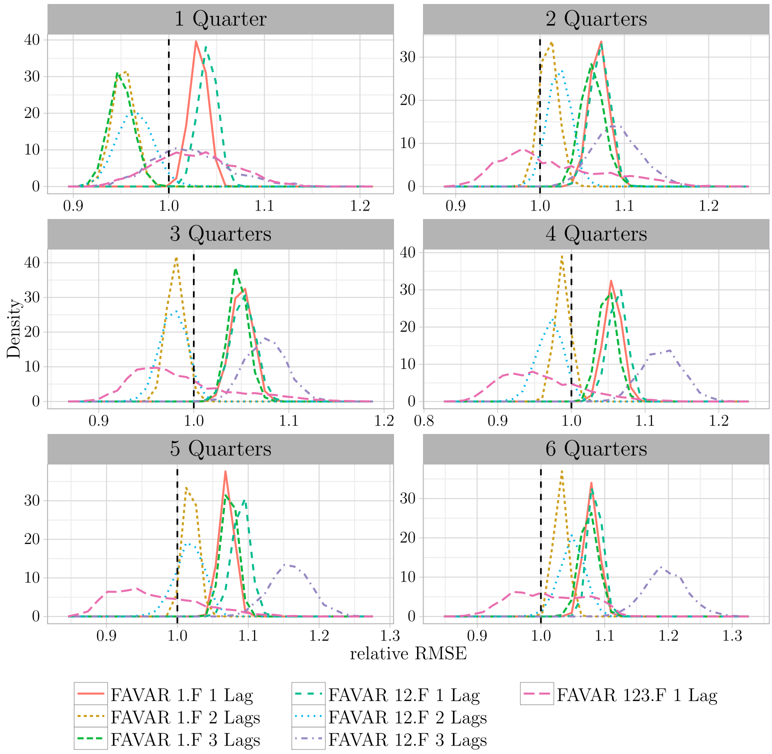

Figure A5. Frequency distribution Estonian headline inflation – reduced-size dataset.

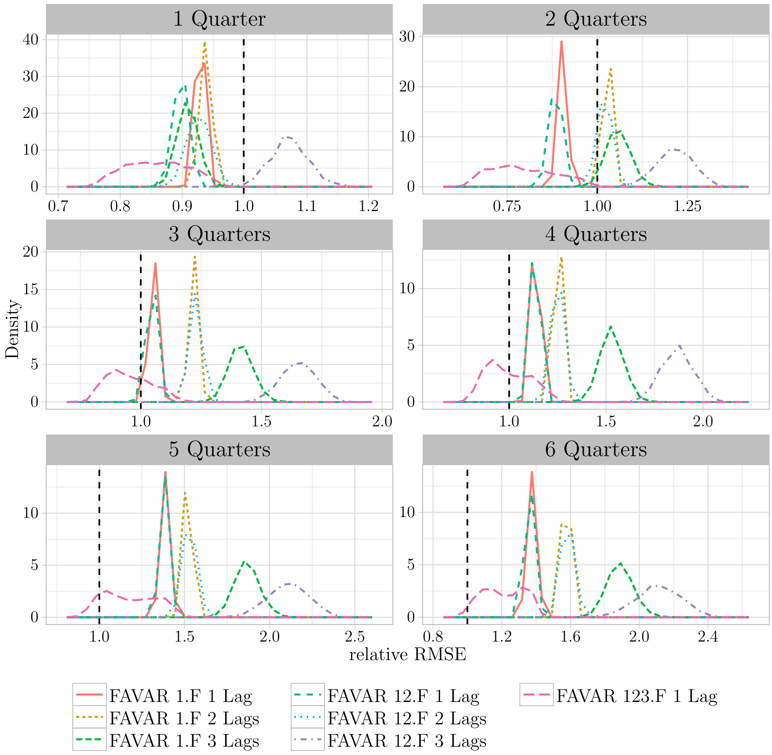

Figure A6. Frequency distribution Estonian core inflation – reduced-size dataset.

Table A4. Correlation of the variables with the first factor.

Variable code	Variable full name	Correlation	*p*-Value
tv_intermgood_sa_no	Turnover and Sales: Intermediate Goods	0.912	.00000
op_intermgood_sa_no	Output: Intermediate Goods	0.907	.00000
tv_total_sa_no	Turnover and Sales: Total Goods	0.904	.00000
op_total_sa_no	Output: Total Goods	0.898	.00000
ft_total_sa_no	Foreign Trade: Total Commodities	0.862	.00000
ppi_ind_finla_sa_no	PPI tradep: PPI Industry Finland	0.857	.00000
empl_u_reg_ne_sa_no	Labor: Unemployment, Total Registered	0.846	.00000
nord_intermgo_sa_no	New Orders: Production of intermediate consumption goods	0.822	.00000
cci_us_sa_no	CLI: US, Coincident Index, Total	0.820	.00000
empl_u_tkh_ne_sa_no	Labor: The new unemployment insurance benefit recipients	0.820	.00000
spread_eur_e_sa_no	Interest margins 6-month Euribor NFC	−0.613	.00002
spread_eur_h_sa_no	Interest margins 6-month Euribor House loans	−0.570	.00008
xunempl_sa_no	Total unemployment	−0.524	.00037
cs_u_n12_sa_no	Surveys: CS, Unemployment exactions over 12 months	−0.466	.00187
empl_u_tkh_av_sa_no	Labor: The average unemployment insurance benefit	−0.465	.00193
neer_br_sa_no	Import ex prices: BIS, Avg. Nom. Broad Effective Exch. Rate	−0.460	.00215
ca_total_sa_no	BOP: Current Account Total	−0.432	.00428
cred_blnc_prc_sa_no	Credit: % of loan portfolio (balance)	−0.416	.00615
cred_cntr_prc_sa_no	Credit: % of loan portfolio (cntrct val.)	−0.383	.01220
ca_goods_net_sa_no	BOP: Estonia, Current Account, Goods, Net, Total	−0.357	.02021

Notes: Reduced dataset ($N = 246$). *p*-Value = .05.

Table A5. Correlation of the variables with the second factor.

Variable code	Variable full name	Correlation	*p*-Value
fin_tg_soc_pe_sa_no	State budget tax revenues, soc. security, pension	0.689	.00000
fin_tg_soc_sa_no	Finance: State budget tax revenues, soc. security	0.683	.00000
fin_tg_soc_me_sa_no	State budget tax revenues, soc. security, health	0.669	.00000
xcgd_sa_no	NULC by hours: GDP total	0.648	.00000
xdge_sa_no	Estonian deflators: General government consumption expenditure	0.647	.00000
ret_rt_food_sa_no	Retail Sales: Food, beverages and tobacco in non-specialised stores	0.644	.00000
empl_wages_sa_no	Labor: Monthly wages	0.616	.00001
ppi_total_sa_no	PPI: Producer Prices, Total	0.594	.00003
ppi_food_sa_no	PPI: Producer Prices, Food and beverages, Index	0.590	.00004
st_it_eur_nfc_sa_no	Interest rates: Short-term interest rates NFC	0.575	.00007
cli_finl_a_sa_no	CLI: Finland, CLI, amplitude adjusted	−0.831	.00000
cli_finl_t_sa_no	CLI: Finland, CLI, tr	−0.706	.00000
sent_sa_no	Surveys: Economic Sentiment, Economic sentiment indicator	−0.700	.00000
cli_ger_a_sa_no	CLI: Germany, CLI, amplitude adjusted	−0.666	.00000
cli_ger_t_sa_no	CLI: Germany, CLI, tr	−0.645	.00000
cli_oecd_a_sa_no	CLI: OECD, CLI, amplitude adjusted	−0.644	.00000
ex_omx_sto_pr_sa_no	External indic: OMXS30 Index, Price Return, EUR	−0.622	.00001
cli_ez_amp_sa_no	CLI: EuroZone, CLI, amplitude adjusted	−0.609	.00002
cli_oecd_t_sa_no	CLI: OECD, CLI, tr	−0.572	.00008
cs_conf_sa_no	Surveys: CS, Confidence indicator	−0.555	.00014

Notes: Reduced dataset ($N = 246$). *p*-Value = .05.

Table A6. Correlation of the variables with the third factor.

Variable code	Variable full name	Correlation	*p*-Value
imf_pfood_sa_no	IMF: Food Price Index, 2005 = 100	0.599	.00003
imf_pfandb_sa_no	IMF: Food and Beverage Price Index, 2005	0.595	.00003
oilfutures_cs_sa_no	ECB commod: IMF IFS (U.K. Brent)	0.537	.00025
ex_brentoil_i_sa_no	External indic: World, ICE, Crude Oil Index, USD	0.533	.00028
imf_pallfnf_sa_no	IMF: All Commodity Price Index, 2005 = 1	0.531	.00030
ppi_food_eu28_sa_no	PPI Manuf of food EU 28	0.529	.00032
imf_poilapsp_sa_no	IMF: Crude Oil (petroleum), Price index	0.528	.00033
imf_pnrg_sa_no	IMF: Fuel (Energy) Index, 2005 = 100	0.525	.00035
ex_crudeoil_i_sa_no	External indic: World, Energy, Oil, Brent, ICE, Average, USD	0.517	.00045
ppi_food_eu15_sa_no	PPI Manuf of food EU	0.516	.00047
cs_fin_l12_sa_no	Surveys: CS, Financial situation of households over *l* 12 months	−0.635	.00001
cs_ec_l12_sa_no	Surveys: CS, General economic situation over *l* 12 months	−0.559	.00012
st_it_usd_nfc_sa_no	Short-term interest rates (up to 1 year) USD NFC	−0.468	.00176
st_it_usd_hl_sa_no	Short-term interest rates (up to 1 year) USD households	−0.461	.00212
cs_fin_n12_sa_no	Surveys: CS, Financial situation of households over *n* 12 months	−0.411	.00693
xwse_sa_no	Nbr of hours worked by wage earners: Services	−0.382	.01245
xese_sa_no	Nbr of employed: Services	−0.378	.01357
fa_total_sa_no	BOP: Estonia, Financial Account, Balance, Total	−0.372	.01522
xose_sa_no	Nbr of hours worked in total economy: Services	−0.370	.01573
cs_s_n12_sa_no	Surveys: CS, Savings over *n* 12 months	−0.368	.01646

Notes: Reduced dataset ($N = 246$). *p*-Value = .05.

Table A7. Headline inflation out-of-sample forecasting results one to six quarters horizon obtained from the benchmark dataset.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
RW	1.174	1.024	0.958	0.968	1.042	1.044
FAVAR 1F. 1 Lag	0.984	0.991	1.000	1.059	1.114	1.082
FAVAR 1F. 2 Lags	0.939	0.953	**0.930**	0.986	**1.019**	**1.011**
FAVAR 1F. 3 Lags	**0.936**	1.006	1.003	1.065	1.082	1.099
FAVAR 12F. 1 Lag	1.051	**0.951**	0.987	1.050	1.128	1.079
FAVAR 12F. 2 Lags	1.076	0.971	1.000	**0.973**	1.091	1.046
FAVAR 12F. 3 Lags	1.183	1.008	1.017	1.002	1.109	1.046
FAVAR 123F. 1 Lag	1.056	0.952	0.980	1.029	1.094	1.051
RMSE, AR model	0.474	1.041	1.578	1.954	2.183	2.539

Notes: RMSE in percentage points. The last observation has been removed from calculation of the RMSE.

Table A8. Core inflation out-of-sample forecasting results one to six quarters horizon obtained from the benchmark dataset.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
VAR	0.	1.084	1.397	1.774	2.17	2.201
RW	1.438	1.678	1.819	2.117	2.324	2.176
FAVAR 1F. 1 Lag	0.889	**0.923**	**1.021**	1.145	1.275	1.322
FAVAR 1F. 2 Lags	0.938	1.033	1.156	1.291	1.404	1.485
FAVAR 1F. 3 Lags	0.931	1.124	1.405	1.643	1.788	1.849
FAVAR 12F. 1 Lag	0.898	0.979	1.102	1.219	1.289	1.362
FAVAR 12F. 2 Lags	1.006	1.223	1.459	1.71	1.94	2.069
FAVAR 12F. 3 Lags	1.001	1.195	1.363	1.627	1.844	1.932
FAVAR 123F. 1 Lag	**0.871**	0.94	1.027	**1.112**	**1.134**	**1.214**
RMSE, AR model	0.342	0.52	0.668	0.748	0.850	1.082

Notes: RMSE in percentage points. The last observation has been removed from calculation of the RMSE.

Table A9. Headline inflation out-of-sample forecasting results one to six quarters horizon obtained from the reduced dataset.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
VAR	1.	1.090	1.089	1.091	1.103	1.118
RW	1.174	1.024	0.958	0.968	1.042	1.044
FAVAR 1F. 1 Lag	1.018	1.033	1.042	1.076	1.087	1.059
FAVAR 1F. 2 Lags	0.991	1.008	0.991	1.042	1.025	1.036
FAVAR 1F. 3 Lags	**0.985**	1.067	1.051	1.115	1.076	1.09
FAVAR 12F. 1 Lag	1.025	1.033	1.045	1.093	1.093	1.071
FAVAR 12F. 2 Lags	1.003	1.014	0.976	1.040	1.037	1.077
FAVAR 12F. 3 Lags	1.061	1.097	1.131	1.196	1.207	1.29
FAVAR 123F. 1 Lag	1.056	**0.951**	**0.908**	**0.928**	**1.023**	**0.916**
RMSE, AR model	0.474	1.041	1.578	1.954	2.183	2.539

Notes: RMSE in percentage points. The last observation has been removed from calculation of the RMSE.

Table A10. Core inflation out-of-sample forecasting results one to six quarters horizon obtained from the reduced dataset.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
RW	1.438	1.678	1.819	2.117	2.324	2.176
FAVAR 1F. 1 Lag	0.900	0.939	1.015	1.083	1.168	1.224
FAVAR 1F. 2 Lags	0.952	1.067	1.191	1.310	1.405	1.504
FAVAR 1F. 3 Lags	0.893	1.101	1.382	1.616	1.742	1.821
FAVAR 12F. 1 Lag	0.868	0.920	1.011	1.085	1.151	1.220
FAVAR 12F. 2 Lags	0.943	1.061	1.199	1.331	1.416	1.502
FAVAR 12F. 3 Lags	1.081	1.261	1.644	1.902	2.040	2.081
FAVAR 123F. 1 Lag	**0.804**	**0.755**	**0.832**	**0.896**	**0.971**	**0.979**
RMSE, AR model	0.342	0.520	0.668	0.748	0.850	1.082

Notes: RMSE in percentage points. The last observation has been removed from calculation of the RMSE.

Table A11. Group-wise transformation scheme.

Group	Class	Transformation
Money	Credit	Second difference
	Deposits	Second difference
	Finance	First difference
	Interest rates	First difference
	Money supply	Second difference
External Balance	BOP	First difference of logarithms for positive series, first difference for series with negative values
	Foreign trade	First difference of logarithms for positive series, first difference for series with negative values
Price Indexes	PPI Tradep	Second difference of logarithms
	PPI	Second difference of logarithms
	HICP tradep	Second difference of logarithms
	Import ex prices	Second difference of logarithms
Real	Output	First difference
	New Orders	First difference
	Retail Sales	First difference
	Turnover and Sales	First difference
	Labor	First difference
Forward Looking	CLI	First difference
	Surveys	First difference
External Indexes	AGRI	First difference
	External Indexes	First difference
	ECB commod	First difference
	IMF	First difference

Notes: Under the benchmark specification, the variables have been transformed individually. The group-wise transformation scheme only applies to a part of the robustness analysis.

Table A12. Headline inflation out-of-sample forecasting results one to six quarters horizon: money.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
RW	0.929	0.909	0.847	0.874	0.912	0.851
FAVAR 1F. 1 Lag	1.007	0.983	0.913	**0.854**	**0.781**	0.741
FAVAR 1F. 2 Lags	0.982	0.965	0.912	0.855	0.783	**0.706**
FAVAR 1F. 3 Lags	1.021	1.004	0.963	0.919	0.867	0.808
FAVAR 12F. 1 Lag	0.982	0.972	0.934	0.919	0.875	0.907
FAVAR 12F. 2 Lags	0.993	**0.955**	**0.908**	0.894	0.869	0.875
FAVAR 12F. 3 Lags	**0.933**	0.960	0.921	0.896	0.875	0.889
FAVAR 123F. 1 Lag	1.179	1.134	1.102	1.115	1.077	1.126
Absolute RMSE, AR model	0.474	1.004	1.666	2.256	2.698	3.000

Note: RMSE in percentage points.

Table A13. Headline inflation out-of-sample forecasting results one to six quarters horizon: external balance.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
RW	0.929	0.909	0.847	0.874	0.912	0.851
FAVAR 1F. 1 Lag	1.058	1.071	1.079	1.090	1.105	1.189
FAVAR 1F. 2 Lags	1.049	**1.001**	**0.962**	**0.962**	**0.938**	**0.991**
FAVAR 1F. 3 Lags	1.120	1.148	1.116	1.162	1.182	1.187
FAVAR 12F. 1 Lag	1.054	1.068	1.072	1.097	1.110	1.189
FAVAR 12F. 2 Lags	1.229	1.124	1.025	1.010	0.994	1.047
FAVAR 12F. 3 Lags	1.378	1.365	1.263	1.290	1.305	1.299
FAVAR 123F. 1 Lag	**1.008**	1.036	1.033	1.077	1.096	1.149
Absolute RMSE, AR model	0.474	1.004	1.666	2.256	2.698	3.000

Note: RMSE in percentage points.

Table A14. Headline inflation out-of-sample forecasting results one to six quarters horizon: real.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
RW	0.929	0.909	0.847	0.874	0.912	0.851
FAVAR 1F. 1 Lag	1.098	1.134	1.131	1.155	1.161	1.177
FAVAR 1F. 2 Lags	**0.909**	**0.985**	**0.970**	**1.013**	**1.029**	**1.021**
FAVAR 1F. 3 Lags	1.010	1.123	1.116	1.155	1.187	1.187
FAVAR 12F. 1 Lag	1.164	1.193	1.175	1.187	1.184	1.201
FAVAR 12F. 2 Lags	0.976	1.041	1.024	1.062	1.077	1.090
FAVAR 12F. 3 Lags	1.188	1.251	1.244	1.312	1.367	1.442
FAVAR 123F. 1 Lag	1.172	1.198	1.176	1.180	1.176	1.188
Absolute RMSE, AR model	0.474	1.004	1.666	2.256	2.698	3.000

Note: RMSE in percentage points.

Table A15. Headline inflation out-of-sample forecasting results one to six quarters horizon: forward looking indexes.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
RW	0.929	0.909	0.847	0.874	0.912	0.851
FAVAR 1F. 1 Lag	**1.111**	**1.169**	1.155	1.14	1.138	1.088
FAVAR 1F. 2 Lags	1.121	1.173	**1.134**	1.106	1.129	1.072
FAVAR 1F. 3 Lags	1.137	1.186	1.139	**1.076**	**1.098**	**1.046**
FAVAR 12F. 1 Lag	1.125	1.186	1.168	1.149	1.147	1.093
FAVAR 12F. 2 Lags	1.159	1.216	1.157	1.120	1.160	1.159
FAVAR 12F. 3 Lags	1.379	1.369	1.301	1.242	1.229	1.167
FAVAR 123F. 1 Lag	1.124	1.182	1.175	1.143	1.134	1.105
Absolute RMSE, AR model	0.474	1.004	1.666	2.256	2.698	3.000

Note: RMSE in percentage points.

Table A16. Headline inflation out-of-sample forecasting results one to six quarters horizon: external indexes.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
RW	0.929	0.909	0.847	0.874	0.912	0.851
FAVAR 1F. 1 Lag	1.037	1.065	1.041	1.046	1.067	1.052
FAVAR 1F. 2 Lags	**0.996**	**1.019**	**0.991**	**0.996**	**1.020**	**1.008**
FAVAR 1F. 3 Lags	1.022	1.052	1.051	1.074	1.111	1.116
FAVAR 12F. 1 Lag	1.161	1.231	1.225	1.325	1.306	1.365
FAVAR 12F. 2 Lags	1.193	1.223	1.259	1.366	1.341	1.406
FAVAR 12F. 3 Lags	1.367	1.357	1.391	1.529	1.554	1.687
FAVAR 123F. 1 Lag	1.137	1.223	1.247	1.353	1.335	1.379
Absolute RMSE, AR model	0.474	1.004	1.666	2.256	2.698	3.000

Note: RMSE in percentage points.

Table A17. Core inflation out-of-sample forecasting results one to six quarters horizon: price indexes.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
RW	1.046	1.115	1.257	1.372	1.521	1.596
FAVAR 1F. 1 Lag	**0.925**	**0.968**	1.199	1.353	1.643	1.726
FAVAR 1F. 2 Lags	1.076	1.191	1.446	1.521	1.652	1.724
FAVAR 1F. 3 Lags	1.058	1.272	1.667	1.760	2.080	2.165
FAVAR 12F. 1 Lag	0.989	1.059	1.306	1.390	1.729	1.779
FAVAR 12F. 2 Lags	1.065	1.260	1.609	1.677	2.038	2.115
AVAR 123F. 1 Lag	0.961	0.976	**1.137**	**1.136**	**1.384**	**1.409**
Absolute RMSE, AR model	0.339	0.516	0.635	0.807	0.797	1.003

Note: RMSE in percentage points.

Table A18. Core inflation out-of-sample forecasting results one to six quarters horizon: external balance.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
RW	1.046	1.115	1.257	1.372	1.521	1.596
FAVAR 1F. 1 Lag	0.990	1.001	1.213	1.359	1.632	1.738
FAVAR 1F. 2 Lags	1.080	1.076	1.223	1.287	**1.492**	**1.615**
FAVAR 1F. 3 Lags	1.159	1.279	1.539	1.720	2.071	2.121
FAVAR 12F. 1 Lag	0.982	0.990	1.189	1.354	1.623	1.733
FAVAR 12F. 2 Lags	1.149	1.212	1.424	1.484	1.767	1.863
FAVAR 12F. 3 Lags	1.289	1.522	1.877	2.061	2.545	2.582
FAVAR 123F. 1 Lag	**0.942**	**0.950**	**1.091**	**1.286**	1.583	1.645
Absolute RMSE, AR model	0.339	0.516	0.635	0.807	0.797	1.003

Note: RMSE in percentage points.

Table A19. Core inflation out-of-sample forecasting results one to six quarters horizon: money.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
RW	1.046	1.115	1.257	1.372	1.521	1.596
FAVAR 1F. 1 Lag	0.930	0.889	0.948	0.925	0.872	0.805
FAVAR 1F. 2 Lags	**0.885**	0.892	**0.947**	**0.922**	**0.812**	**0.724**
FAVAR 1F. 3 Lags	0.930	0.905	0.967	0.966	0.892	0.810
FAVAR 12F. 1 Lag	0.939	**0.886**	0.976	1.005	1.003	1.026
FAVAR 12F. 2 Lags	0.950	0.972	1.096	1.137	1.271	1.316
FAVAR 12F. 3 Lags	1.059	0.993	1.131	1.213	1.326	1.399
FAVAR 123F. 1 Lag	0.952	0.901	0.967	0.954	0.870	0.836
absolute RMSE, AR model	0.339	0.516	0.635	0.807	0.797	1.003

Note: RMSE in percentage points.

Table A20. Core inflation out-of-sample forecasting results one to six quarters horizon: real.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
RW	1.046	1.115	1.257	1.372	1.521	1.596
FAVAR 1F. 1 Lag	0.971	0.984	1.201	1.356	1.684	1.636
FAVAR 1F. 2 Lags	0.925	**0.953**	**1.114**	**1.164**	**1.475**	**1.480**
FAVAR 1F. 3 Lags	0.939	1.117	1.461	1.597	2.007	2.033
FAVAR 12F. 1 Lag	0.966	1.042	1.352	1.513	1.878	1.830
FAVAR 12F. 2 Lags	**0.910**	0.981	1.217	1.296	1.668	1.674
FAVAR 12F. 3 Lags	0.955	1.225	1.655	1.858	2.410	2.473
FAVAR 123F. 1 Lag	0.952	1.017	1.309	1.464	1.802	1.758
Absolute RMSE, AR model	0.339	0.516	0.635	0.807	0.797	1.003

Note: RMSE in percentage points.

Table A21. Core inflation out-of-sample forecasting results one to six quarters horizon: forward looking indexes.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
RW	1.046	1.115	1.257	1.372	1.521	1.596
FAVAR 1F. 1 Lag	1.033	1.096	1.284	1.336	1.52	**1.432**
FAVAR 1F. 2 Lags	0.995	1.168	1.420	1.446	1.781	1.782
FAVAR 1F. 3 Lags	**0.912**	**1.019**	**1.261**	**1.208**	1.485	1.51
FAVAR 12F. 1 Lag	1.028	1.109	1.323	1.379	1.563	1.443
FAVAR 12F. 2 Lags	0.955	1.191	1.496	1.537	1.891	1.937
FAVAR 12F. 3 Lags	0.937	1.078	1.389	1.356	**1.479**	1.489
FAVAR 123F. 1 Lag	1.011	1.101	1.300	1.367	1.566	1.448
Absolute RMSE, AR model	0.339	0.516	0.635	0.807	0.797	1.003

Note: RMSE in percentage points.

Table A22. Core inflation out-of-sample forecasting results one to six quarters horizon: external indexes.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
RW	1.046	1.115	1.257	1.372	1.521	1.596
FAVAR 1F. 1 Lag	0.943	0.915	1.066	1.151	1.339	1.358
FAVAR 1F. 2 Lags	0.801	**0.823**	**0.979**	**1.068**	**1.233**	**1.284**
FAVAR 1F. 3 Lags	0.807	0.845	1.112	1.268	1.484	1.526
FAVAR 12F. 1 Lag	0.994	1.015	1.245	1.459	1.694	1.750
FAVAR 12F. 2 Lags	**0.781**	0.888	1.205	1.488	1.771	1.843
FAVAR 12F. 3 Lags	0.994	1.131	1.496	1.732	2.141	2.342
FAVAR 123F. 1 Lag	1.012	1.092	1.380	1.558	1.803	1.820
Absolute RMSE, AR model	0.339	0.516	0.635	0.807	0.797	1.003

Note: RMSE in percentage points.

Table A23. Core inflation out-of-sample forecasting results one to six quarters horizon: external balance.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
RW	1.046	1.115	1.257	1.372	1.521	1.596
FAVAR 1F. 1 Lag	0.990	1.001	1.213	1.359	1.632	1.738
FAVAR 1F. 2 Lags	1.080	1.076	1.223	1.287	**1.492**	**1.615**
FAVAR 1F. 3 Lags	1.159	1.279	1.539	1.720	2.071	2.121
FAVAR 12F. 1 Lag	0.982	0.990	1.189	1.354	1.623	1.733
FAVAR 12F. 2 Lags	1.149	1.212	1.424	1.484	1.767	1.863
FAVAR 12F. 3 Lags	1.289	1.522	1.877	2.061	2.545	2.582
FAVAR 123F. 1 Lag	**0.942**	**0.950**	**1.091**	**1.286**	1.583	1.645
Absolute RMSE, AR model	0.339	0.516	0.635	0.807	0.797	1.003

Note: RMSE in percentage points.

Table A24. Core inflation out-of-sample forecasting results one to six quarters combination of the first factor from the subgroups.

	1 qt.	2 qt.	3 qt.	4 qt.	5 qt.	6 qt.
Benchmark AR	1.000	1.000	1.000	1.000	1.000	1.000
FAVAR 6 subgroups 1 Lag	1.036	1.428	1.912	2.169	2.905	3.046
FAVAR 6 subgroups 2 Lags	1.226	1.816	2.717	3.091	4.299	4.546
FAVAR 6 subgroups 3 Lags	1.721	2.610	4.108	5.079	7.194	7.855
FAVAR 3 subgroups 1 Lag	1.088	1.243	1.430	1.354	1.191	1.062
FAVAR 3 subgroups 2 Lags	1.379	1.818	2.436	2.489	2.987	2.820
FAVAR 3 subgroups 3 Lags	1.410	1.870	2.387	2.702	3.828	4.039
Absolute RMSE, AR model	0.339	0.516	0.635	0.807	0.797	1.003

Notes: RMSE in percentage points. The six subgroups are Price Indexes, External Balance, Money, Real, Forward Looking Indexes and External Indexes. From every subgroups the first factor is extracted. The reduced FAVAR model includes Price Indexes, Money and Real factors.

Appendix 2

Publication II
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Noise shocks and business cycle fluctuations in three major European Economies

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Abstract
This paper investigates how supply noise and demand noise contribute to business cycle fluctuations in three major European economies. A structural vector autoregressive model is used to identify supply, demand, supply noise and demand shocks. The identification scheme is built on nowcast errors of output growth and the inflation rate that are derived from the Consensus Economics Survey. The results indicate that positive supply noise and positive demand noise shocks have an expansionary effect on output, but their magnitude differs across countries. The two shocks contribute equally to business fluctuations, and jointly, they account for around one quarter of the total variation in GDP in each of the three countries.

Keywords Business cycles · Noise shocks · SVAR · Survey expectations

JEL Classification E31 · E32 · E58

1 Introduction

There is a widespread belief that changes in expectations about economic fundamentals can be an independent driver of macroeconomic fluctuations if there are no changes in the current fundamentals themselves. This belief dates back to Pigou (1929), who coined the idea that 'wave-like swings in the mind of the business world between errors of optimism and pessimism' are the source of economic fluctuations.

There are different interpretations of how optimism or pessimism can shape the business cycle. The literature finds three strands of thought on how economic sentiment and beliefs matter for business cycle fluctuations. First, the irrational animal spirits strand of thought sees psychological waves of optimism and pessimism driven by

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random shocks as the cause of macroeconomic fluctuations. The psychological waves are not backed up by fundamentals and so they eventually lead to a bust (Keynes 1936; Akerlof and Shiller 2010).

Advocates of the theory of self-fulfilling animal spirits (Farmer 1999, 2012a, b; Benhabib et al. 2016; Bacchetta and Wincoop 2013) also see that the root of macroeconomic fluctuations lies in the animal spirit style of fluctuations, but believe that actions that follow these fluctuations lead to changes in fundamentals. This makes the initial boom or bust in confidence both rational and self-fulfilling.

The news view argues that agents have access to a non-measurable source of imperfect information. As the agents are imperfectly informed, they may form misperceptions about the state of economic fundamentals. How imperfect information affects consumer expectations has received growing interest in the recent literature on macro-news. The impact of macroeconomic news on households inflation expectations has received particular attention. One source of misperceptions is noise shocks, which affect the signals that agents receive. Dräger and Lamla (2017) find evidence of imperfect information when consumers form expectations about inflation.

The driving force of any prediction is a diverse set that contains information about future policies or future demographic trends, or news about future technologies and future prices.[1] Waves of optimism occur when agents receive the information that new market opportunities will develop in the future. This causes firms to increase investment immediately so they can meet the new demand patterns when they are realised in the future. At the same time consumers increase their consumption as they feel they will be richer in the future. If the information is valid and the market opportunities do actually materialise in the future, the boom does not have to be followed by a crash. However, if the agents make an error and become overly optimistic, the boom will be followed by a crash.

Settings in which the information received by the agents may turn out to be validated by future developments, or may be proved wrong as future events do not align with the original information, are usually referred to as noise formulation. In essence, news-driven business cycles arise because of information, and errors made when noise shocks affect the information.

Beaudry and Portier (2006) reignited the idea of business cycles driven by non-fundamental factors by providing empirical evidence that news about future productivity could explain half the fluctuations in GDP. Their estimates also implied that news can create business cycle comovements, because hours and output rose with the arrival of new information.

Beaudry and Lucke (2010) reach similar conclusions using a different identification approach. At the other pole of the debate, Kurmann and Otrok (2013), Barsky and Sims (2012) and Barsky et al. (2015) find that news-driven business cycles play only a limited role. A comprehensive summary of the literature can be found in Beaudry and Portier (2014).

Some papers have highlighted problems with the Beaudry et al. identification method (Kurmann and Mertens 2014; Forni et al. 2014), in particular the problem

[1] Empirical evidence suggests that households reacts to news to form expectations about future price changes (Wang et al. 2020). Further evidence suggests that households sometimes overreact when updating inflation news depending on the source of the news and household demographics (Easaw et al. 2013).

of non-fundamentalness. One approach proposed as a solution has been to increase substantially the number of observables by using a factor augmented structural vector autoregressive (FAVAR) model when estimating the effects of news shocks (Forni and Gambetti 2014).[2] Other authors have started to use the expectations of professionals in their estimation methods to uncover noise shocks (Fujiwara et al. 2011; Milani 2011; Miyamoto and Nguyen 2014).

Another area of ongoing research is whether it is only misperceptions about supply that can affect the fluctuations of macroeconomic variables. This question is driven by the observation that presumed noise shocks often resemble demand shocks. Lorenzoni (2009) shows with a theoretical model that supply noise shocks are observationally indistinguishable from fundamental demand shocks.

In a recent paper, Benhima and Poilly (2021) propose a model for assessing the effects of a demand noise shock that also uses survey expectations of professional forecasters in their identification approach.[3][4]

Using a structural vector autoregressive (SVAR) model that includes nowcast errors about output and inflation, they identify supply and demand noise shocks in the US. Their results indicate that demand-related noise shocks are recessionary and contribute considerably to output fluctuations. In their reasoning about the dynamics of the demand noise shock, Benhima and Poilly (2021) conclude that monetary policy and informational frictions play a key role in driving the recessionary effects.[5]

Most of the literature focuses on the effects of non-fundamental shocks in large closed economies. Almost all the empirical studies that employ the survey expectations methodology use data from the US, and only a few studies take a comparative approach and survey the effects of such shocks in other economies. Kamber et al. (2017) develop a small open economy model to identify the effects of news shocks in four small, open, advanced economies: Australia, Canada, New Zealand and the UK. Their results indicate that news about TFP causes a considerable positive comovement between GDP, hours worked, consumption and investment in all the economies in their study.

2 The results of Forni and Gambetti (2014) indicate that news shocks have a smaller role in explaining business cycle fluctuations, which contrasts with the findings of Beaudry and Portier (2006). In more recent work, Nam and Wang (2019) also use a larger VAR system but use sign restrictions to identify what they call 'optimism' shocks. Their results show that their optimism shocks resemble news shocks in the response they get from total factor productivity (TFP), consumption, investment and output.

3 While the reduced form model of Benhima and Poilly (2021) features a combined structure of incomplete and noisy information, most of the literature emphasises that incomplete news and wrong news usually stem from distinct information structures. The case when the news can be wrong is usually referred to as noise formulation (Beaudry and Portier, 2014).

4 Demand noise shocks in the model can be influenced by misperceptions about prices. This links the model to the growing literature on the impact of macroeconomic news on the spending and investment decisions of agents.For firms, Coibion et al. (2020) use Italian survey data to study the causal effects of inflation exceptions. They show that changes in firms inflation expectations affect investment and employment. In a another study, Coibion et al. (2022) analyse the results from a randomised control experiment on inflation news. They find that treated households who receive targeted news about inflation change their inflation expectations and change their spending and saving behaviour.

5 The nexus of monetary policy, supply and demand shocks and animal spirits is also discussed in, for example, Sheen and Wang (2016). They argue that a central bank needs to be concerned about possible animal spirit expectations in particular when technology shocks are prevalent. Misidentifying true animal spirits as rational expectations can have potentially high costs as it can impose a sub-optimal monetary policy rule.

Brzoza-Brzezina and Kotłowski (2020) show how the effect of confidence shocks can be transmitted internationally. They argue that news-type shocks can travel across borders as much as sentiment-type shocks can, through direct linkages like the media, and indirect ones such as trade or financial integration. Estimating a VAR/VECM type of model, they show that confidence shocks from the euro area play an important role in explaining variations in Polish GDP.

In this paper, I focus on the effects of supply and demand shocks, both fundamental and noise shocks, in three major European economies. I use data from the Consensus Economics Survey to construct time series for the nowcast errors of output growth and inflation for France, Germany and Italy. The nowcast errors are the differences between the real time forecast of the survey participants for output growth and inflation and the actual data in the first release from the national statistical offices. This means the nowcast errors measure misperceptions about output and prices in real time.

Benhima and Poilly (2021) have provided a general framework for identifying both supply noise shocks and demand noise shocks. I follow their theoretical framework and use three European economies as applications. The identification scheme builds on the idea that the errors made by rational nowcasters need to be internationally consistent. A demand shock that drives a positive correlation between GDP growth and the inflation rate should also cause a positive correlation between the nowcaster's error in output and the nowcast error for inflation. The baseline VAR model includes GDP growth, the inflation rate, the nowcast error for GDP growth and the nowcast error for the inflation rate.

The main results indicate that positive supply and positive demand noise shocks both have expansionary effects on output, but the magnitude of the effect differs slightly across countries. Output reacts more strongly to noise shocks in Germany and Italy, while GDP and inflation show a slightly weaker response in France. The expansionary response of GDP to supply noise shocks is observationally similar in shape to the effects of a fundamental demand shock, especially in Germany. This is in line with the theoretical arguments of Lorenzoni (2009). Benhima and Poilly (2021) extend this line of argument by showing that the effects of positive demand noise shocks may potentially resemble the effects of negative supply noise shocks. I cannot confirm those results from my analysis. A positive demand noise shock has an expansionary effect on GDP in France, Germany and Italy, though the effect seems insignificant for Italy.

Second, I find that demand noise shocks have a limited effect on the variation in output growth. Demand noise shocks explain on average 11% of the volatility in output growth. Supply noise shocks explain a slightly larger fraction of the variation in output growth in the three European economies, ranging from 11 to 14%. This contrasts with the findings of Benhima and Poilly (2021), who find that demand noise shocks contribute 23% of output growth volatility, while supply noise shocks only explain around 8% of the volatility in GDP growth.

I contribute to the existing literature in two ways. First, I provide comparative evidence from three large European economies that supply and demand noise shocks have short-run implications for output growth. To the best of my knowledge, this is the first study of the effects of noise shocks for France, German and Italy. My second contribution is that I show that although some dynamics are similar for the set of

European countries and for the USA, the response of output growth to a positive demand noise shock is different.

The paper is structured as follows. Section 2 documents the empirical model and the set of identifying restrictions. Section 3 discusses the data. In Sect. 4, I present the empirical results. In Sect. 5, I perform a number of robustness tests around the baseline identification scheme. The final section concludes.

2 Methodology

This section starts out by describing the cornerstones of the theoretical model. The second part describes the empirical model and the SVAR estimation strategy.

2.1 Theoretical model

The model develop by Benhima and Poilly (2021) extends the New Keynesian model of Galí (2015) by including noisy information about both supply shocks from technology and demand shocks from preferences. The dispersed information model consists of three agents that make decisions under conditions of uncertainty, and a representative nowcaster. The role of the nowcaster in the model is to survey the economy and publish nowcasts, which allows the survey expectations to be distinguished from the expectations of the agents. The island structure of the model is similar to that of Lorenzoni (2009), and it includes households, firms, a central bank and nowcasters. The islands are inhabited by a continuum of households who work and consume a final good. A continuum of oligopolistic firms produce differentiated intermediate goods that are used by a competitive firm to produce a final good. The households have preferences for consumption and labour supply. Firms are aware of the technology they use to produce the intermediate goods. Monetary policy is conducted by a central bank that shapes expectations for inflation and sets the interest rate.

Agents learn about the future either by observing the shocks directly or by learning about them from the public and private signals of other agents. Firms and households receive private information that is subject to an idiosyncratic noise shock. In addition, firms, households, the central bank and the nowcasters also receive a public signal about technology and preferences that may potentially be noise.[6] Signals of technology can be viewed as a sort of supply shock that alters the productivity of labour of the firm, while preference shocks can be thought of as demand shocks that shift the factor of time preferences of households. While technology shocks have a permanent component, preference shocks are only transitory. From the firm's perspective, prices depend on the public signal and on the demand shock. Higher-order beliefs arise with dispersed information as strategic complements in price-setting lead the firms to set higher prices when they expect other firms will be doing the same thing. The central bank is setting

[6] Public signal refers in the context of this theoretical model to public information about technology or preferences that agents receive.

Table 1 New Keynesian model: sign propositions

	y_t	π_t	$E_t{}^s(y_t) - y_t$	$E_t{}^s(\pi_t) - \pi_t$
Fundamental supply	+ permanently	−	−	+
Supply noise	+	+	+	−
Fundamental demand	+	+	−	−
Demand noise	−	+	+	+

y_t output, π_t inflation, $E_t{}^s(y_t) - y_t$ output expectation errors, $E_t{}^s(\pi_t) - \pi_t$ inflation expectation errors

the nominal interest rate following a Taylor rule in response to the public signal it receives.[7] Table 1 summarises the key proposition of the model.

We may first focus on how fundamental and noise shocks affect output, y_t, and inflation, π_t, in Table 1. In a model where agents receive private and public signals, a positive fundamental supply shock drives a positive response from output and a negative response from inflation. This is a standard assumption in New Keynesian models. Consumers observe a positive signal about productivity and start to increase their consumption. The permanent positive productivity shock also allows firms to cut their prices as they respond to lower marginal costs.

A supply noise shock should have a temporary positive effect on output and a positive effect on inflation. In this way, the behaviour of output and inflation resembles that seen in fundamental demand shocks. Consumers observe a productivity shock and, as in the first case, increase their consumption. However, the anticipated increase in productivity does not materialise.[8] As the increase in demand is not matched by an increase in actual productivity, firms raise their prices in anticipation of higher marginal costs. The central bank accentuates the positive response of output as it also misjudges the productivity shock. This leads it to cut interest rates in expectation of lower inflation, stimulating aggregate demand.

The third row in Table 1 indicates both the expansionary and inflationary effects of fundamental demand shocks. This assumption is also standard in New Keynesian models. Firms receive a signal about aggregate demand, such as a change in preferences. Expecting higher costs they raise their prices.

The last row describes the effects of demand noise shocks. These effects are more ambiguous than those of the other shocks. First, demand noise shocks have a temporary negative effect on output. The recessionary effect is driven by the reaction of the central bank. Observing a noisy public signal about demand, the central bank raises interest rates. The higher interest rate leads consumers to curb consumption, causing output to fall. However, this result depends on the parameterisation and certain assumptions that are imposed on the model. The positive response from inflation is conditional on the assumption that firms anticipate an overall rise in aggregate demand. When firms receive a public signal of a preference shock, they anticipate both a positive

7 In the baseline case of the theoretical model by Benhima and Poilly (2021), the central bank follows a Taylor rule with zero weight on the output. This means that the central bank only has an inflation target.

8 Consumers and firms do not share the same information set. The information set of both agents is made up of potentially noisy public signal and private signals of demand and supply shocks.

demand shock and a rise in the interest rate, which should have a negative effect on aggregate demand. That in turn depends on the interplay between the slope of the Phillips curve, the parameters of the reaction function of the central bank, and the informational advantage that firms have over the central bank.[9] Hence, the effect for inflation depends on the overall effect of aggregate demand.

For the expectation errors, the model proposes a negative effect from survey expectations on output, $E_t{}^s(y_t) - y_t$, and positive effect on the survey expectation for inflation, $E_t{}^s(\pi_t) - \pi_t$ following fundamental supply shocks (see Table 1 columns three and four). As nowcasters underestimate output growth and overestimate inflation, a positive fundamental supply shock has a negative effect on the errors in survey expectations for output and a positive effect on the survey expectation error for inflation.[10]

A supply noise shock has a positive effect on the expectation error for output and a negative effect on the survey expectation error for inflation. If the surveyors underestimate the response of output to a fundamental supply shock, a supply noise shock drives them to overestimate output when they are faced with a signal about productivity. As the expectation of output is smaller than the realisation of it, the surveyors overestimate the response of inflation, causing a negative effect on the survey expectation error for inflation.

The model suggests that in a similar fashion to the dynamics of a fundamental supply shock, positive fundamental demand shocks have a negative effect on the survey expectation error for output. When survey expectations underreact to fundamental demand shocks, the surveyors also form expectations for inflation that are lower than what is realised, leading to a negative response from the survey error for inflation.

Finally, the model proposes that demand noise shocks should have a positive effect on both the survey expectation error for output and the survey expectation error for inflation. The public signal in noise shocks makes the surveyors overly optimistic. The surveyors anticipate that inflation will increase when they receive a positive signal about demand. However, if the signal was driven by noise, inflation will not materialise fully. This means that the surveyors have overestimated inflation, and this in turn means that the effect of the survey expectation on inflation is positive.

2.1.1 Addressing non-fundamentalness

Firms and households make decisions under conditions of uncertainty as they cannot always distinguish between a fundamental shock and a noise shock when they receive news about the future that they then act upon. Neither can an econometrician with the same set of information that the agents have distinguish between fundamental and noise shocks. As Blanchard et al. (2013) point out, with imperfect information the VAR does not have a unique moving average (MA) representation as the econometrician might not be able to recover the coefficients or the shock from the current and past values of

[9] Firms are better able to detect noise shocks than the central bank when the precision of the private signal they receive is high relative to that of the public signal that is shared by both the firms and the central bank.

[10] Note that the effect on the survey expectations error is conditional on the model being specified so that agents receive a private signal. Without a private signal, fundamental supply and supply noise shocks have no effect on the survey expectation error for output, and fundamental demand and demand noise shocks have no effect on the survey expectation error for inflation.

the stochastic process. In the context of research into the news-driven business cycle, this problem can render the results from SVAR methods meaningless.

The practical response of the literature to this problem has been to include information in the model that is available to the econometrician but not contemporaneously to the nowcaster.[11] To understand why the dispersed information structure of the model is essential when I want to disentangle fundamental shocks from noise shocks, consider a simple reduced form model with demand shocks and demand noise shocks. Households and firms receive private information on top of the public signal. To identify the fundamental shock and the noise shock, it is sufficient that households have more information about demand than the nowcaster, who only receives a public signal. When there is less information, the noise shock affects the survey expectation of output but not the actual contemporaneous realisation of output itself. The informational advantage over the nowcaster can come from including a measure of misperceptions, which can be the nowcast error for output and inflation growth, as the econometrician can observe the actual realisation of output, which is not available to the nowcaster contemporaneously.

2.2 Estimation and identification strategy

The theoretical model allows for testable assumptions. To analyse the effects of supply noise shocks and demand noise shocks on output and inflation, I estimate a SVAR model using a set of restrictions that come from the proposition outlined in Sect. 2.1.

The canonical VAR model that I estimate is:

$$Y_t = \Phi(L)Y_t + \nu_t \tag{1}$$

where $Y_t = (Y_{1,t}, \ldots Y_{n,t})$ is a vector of observables, L is the lag operator, Φ is the matrix of estimated parameters, and ν_t is a vector of reduced form residuals with $\nu_t \sim$ iid $(0, \Sigma)$.

For the structural VAR I follow the same estimation strategy as in Benhima and Poilly (2021). I implement the sign and zero restrictions using the algorithm of Arias et al. (2018). Instead of drawing the parameters from the posterior distribution of a Bayesian VAR, I use a Monte Carlo strategy as suggested by Hamilton (2020) to generate a set of coefficients $\hat{\Phi}(L)$ that are drawn from the asymptotic distribution of the estimated reduced-form parameters. Draws from the asymptotic distribution of the variance-covariance matrix of the reduced-form residuals are used to construct the matrix $\hat{\Sigma}$. This estimation technique is conceptually equivalent to using a flat prior distribution. The baseline VAR model is estimated for each country individually.

The observables in the VAR are:

$$Y_t = [\Delta y_t, \pi_t, E_t\{\Delta y_t\} - \Delta \tilde{y}_t, E_t\{\pi_t\} - \tilde{\pi}_t] \tag{2}$$

[11] Altering the information set of the econometrician to address the problem of potential non-invertibility is done in many studies of how expectations affect economic fluctuations. For example, studies by Chung and Leeper (2007), Romer and Romer (2010), Ramey and Vine (2011) and Leeper et al. 2013 add additional variables to the model to align the information set used by the econometrician and the agents in the context of fiscal policy analysis.

Table 2 Baseline identification strategy: sign restrictions

	y_t	π_t	$E_t\{\Delta y_t\} - \widetilde{y}_t$	$E_t\{\pi_t\} - \widetilde{\pi}_t$
Fundamental supply	> 0 (permanently)	X	X	X
Supply noise	> 0	X	> 0	< 0
Fundamental demand	X	> 0	< 0	< 0
Demand noise	X	> 0	> 0	> 0

The response of GDP is constructed by taking the sum of the cumulative response of GDP growth. Sign restrictions are imposed on the impact. An X corresponds to an unrestricted sign

Δy_t is the annualised growth rate of real GDP, and π_t is the annualised consumer price index (CPI) inflation rate. The third term reflects the nowcast errors of real GDP, and the fourth term reflects the errors of CPI inflation. The nowcast errors of real GDP are calculated as $E_t\{\Delta y_t\} - \Delta\tilde{y}_t$, which is the difference between the mean nowcast of Consensus Economics and the first release GDP estimate from the national statistical office. The nowcast error of CPI inflation, $E_t\{\pi_t\} - \tilde{\pi}_t$, is calculated in the same way.

I aim to disentangle fundamental supply and demand shocks from supply and demand noise shocks. The identifying restrictions needed for this are based on the set of sign restrictions from a structural New Keynesian model. Table 2 summarises the set of sign restrictions of the SVAR model needed to identify the shocks.

Let us first focus on the fundamental shocks. A positive fundamental supply shock drives a positive response from output growth and a negative response from inflation. For our baseline identification strategy, it is only necessary to restrict the response of GDP to be positive. I impose that only fundamental supply shocks have a long-run effect on GDP by taking the sum of the cumulated impulse responses of GDP growth as in Armantier and Quah (1989). Other fundamental and noise shocks are only transitory.

A positive response from GDP and a positive response from inflation to a fundamental demand shock is also a standard assumption in New Keynesian models. For the restrictions of the errors I assume, following from the theoretical model, that when nowcasters overestimate a fundamental demand shock, the nowcast errors of GDP and inflation must be underestimated. As I am particularly interested in understanding the response of GDP to fundamental demand shocks, I leave the response of output growth unrestricted.

For the restrictions of the noise shocks, I first impose a positive response from output growth to a supply noise shock. As with the fundamental supply shocks, I leave the response of inflation unrestricted. Finally, I restrict the response of the endogenous variables to demand noise shocks. The first thing to note is that I leave the response of output growth to demand noise shocks unrestricted, as I did for fundamental demand shocks. Second, I restrict the response of inflation to be positive. The response of inflation can also be restricted to be negative, as this helps in distinguishing between negative fundamental demand shocks and positive demand noise shocks. Looking only at the restrictions of the errors might not allow these two shocks to be disentangled if there are no restrictions on the response of GDP. This means I need to assume that there is a positive response from inflation so that I can distinguish between negative fundamental demand shocks and positive demand noise shocks.

Another important feature of the baseline identification scheme is that supply noise shocks affect the expectation errors with opposite signs, while fundamental demand shocks and demand noise shocks drive the expectation errors in the same direction. This allows for a clearer distinction between supply noise and the two demand shocks.[12]

3 Data

The main data source for studies analysing the effects of expectations on macroeconomic fluctuations using a survey-based expectation approach has been the US Survey of Professional Forecasters (SPF).[13] The US SPF is conducted on a quarterly basis, and the survey panellists are asked to provide their estimates for output growth and inflation for the current quarter and for longer horizons.

My analysis assesses the effects of expectational errors on business cycle fluctuations in Europe.[14] As I am particularly interested in whether supply and demand side noise shocks have different effects across the biggest European economies, I require information on nowcasts for individual countries.[15]

I propose to use data from the Consensus Economics survey, as that survey is closest in design to the US SPF. Consensus Economics is a private survey firm that polls more than 700 private-sector individuals and economic research institutes.[16] The Consensus Economics survey is conducted on a monthly basis and provides nowcasts and forecasts for a large set of macroeconomic variables for different countries. Like in the US SPF, survey panellists receive a questionnaire each month on the Monday of the week that contains the 15th of the month. The survey participants submit their nowcasts for the quarterly year-on-year percentage change in private consumption and the national consumer prices by the following Monday.

The survey participants are asked to provide quarter-on-quarter and year-on- year nowcasts for GDP. To be consistent in the reference point of the nowcast, I use the year-on-year errors in the baseline specification of the model. In the robustness section,

[12] Without the restrictions on the expectational errors, a temporary supply shock such as an oil price shock could, for example, be confused with either of the demand shocks.

[13] The SPF is also frequently used as the benchmark for assessing forecasting models (Giannone et al. 2008).

[14] The Federal Reserve Bank of Philadelphia conducts the survey of professional forecasters for the USA. For Europe, the European Central Bank Survey of Professional Forecasters (ECB SPF) collects information on expected rates of inflation, real GDP growth and other macroeconomic variables in the euro area at several horizons (Garcia 2003). The ECBs SPF is publicly available and widely used in the forecasting domain, but the survey design differs too strongly from that of the US SPF to be useable for our purposes. First, it is only available for the euro area but not for individual countries, and more importantly it does not provide nowcasts for the current quarter but only forecasts for longer horizons.

[15] To calculate the nowcast errors I also need the first release data for GDP growth and inflation for our set of countries. The length of my sample is restricted not only by the availability of the Consensus Economics nowcasts but also by the availability of the published first release data.

[16] For Germany, for example, those pollsters include the German Econ Institute, Allianz insurance, Goldman Sachs and Deutsche Bank. For Italy, they include ABI, Centro Europa Ricerche, Confindustria and UniCredit. For France, they include Societe Generale, Euler Hermes, OFCE and Capital Economics.

I show the results when the errors are calculated from the quarter-on-quarter GDP nowcasts. To make the results more comparable to the studies from the US I annualise all the variables that enter the VAR.

Reliable nowcasts and first release estimates of GDP and inflation are available from 2003Q1 for France and Germany and from 2003Q2 for Italy. The sample ends in 2019Q4 to avoid the large distortionary effects that the Covid-19 pandemic had on key macroeconomic variables. I use all the available data in the baseline estimation, while some robustness checks are done in Section 5.

No flash estimates for output growth for the latest quarter exist from public data sources but the forecasters need to be aware of output growth in the preceding quarters to provide estimates for year-on-year GDP growth rates. This means that the only uncertainty should arise from the unknown output growth and inflation in the current quarter when they provide their estimates for the year-on-year percentage changes. The forecasters are aware of the final release data for inflation of the first month of the quarter, and at least the first release data on inflation in the second month of the quarter. As the inflation rates for the first and the second months are known, the forecasters have to provide an estimate for the last month of the quarter to construct the quarterly year-on-year inflation rate. I do not have the data to disaggregate the nowcasts and so I use the survey's mean nowcast.[17]

Our analysis is based on the nowcast errors. The nowcast errors are computed as the difference between the nowcast predictions of GDP growth and inflation from the Consensus Economics survey, and the first-release data for actual real GDP growth and actual inflation. The first-release data are obtained from the national statistical offices. Figure 11 in the Appendix shows the difference between the errors calculated from first release data and the errors calculated from the final release data in France, which arise from more exact second release estimates and data revisions. The final release data, or the most recent series, incorporate changes in the methodology of the national accounts and data revisions that cannot be foreseen by the forecaster, which might bias the results (Croushore 2010).

Figure 1 depicts the nowcast errors of GDP and the nowcast errors of inflation. Observations in the top left quadrant reflect nowcasts where survey participants underestimated GDP growth but overestimated inflation. The bottom left quadrant shows nowcasts where GDP growth was overestimated and inflation was underestimated. The figure shows that nowcast errors tend to be equally centred around zero. A standard t-test against zero cannot reject the hypothesis that the means are different from zero for either Germany or France. For the Italian GDP errors, there is weak evidence that the GDP nowcast errors are different from zero. This indicates that survey participants do not systematically overpredict or underpredict contemporaneous output growth or the inflation rate. With few exceptions, the errors for each time observation overlap or are close to each other.

From Table 8 in Appendix, I see positive correlations between the nowcast errors of GDP growth across countries. The correlation coefficient ranges from 0.36 in the year-on-year GDP nowcast errors between France and Italy, to 0.58 between Germany

[17] Disaggregated data are available for the US SPF. Researchers tend to use median nowcast errors in their models as they are less prone to outliers than the mean nowcast errors (Enders et al. 2021).

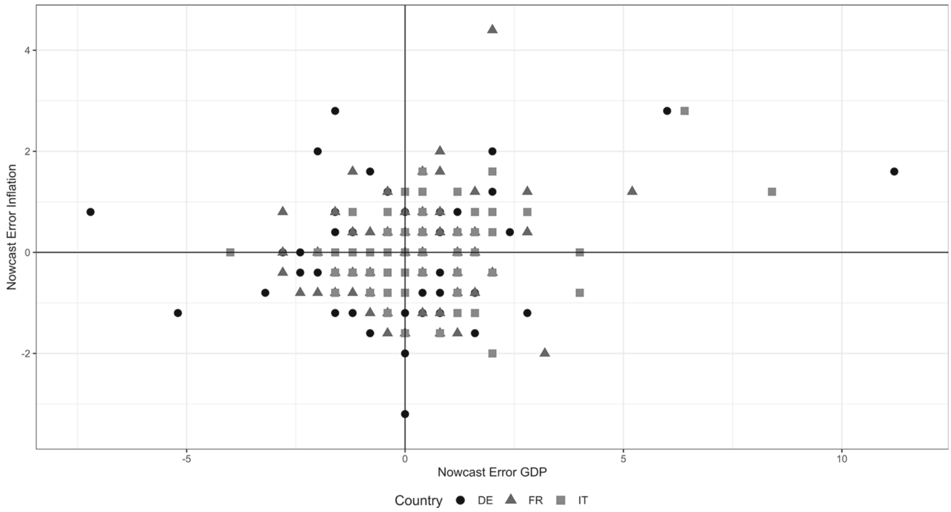

Fig. 1 GDP growth and inflation nowcast errors. Nowcast errors of real GDP growth and consumer price inflation in annualised percentage points. Sample for Germany and France: 2003Q1–2019Q4. Sample for Italy: 2003Q2–2019Q4

and Italy. As the quarterly GDP growth nowcast errors exhibit a strong positive correlation with the yearly GDP growth nowcast errors within a country, the cross-country correlation of the quarterly nowcast errors is also positively correlated. Even more so, the yearly nowcast errors for inflation show a strong positive correlation ranging from 0.43 to 0.63. There are a few markedly larger nowcaster errors in the top right quadrants.

From Fig. 11, we can see that those errors for France can be traced back to certain episodes during the Great Recession of 2009. The nowcasters presumably underestimated the large decline in GDP and consequently overestimated that consumer prices would be higher than they actually turned out to be. The German data also show larger nowcast errors for GDP growth and inflation during the recovery period of 2010 when the nowcasters underestimated GDP growth but also underestimated inflation (see Fig. 12 in the Appendix).

I provide summary statistics for the time series in Table 3. The nowcast errors are measured in annualised percentage points. The mean and standard deviation of the inflation nowcast errors are comparable across countries. As the survey participants have more information on past consumer price changes when they make their nowcasts, the errors associated with those forecasts are smaller than the error stemming from GDP forecasts. Comparing the GDP nowcast errors from the first release data shows that the GDP growth nowcast errors of Italy and France have a smaller variation around the mean, and that the standard error is considerably larger for Germany. The standard errors and the maximum realisations of the year-on-year and quarter-on-quarter observations of the nowcast errors appear similar. From Tables 5, 6, and 7, it is also visible that the year-on-year and quarter-on-quarter GDP nowcast errors are both strongly positively correlated. These observations support the idea that year-on-year nowcast errors can be interpreted as conditional quarter-on-quarter nowcast errors.

Table 3 Summary statistics

	Mean	SD	Min	Max
Germany (2003Q1–2019Q4)				
GDP	1.30	3.60	− 18.70	8.92
GDP nowcast error final release QoQ	0.05	2.73	− 5.20	14.80
GDP nowcast error final release YoY	− 0.64	3.41	− 10.00	11.20
GDP nowcast error first release QoQ	0.28	2.13	− 5.20	11.20
GDP nowcast error first release YoY	− 0.01	2.32	− 7.20	11.20
Inflation	1.44	1.15	− 1.29	4.57
Inflation nowcast error final release YoY	0.22	1.29	− 2.40	3.60
Inflation nowcast error first release YoY	0.02	1.09	− 3.20	2.80
France (2003Q1–2019Q4)				
GDP	1.23	1.90	− 6.64	4.16
GDP nowcast error final release QoQ	− 0.05	1.35	− 3.20	4.80
GDP nowcast error final release YoY	− 0.79	2.41	− 4.80	7.60
GDP nowcast error first release QoQ	0.11	1.12	− 3.20	2.80
GDP nowcast error first release YoY	0.15	1.49	− 2.80	5.20
Inflation	1.34	1.19	− 1.44	4.38
Inflation nowcast error final release YoY	0.07	1.18	− 2.00	4.80
Inflation nowcast error first release YoY	0.05	1.07	− 2.00	4.40
Italy (2003Q2–2019Q4)				
GDP	0.10	2.70	− 11.10	4.66
GDP nowcast error final release QoQ	0.41	2.04	− 3.50	9.18
GDP nowcast error final release YoY	0.18	3.18	− 7.01	13.46
GDP nowcast error first release QoQ	0.47	1.56	− 3.20	7.60
GDP nowcast error first release YoY	0.54	1.82	− 4.00	8.40
Inflation	1.48	1.34	− 2.41	4.24
Inflation nowcast error final release YoY	0.36	0.97	− 1.60	2.80
Inflation nowcast error first release YoY	0.05	0.84	− 2.00	2.80

DP—real GDP growth, seasonally adjusted; Inflation—consumer price inflation, seasonally adjusted; GDP nowcast error—difference between the Consensus Economics nowcast of year-on-year GDP growth and the first release estimate of GDP published by the national statistical offices; Inflation Nowcast Error—difference between the Consensus Economics nowcast of year-on-year consumer price inflation and the first release estimate of consumer price inflation published by the national statistical offices

All data are of quarterly frequency and have been annualised. Means are tested against a zero based standard t-test

4 Results

Here I present the results of my estimation. I seek to extract fundamental and noise shocks from the nowcast errors to determine how they affect GDP fluctuations.

4.1 Impulse response analysis

This section discusses the impulse response functions for each country. In the baseline estimation I use the nowcast errors computed for the first-release data and four lags. Figure 2 shows the IRFs for France, Fig. 3 the results for Germany and Fig. 4 the impulse response functions for Italy. The thick, solid line shows the median impulse responses of real GDP in levels, the inflation rate, the nowcast errors of GDP and the nowcast errors of inflation following fundamental and noisy shocks to both supply and demand. The dotted lines indicate the 16 and 84% confidence regions. Those intervals can be interpreted as confidence bands surrounding the median parameter estimate as they are calculated using Monte Carlo sampling.

In the top row, I show the response of GDP, inflation and nowcast errors to fundamental supply shocks. Positive fundamental supply shocks have an expansionary effect on output. A positive fundamental supply shock has the strongest effects in Germany, followed by Italy and then France. The deflationary response of inflation is genuine and is in line with standard assumptions in Germany and France. Italian inflation also falls following a fundamental supply shock but the response is not statistically significant. Even though the response of the GDP and inflation nowcast errors

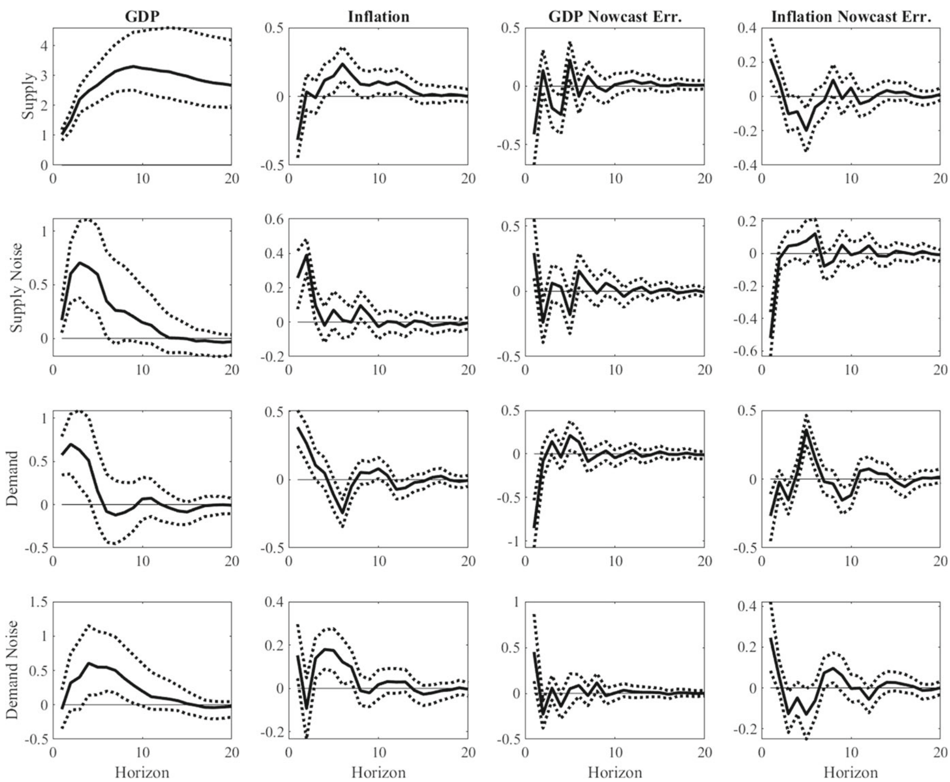

Fig. 2 IRF Benchmark Estimation—France. The solid lines depict the median impulse responses function. The 16th and 84th percentile confidence regions are marked by the dotted lines

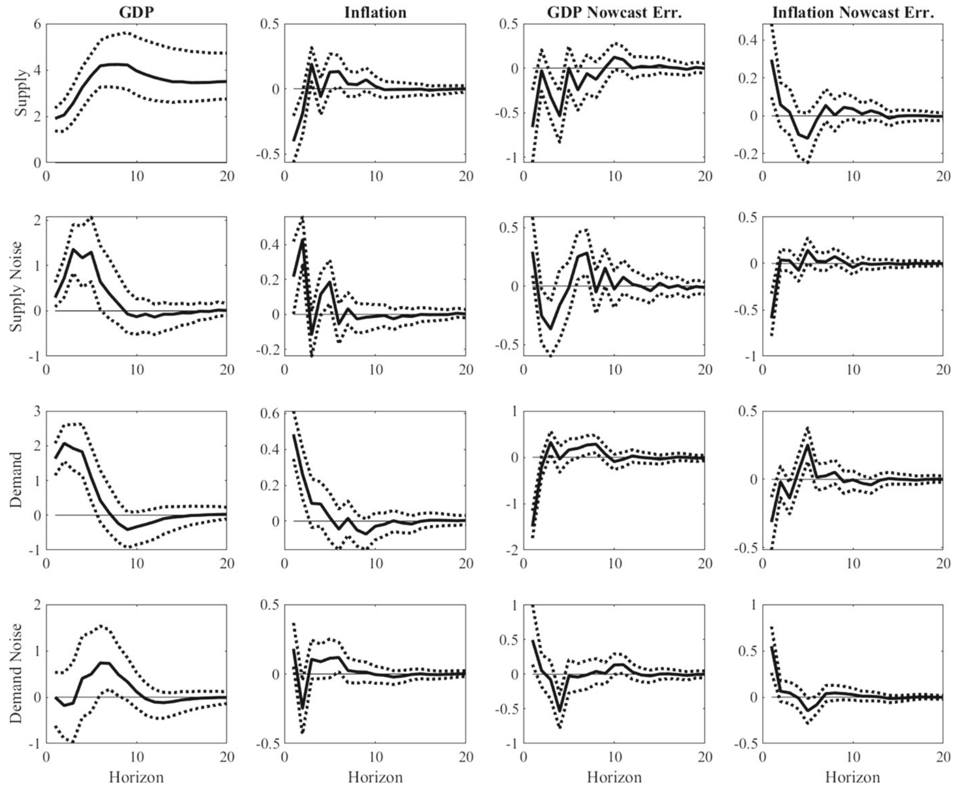

Fig. 3 IRF Benchmark Estimation—Germany. The solid lines show the median impulse responses function. The 16th and 84th percentile confidence regions are marked by the dotted lines

are both left unrestricted, the median response of the GDP nowcast errors at impact is negative for all the countries and the responses of the inflation nowcast errors are positive. I observe almost no systematic effect after the impact period. The negative response of the GDP nowcast errors and the positive response of the inflation nowcast errors are exactly in line with the theoretical predictions of the model.

The response of GDP to a supply noise shock is expansionary and peaks after three quarters, though the magnitude differs between countries. With a supply noise shock that causes the GDP nowcast error to increase by 0.25% point on impact, GDP expands by approximately 1.2% points after two quarters in Germany, while a similarly sized shock raises output in France by only 0.6% point. The hump-shaped response of Italy's GDP is similar to that of Germany, but it levels out slightly faster. Note that the identifying assumption for the supply noise shock only restricts the impulse response on impact but not the dynamics of the adjustment.

The response of output to the fundamental demand shocks is left unrestricted. In line with the theoretical predictions, output expands following a positive fundamental demand shock. The effect is visible for Germany and France, where the response of GDP peaks in around the third or fourth quarter and then gradually levels out.

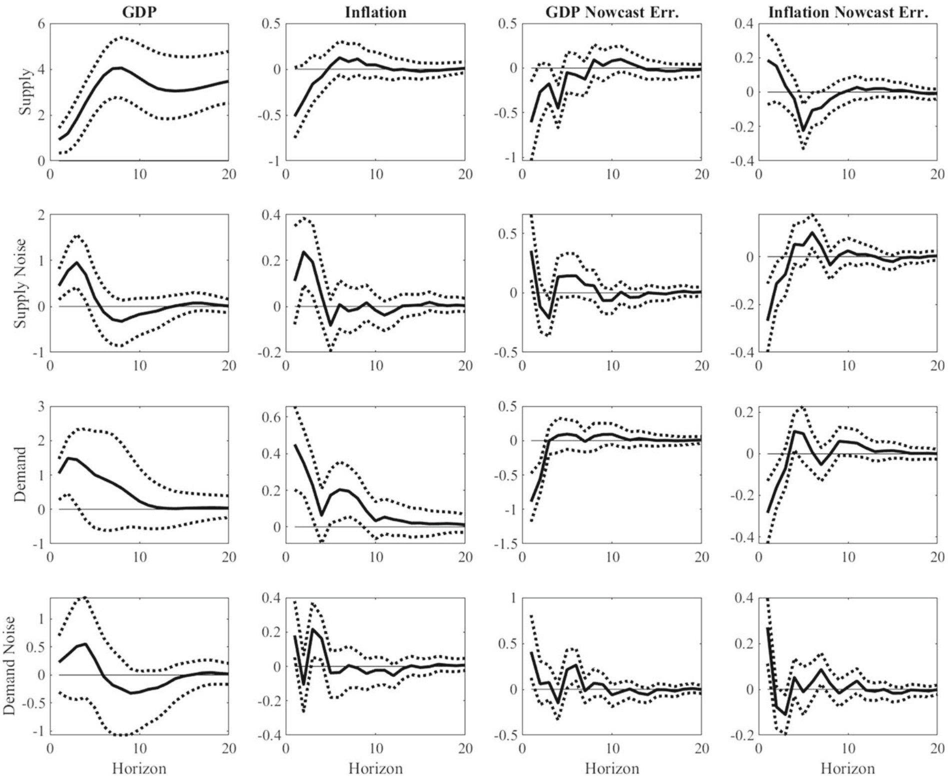

Fig. 4 IRF Benchmark Estimation—Italy. The solid lines show the median impulse responses function. The 16th and 84th percentile confidence regions are marked by the dotted lines

For Italy, a fundamental demand shock does not lead to the characteristic hump-shaped effect on GDP, but the results are statistically not different from zero after two quarters. The positive co-movement of output and inflation across the two shocks echoes the theoretical predictions of Lorenzoni (2009). This means that observing only the response of output and inflation would not allow the researcher to determine if the economy had been hit by a fundamental demand shock or if the agents in the economy had overestimated a permanent positive technology shock for example. Furthermore, inflation responds more slowly after a fundamental demand shock, decaying after the initially restricted response in quarters three or four.

Even though I restricted only the contemporaneous response of output to the supply noise shock and left the response to the demand noise shock unrestricted, the response of output is expansionary and quite persistent. In contrast to the baseline prediction of the theoretical model, my results for all three countries suggest that demand noise shocks are first weakly expansionary before slowly dying out. The effect of a demand noise shock seems to be strongest in Germany, and French GDP shows a slightly weaker response. The response of Italian GDP is similar in magnitude to the response of French GDP but is statistically insignificant for all periods. The weakly expansionary response of GDP to a demand noise shock stands in contrast to the results of Benhima and Poilly (2021), who find for the US that demand noise shocks are recessionary. The response of the nowcaster errors of output to all shocks die out relatively fast in each country. Comparing the responses of the nowcast errors suggests that informational frictions have a persistent effect on fluctuations in output and inflation in the short run and also in the medium run, while forecasters update their forecasts using new information quickly and do not make persistent mistakes. The responses of the French and Italian nowcast errors for inflation seem to be more volatile, and it takes them longer to die out following both the fundamental supply noise shock and the fundamental demand noise shock. In contrast, the German nowcast error of inflation responses seems to die out very quickly after the initial response on impact.

The more persistent responses of the inflation nowcast errors in France and Italy might indicate that forecasters there are biased toward a different inflation target to that of the German forecasters, making the French and Italian forecast errors more correlated. The accuracy, bias and persistence of forecast errors in Europe is discussed by Fioramanti et al. (2016). They analyse the accuracy of the European Commission's forecasts, and they also survey the OECD, the IMF, a consensus forecast of market economists, and the ECB forecasts. They find that forecast errors were larger and to a certain degree also more persistent in the crisis and post-crisis period (2008–2014) than in the pre-crisis period (2000–2007). Interestingly, GDP in Germany and Italy seems to react slightly more strongly to noise shocks than French GDP does.

From Table 3, we can see that output volatility is highest in Germany and Italy. Not surprisingly, the variation of the GDP nowcast errors is also highest for Germany and Italy. The maximum German nowcast errors are almost twice as large as the French ones. The quantitative effect on output in response to noise shocks in the empirical model is in that respect consistent with the data.

4.2 Variance decomposition

To find how much noise shocks drive business cycle fluctuations, I compute the variance decomposition using the baseline VAR model. Table 4 shows the results. I find that noise shocks account for about one quarter of the variation in GDP growth. The contribution is fairly similar across the countries, ranging from 23% in Italy and 22% in France to 25% in Germany. The explained variation for output growth is smaller than that obtained by Benhima and Poilly (2021), who find that around 31% of the total fluctuation in output can be explained by noise shocks. In sum, the contribution of supply noise shocks and demand noise shocks to GDP fluctuations is fairly large.

However, supply noise shocks and demand shocks contribute quite differently to the variation, with demand noise shocks driving the variation in output growth in the USA. In the USA, supply noise shocks only explain 8% of GDP growth volatility, while 23% is explained by demand noise shocks. For Germany, the contributions of supply and demand noise shocks do not differ greatly. The results for the European sample in this paper are closer to the findings by Enders et al. (2021), who find that 'optimism' shocks, or noise shocks, account for about 20% of short-run output volatility.

The first and the third columns of Table 4 show the unconditional variance decomposition for fundamental shocks. Fundamental supply shocks account for 39% of the volatility in output growth in Germany and for 55% in France, while demand shocks

Table 4 Baseline estimation: unconditional variance decomposition

	Supply	Supply noise	Demand	Demand noise
France				
GDP growth	0.55 [0.42, 0.69]	0.11 [0.05, 0.19]	0.18 [0.10, 0.29]	0.11 [0.06, 0.20]
Inflation	0.27 [0.17, 0.40]	0.23 [0.14, 0.34]	0.29 [0.18, 0.43]	0.16 [0.10, 0.23]
GDP Nowcast err	0.21 [0.12, 0.34]	0.15 [0.08, 0.25]	0.38 [0.22, 0.54]	0.18 [0.09, 0.38]
Inflation Nowcast err	0.18 [0.10, 0.29]	0.29 [0.17, 0.43]	0.32 [0.20, 0.47]	0.16 [0.08, 0.27]
Germany				
GDP growth	0.39 [0.27, 0.53]	0.14 [0.08, 0.23]	0.32 [0.21, 0.43]	0.11 [0.06, 0.19]
Inflation	0.25 [0.15, 0.37]	0.26 [0.16, 0.38]	0.27 [0.18, 0.40]	0.18 [0.11, 0.26]
GDP Nowcast err	0.22 [0.14, 0.32]	0.14 [0.09, 0.22]	0.44 [0.31, 0.56]	0.16 [0.09, 0.28]
Inflation Nowcast err	0.15 [0.07, 0.26]	0.31 [0.15, 0.50]	0.19 [0.10, 0.33]	0.28 [0.12, 0.48]
Italy				
GDP growth	0.44 [0.29, 0.60]	0.13 [0.06, 0.25]	0.25 [0.12, 0.41]	0.11 [0.04, 0.23]
Inflation	0.38 [0.19, 0.58]	0.10 [0.05, 0.22]	0.32 [0.17, 0.50]	0.13 [0.07, 0.22]
GDP Nowcast err	0.29 [0.16, 0.50]	0.13 [0.07, 0.21]	0.36 [0.19, 0.52]	0.16 [0.08, 0.29]
Inflation Nowcast err	0.30 [0.16, 0.45]	0.19 [0.10, 0.32]	0.25 [0.14, 0.43]	0.20 [0.13, 0.28]

The unconditional variance decomposition is computed for each successful draw. The upper number reports the median value, and the numbers in brackets are the 16th and 84th percentile values of the variance decomposition distribution

account for 18% in France and for 32% in Germany. In Italy, I find the contribution of fundamental demand shocks to output fluctuations to be around 25%. The estimates for the fundamental demand shocks are also larger than in Benhima and Poilly (2021). Surprisingly, fundamental supply shocks contribute from 25% of inflation volatility in Germany to up to 38% in Italy. This contrasts with the findings of Benhima and Poilly (2021), who report that productivity shocks make only a minor contribution to inflation variance.

The Appendix presents the conditional variance decomposition for France in Fig. 14, for Germany in Fig. 15, and for Italy in Fig. 16. Fundamental supply shocks contribute, by construction, most to GDP over longer horizons. The share of explained variance from other shocks differs across countries, with demand shocks accounting for almost half of the GDP fluctuations in Germany and Italy in the first two to three quarters. The contribution of demand noise shocks starts to increase from the second quarter in France but then levels out quickly. A similar pattern can be observed in Italy. In Germany, however, demand noise shocks explain only a small variation in GDP from the sixth quarter. Clearly, fundamental shocks are the driving force of variations in GDP in the three biggest economies in Europe. This indicates that demand noise shocks play a minor but not insignificant role in explaining variations in short-run GDP; this is a factor that has been neglected in the existing noise-driven business cycle literature. Note however that noise shocks contribute considerably to the variation in inflation in all the countries. Supply noise shocks and fundamental demand shocks explain the bulk of the variation in inflation in Italy and Germany across all horizons.

In France, demand noise shocks contribute between 20 and 40% of the variation in inflation starting from quarter five and running until the end of the forecast horizon.

The observed differences in how real GDP growth responds to demand noise shocks in my analysis and in that of Benhima and Poilly (2021) have multiple possible causes. One of them could be that the results are driven by genuine differences in the industry structure that determine the composition of the information set of European firms and US firms. Furthermore, differences in consumer sentiments and demand patterns in the US and in the three European countries might affect the results. Kappler and Aarle (2012) argue that agents may start to frame news in periods when economic sentiments are declining or improving strongly. In doing so, the agents emphasise news that is in line with their individual economic sentiment and downplay news that is not in line with it. As the business cycles and economic sentiment shifts in the USA and the euro area are partly desynchronised during the sample of common observations, we might assume there to be differences in the effects of demand noise shocks.

Additionally, differences in the information set of the European Central Bank (ECB) and the Federal Reserve and differences in how effective the transmission process of monetary policy is might also affect the results. Whereas the Federal Reserve conducts monetary policy for quite a homogeneous set of individual states in the US, the ECB faces a more complex challenge. It has to conduct monetary policy for all parts of the euro area, taking account of the reduced synchronisation between the stages of the business cycle, the institutional differences, the fragmented fiscal frameworks, and the incomplete nature of the financial markets. This all means that the correct stance of monetary policy is different for different parts of the euro area.

Finally, the differences between the results for the three large economies in Europe and those for the USA can also be driven by differences in the sample under observation. Benhima and Poilly (2021) use spans from 1968 to 2017 for their sample, but the data available for Europe are much shorter. The robustness section of Benhima and Poilly (2021) indicates that changing the sample size can change the relative importance of supply noise shocks. The estimation period in my study is dominated by the Great Recession and the European debt crisis, whose long-lasting effects weighed more heavily on European economies than on the USA.

4.3 Historical decomposition

In this section, I analyse the cumulative effects of the set of structural shocks on real GDP growth over the sample period.[18]

Figure 5 illustrates the use of the historical decomposition in understanding real GDP growth in France from 2004 to 2020. Figures 6 and 7 focus on the role of the structural shocks in explaining real GDP growth in Germany and Italy, respectively.

Variations in real GDP growth in all three countries can mainly be attributed to the effects of fundamental supply shocks. GDP growth in France and Italy was first affected by fundamental supply shocks in the run up to the Great Recession of 2008-2009, while fundamental supply shocks contributed less to real output growth until the first quarter of 2009.

[18] The historical decompositions for the inflation rate are available upon request.

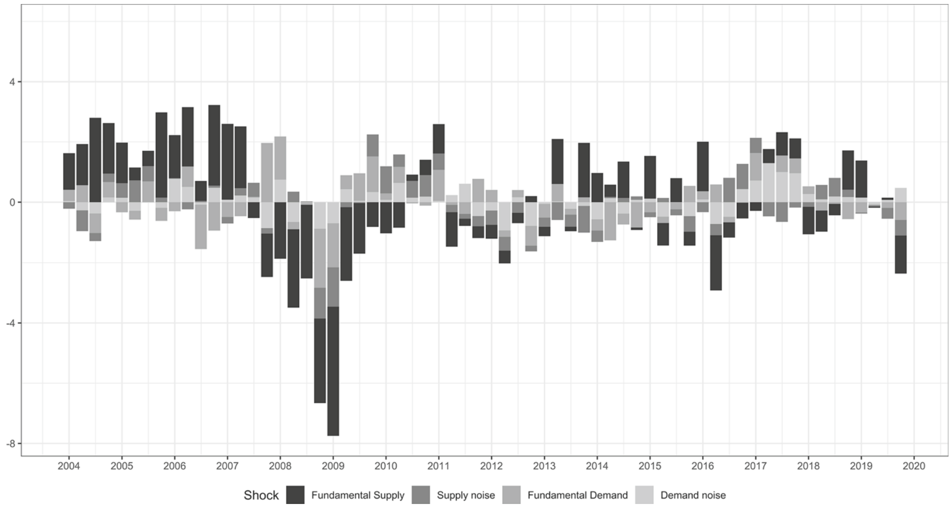

Fig. 5 Historical Decomposition of GDP growth—France. The historical decomposition is obtained by taking the median from the set of all the accepted draws in the baseline SVAR

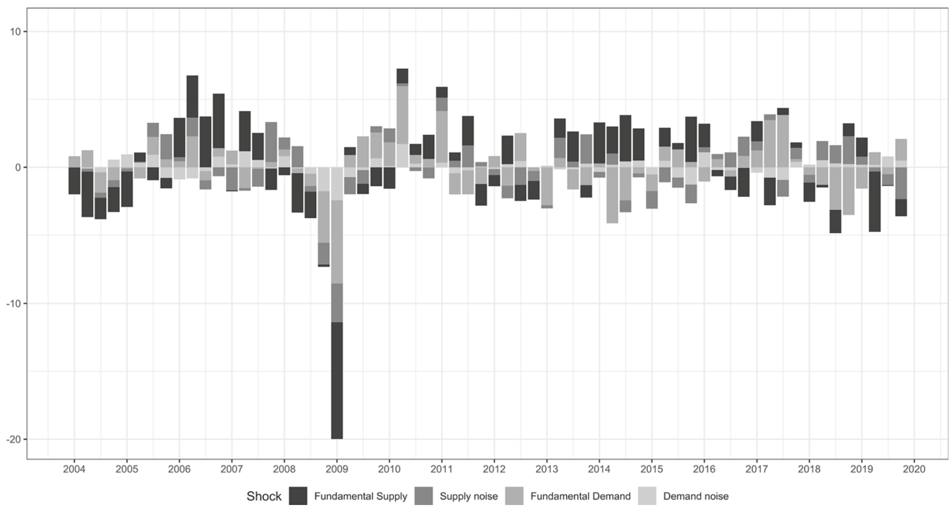

Fig. 6 Historical Decomposition of GDP growth—Germany. The historical decomposition is obtained by taking the median from the set of all the accepted draws in the baseline SVAR

During periods of economic and financial stress, the supply noise shock, and to a lesser degree the demand noise shock, contributed to the negative growth in output. This is particularly visible in the Great Recession of 2008 and 2009. For Italy, supply noise and demand noise shocks also affected output growth from the middle of 2011 to the middle of 2014. This coincides with the European debt crisis which started 2009 in Greece but gained a foothold in other countries such as Ireland, Portugal and particularly Italy from 2010. It seems that Italy experienced a twin fundamental demand shock and noise demand shock that contributed to a decline in output growth.

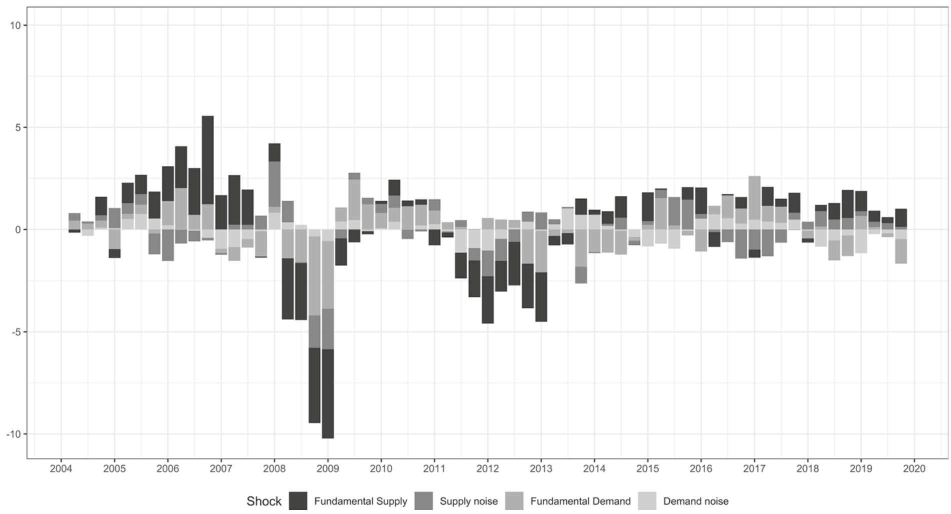

Fig. 7 Historical Decomposition of GDP growth—IT. The historical decomposition is obtained by taking the median from the set of all the accepted draws in the baseline SVAR

The finding that the effects of supply shocks and demand shocks are fairly persistent during times of financial crisis is in line with papers studying the effects of financial shocks, such as Fornari and Stracca (2012).

Another observation from the historical decomposition is that the effects of positive noise shocks persist for two to three periods before being eclipsed by negative noise shocks in subsequent periods. This is in line with the argument that even though noise shocks can drive economic fundamentals, their effects are short-lived as agents update their information set and learn about the true state of the economy.

5 Robustness tests

In this section, I perform a range of robustness tests. First, I test whether the results depend on the use of year-on-year or quarter-on-quarter nowcast errors. In the second robustness test, I extend the lag length of the VAR. The third robustness test analyses the effects of supply and demand shocks when the latest release nowcast errors are used in the estimation. The figures and tables are presented in the Appendix.

In the baseline specification the nowcast errors of GDP are calculated as the difference between the year-on-year GDP growth rate nowcast and the year-on- year first release estimate of the statistical office. Under the assumption that the GDP growth of the previous three quarters is known to the survey participants, the only uncertainty should stem from the nowcast in the current quarter. That all of the nowcast error stems only and entirely from the misperceptions in the most recent quarter cannot, however, be ruled out. Survey participants could, for example, make errors when summing up the GDP growth of the previous quarters. Therefore, I estimate the VAR model with the GDP nowcaster errors calculated at a quarter-on-quarter frequency rather than a year-on-year frequency. I use the nowcast of quarterly seasonally adjusted GDP growth from Consensus Economics and the first release estimate of quarter-on-quarter GDP growth, which the national statistical office provides in seasonally adjusted form, to calculate the errors. These nowcast errors are then annualised. The other variables in the VAR system, the sample length, and the lag structure remain unaltered.

Figure 17 shows the impulse response functions for France, Fig. 18 shows them for Germany, and Fig. 19 for Italy.

Using the GDP nowcast errors based on quarter-on-quarter estimates does not change the results significantly in France or in Germany. The response of a fundamental demand shock in Italy is slightly more pronounced. A demand shock is still expansionary and all the shocks except the fundamental supply shock are still transitory. Given the observation that the results are stable with respect to the nowcasting reference point, it is possible that the VAR results would not be different for quarter-on-quarter nowcasts for inflation if they were available.

Table 9 in the Appendix shows the unconditional variance decomposition of the model where the GDP nowcast errors are calculated from quarter-on-quarter data. As expected, the results are very similar to the baseline specification. In Italy the variation explained by noise decreases marginally by 3% points but the overall picture remains the same.

Extending the lag length from four lags to eight lags comes closer to the baseline specification of Benhima and Poilly (2021). The effect of using a lag length of eight is shown in Fig. 20 for France, in Fig. 21 for Germany, and in Fig. 22 for Italy.

The responses of GDP growth following fundamental supply, supply noise and demand noise shocks are similar in shape for France. The magnitude however, seems to be larger than in the baseline specification. Surprisingly, a positive fundamental demand shock seems to have contractionary effects on real GDP growth but the results are not statistically significant.

Extending the lag length to eight for Germany leads to more volatile responses in GDP growth following any kind of shock. The shape of the responses is similar to, though more volatile than, that for the baseline specification. Both fundamental supply and supply noise shocks produce impulse responses in GDP growth that are approximately half the size of that in the baseline scenario.

The responses of GDP growth in Italy are even less pronounced than they are in the baseline specification. With a lag length of eight, the response of GDP growth tends to become insignificant following any kind of supply or demand shock.

Table 10 in the Appendix shows the unconditional variance decomposition when the baseline model is estimated with eight lags. With the eight-lag specification, more variation in GDP growth is explained by noise shocks. The variance explained by supply noise and demand noise shocks in France for example is almost twice as large as that in the specification with eight lags. The increase in explained variance is also visible from the conditional variance decomposition. Figure 23 shows the conditional variance decomposition for France. Noise shocks explain around half of the total variance in output growth fluctuations in quarter four to quarter six.

Finally, I analyse the impact of the latest release nowcast errors.[19] Final release nowcast errors are computed as the difference between the final release estimate of the national statistical office and the Consensus Economics nowcast. The final data published by the statistical offices can contain data revisions that stem from changes to the statistical methodology. Since nowcasters do not always observe the final release data, their information set is influenced by the choice of the data vignette.[20] Differences between vintage data and final release data might therefore impact econometric estimates (Croushore and Stark 2003).

The impulse response analysis does indeed show that the choice of the data vignette can matter for the statistical inference. Figure 26 illustrates that using final release data from France changes the direction of certain impulse responses. A positive fundamental demand shock leads to a minor increase in GDP growth for three quarters for example, but this is then followed by a contraction in output growth. Equally, a positive fundamental supply shock is followed by a much larger increase in GDP growth. This pattern however is not uniform across countries, and Fig. 26 shows that when final release data are used, a positive supply noise shock tends to increase output growth only slightly but leads to a contraction in output growth that reaches the bottom in quarter six after the shock. A larger response of output growth is also visible for Italy (see Fig. 26). This can partly be explained by the observation that the minimum and maximum nowcast errors tend to be larger for latest release data than for first release data. Using latest release data has no systematic effect on the unconditional variance decomposition (see Table 11). The overall explained variance of noise shocks is very similar to the baseline case. The marginally greater variation in GDP growth in Germany is explained more by fundamental supply shocks than fundamental demand shocks when the latest release data are used.

6 Conclusion

The news view of business cycles provides a framework for understanding how noise shocks can influence expectations about future economic developments and so drive the business cycle even when current fundamentals remain unaltered. There is some evidence for fluctuations in the business cycle being driven by demand noise in the USA, but little is known about how misperceptions of supply and demand affect output and inflation in Europe.

In this paper, I employ the general framework of Benhima and Poilly (2021) to analyse the effects of supply noise shocks and demand noise shocks in three major European economies. An SVAR model is estimated in order to disentangle noise shocks from fundamental shocks. One key component of the empirical identification strategy is nowcast errors, which are computed from the nowcasts of participants in

[19] Latest release data represents the last published data for a data point. In most cases this will be the final release data from the statistical office, ex post data revisions are also part of the final release data.

[20] In my analysis nowcasters might not observe the final release data for the real GDP growth of the previous quarter. Similarly, nowcasters have a larger information set when forming expectations about the year-on-year consumer price inflation rate, but they previous quarter year-on-year inflation rate might be subject to data revisions.

the Consensus Economics survey and the first release estimates of GDP growth and consumer price inflation provided by the national statistical offices.

The main conclusions are as follows. First, I provide evidence of expansionary effects on output from both supply noise shocks and demand noise shocks in all three countries. The response is more pronounced in Germany and Italy than in France. The response of GDP growth and inflation to a supply noise shock is observationally similar to their response following a demand shock. That observation has already been pointed out by Lorenzoni (2009). Benhima and Poilly (2021) have argued that the reverse conclusion should also hold. Negative demand noise shocks should create an observationally similar response in output to that of fundamental supply shocks. The analysis of the three European samples, however, does not support this hypothesis. Positive demand noise shocks lead to an expansionary response in output in all three countries, though the response is statistically insignificant in Italy.

Second, the results of the variance decomposition show that supply noise and demand noise contribute to very similar degrees in explaining the volatility in output growth at business cycle frequencies. The joint contribution amounts to around 24% with no notable differences across countries.

The historical decomposition provides some tentative evidence that noise shocks had some fairly large and persistent effects on output growth during periods of economic and financial stress. This seems particular pronounced in the case of Italy, which was not only affected in the Great Recession but also by the European debt crisis.

The observed differences in how real GDP growth responds to demand noise shocks in my analysis and in that of Benhima and Poilly (2021) can have multiple causes. Differences in industry structure and differences between the US and Europe in the information set of monetary policy makers may be one factor driving the difference in the results. Another factor that may explain the difference in results is that the US sample covers important macroeconomic episodes such as the Great Moderation in the USA that might influence the relative importance of fundamental and noise shocks. In this spirit, the magnitude and duration of the Great Recession and the European debt crisis might also weigh on how output growth reacts to noise shocks. I leave further investigation of these issues to future research.

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Declarations

Conflict of interest The author has no conflicts of interest to declare that are relevant to the content of this article.

Appendices

A Data and description

See Appendix Figs. 8, 9, 10, 11, 12 and 13 and Table 5, 6, 7 and 8.

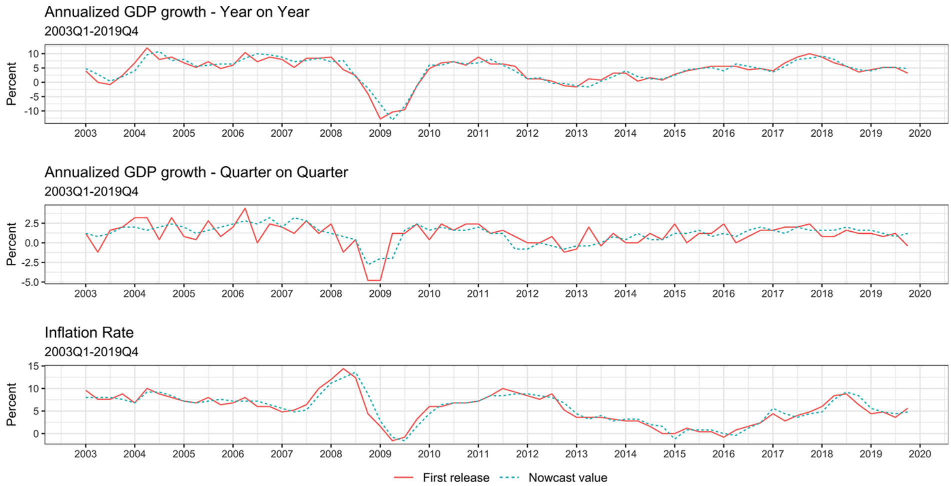

Fig. 8 Nowcast and official first release data—France. The solid red line shows the first release value provided by the national statistical office. The dotted turquoise line shows the mean nowcast for the current quarter provided by Consensus Economics

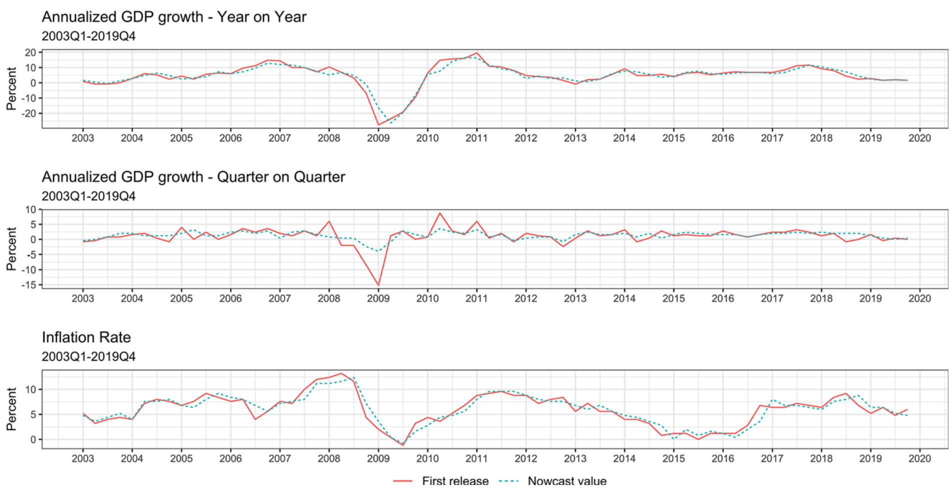

Fig. 9 Nowcast and official first release data—Germany. The solid red line shows the first release value provided by the national statistical office. The dotted turquoise line shows the mean nowcast for the current quarter provided by Consensus Economics

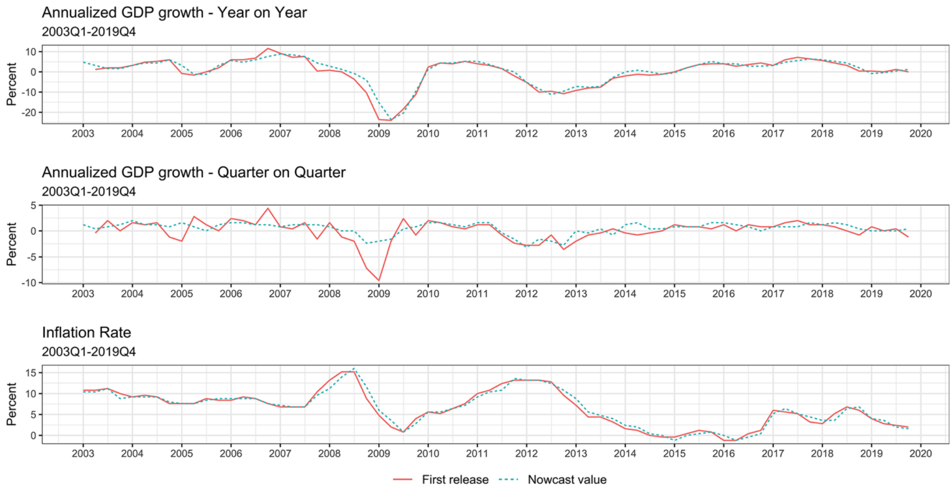

Fig. 10 Nowcast and official first release data—Italy. The solid red line shows the first release value provided by the national statistical office. The dotted turquoise line shows the mean nowcast for the current quarter provided by Consensus Economics

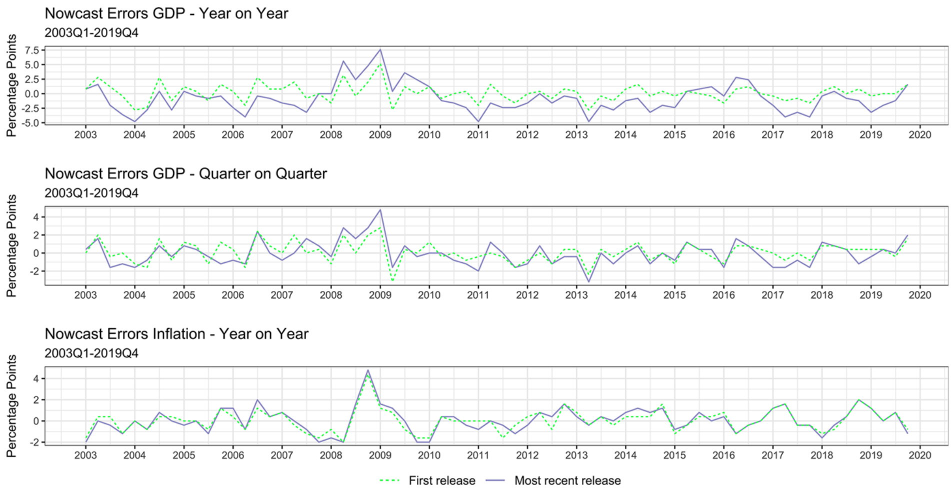

Fig. 11 Nowcast errors based on first and final release data—France. The first release nowcast errors are calculated as the difference between the Consensus Economics survey nowcast and the first release data of the national statistical office. The final release nowcast errors are calculated as the difference between the Consensus Economics survey nowcast and the latest available data of the national statistical office. All data are in annualised terms

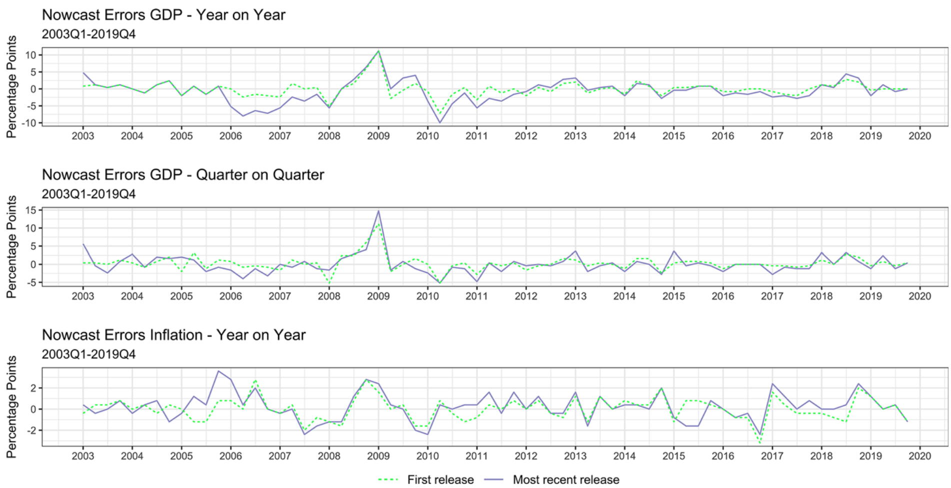

Fig. 12 Nowcast errors based on first and final release data—Germany. The first release nowcast errors are calculated as the difference between the Consensus Economics survey nowcast and the first release data of the national statistical office. The final release nowcast errors are calculated as the difference between the Consensus Economics survey nowcast and the latest available data of the national statistical office. All data are in annualised terms

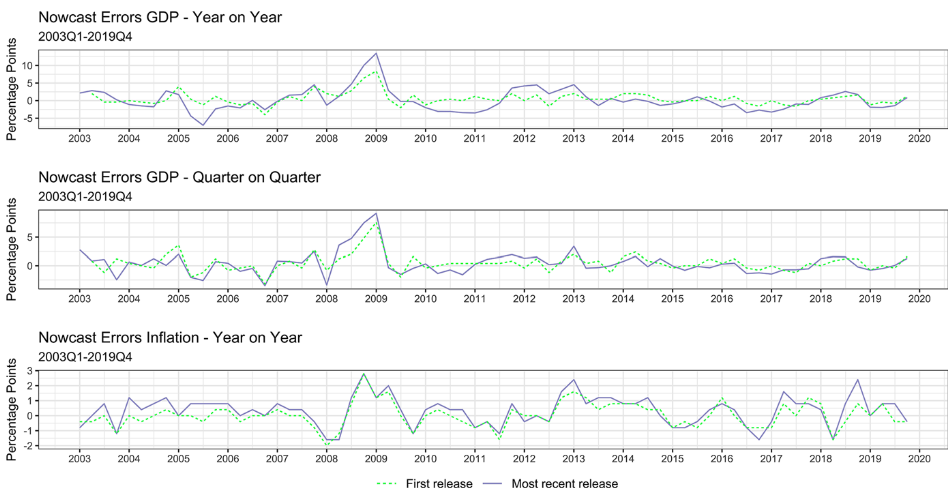

Fig. 13 Nowcast errors based on first and final release data—Italy. The first release nowcast errors are calculated as the difference between the Consensus Economics survey nowcast and the first release data of the national statistical office. The final release nowcast errors are calculated as the difference between the Consensus Economics survey nowcast and the latest available data of the national statistical office. All data are in annualised terms

Table 5 Correlation Table—DE

	GDP	GDP nowcast error final rel. QoQ	GDP nowcast error final rel. YoY	GDP nowcast error first rel. YoY	GDP nowcast error first rel. QoQ	Inflation nowcast error first rel. YoY	Inflation	Inflation nowcast error final rel. YoY
GDP	*	− 0.96	− 0.78	− 0.79	− 0.77	− 0.15	0.18	− 0.19
GDP nowcast error final rel. QoQ	− 0.96	*	0.77	0.79	0.78	0.10	− 0.16	0.15
GDP nowcast error final rel. YoY	− 0.78	0.77	*	0.84	0.77	0.12	− 0.20	0.14
GDP nowcast error first rel YoY	− 0.79	0.79	0.84	*	0.95	0.21	− 0.25	0.24
GDP nowcast error first rel. QoQ	− 0.77	0.78	0.77	0.95	*	0.19	− 0.22	0.25
Inflation nowcast	− 0.15	0.10	0.12	0.21	0.19	*	− 0.29	0.73
Error first rel. YoY Inflation	0.18	− 0.16	− 0.20	− 0.25	− 0.22	− 0.29	*	− 0.19
Inflation nowcast error final rel. YoY	− 0.19	0.15	0.14	0.24	0.25	0.73	− 0.19	*

Sample 2003Q1–2019Q4

Table 6 Correlation Table—FR

	GDP	GDP nowcast error final rel. QoQ	GDP nowcast error final rel. YoY	GDP nowcast error first rel. YoY	GDP nowcast error first rel. QoQ	Inflation nowcast error first rel. YoY	Inflation	Inflation nowcast. error final rel. YoY
GDP	*	− 0.80	− 0.77	− 0.58	− 0.49	− 0.27	0.28	− 0.31
GDP nowcast error final rel. QoQ	− 0.80	*	0.77	0.75	0.76	0.04	− 0.08	0.11
GDP nowcast error final rel. YoY	− 0.77	0.77	*	0.68	0.59	0.06	− 0.18	0.08
GDP nowcast error first rel YoY	− 0.58	0.75	0.68	*	0.89	0.16	− 0.15	0.21
GDP nowcast error first rel. QoQ	− 0.49	0.76	0.59	0.89	*	0.15	− 0.10	0.20
Inflation nowcast	− 0.27	0.04	0.06	0.16	0.15	*	− 0.56	0.93
Error first rel. YoY Inflation	0.28	− 0.08	− 0.18	− 0.15	− 0.10	− 0.56	*	− 0.63
Inflation nowcast error final rel. YoY	− 0.31	0.11	0.08	0.21	0.20	0.93	− 0.63	*

Sample 2003Q1–2019Q4

Table 7 Correlation Table—IT

	GDP	GDP nowcast error final rel. QoQ	GDP nowcast error final rel. YoY	GDP nowcast error first rel. YoY	GDP nowcast error first rel. QoQ	Inflation nowcast error first rel. YoY	Inflation	Inflation nowcast. error final rel. YoY
GDP	*	− 0.91	− 0.85	− 0.70	− 0.68	− 0.44	0.07	− 0.30
GDP nowcast error final rel. QoQ	− 0.91	*	0.80	0.77	0.79	0.40	− 0.08	0.28
GDP nowcast error final rel. YoY	− 0.85	0.80	*	0.73	0.71	0.39	− 0.08	0.29
GDP nowcast error first rel YoY	− 0.70	0.77	0.73	*	0.91	0.30	− 0.05	0.23
GDP nowcast error first rel. QoQ	− 0.68	0.79	0.71	0.91	*	0.31	− 0.16	0.22
Inflation nowcast error first rel. YoY	− 0.44	0.40	0.39	0.30	0.31	*	− 0.48	0.87
Inflation	0.07	− 0.08	− 0.08	− 0.05	− 0.16	− 0.48	*	− 0.36
Inflation nowcast error final rel. YoY	− 0.30	0.28	0.29	0.23	0.22	0.87	− 0.36	*

Sample 2003Q2–2019Q4

Table 8 Cross-country correlations

	DE—GDP nowcast error first rel. YoY	DE—GDP nowcast error first rel. QoQ	DE—Infl nowcast error first rel. YoY	FR—GDP nowcast error first rel. YoY	FR—GDP nowcast error first rel. QoQ	FR—Infl nowcast error first rel. YoY	IT—GDP nowcast error first rel. YoY	IT—GDP nowcast error first rel. QoQ	IT—Infl nowcast error first rel. YoY
DE—GDP nowcast error first rel YoY	*	0.95	0.22	0.52	0.47	0.27	0.58	0.63	0.30
DE—GDP nowcast error first rel. QoQ	0.95	*	0.19	0.53	0.49	0.24	0.55	0.59	0.31
DE—Infl. nowcast error first rel. YoY	0.22	0.19	*	0.20	0.20	0.66	0.26	0.30	0.43
FR—GDP nowcast error first rel YoY	0.52	0.53	0.20	*	0.89	0.17	0.36	0.38	0.01
FR—GDP nowcast error first rel. QoQ	0.47	0.49	0.20	0.89	*	0.15	0.34	0.36	− 0.00

Table 8 (continued)

	DE—GDP nowcast error first rel. YoY	DE—GDP nowcast error first rel. QoQ	DE—Infl nowcast error first rel. YoY	FR—GDP nowcast error first rel. YoY	FR—GDP nowcast error first rel. QoQ	FR—Infl nowcast error first rel. YoY	IT—GDP nowcast error first rel. YoY	IT—GDP nowcast error first rel. QoQ	IT—Infl nowcast error first rel. YoY
FR—Infl. nowcast error first rel. YoY	0.27	0.24	0.66	0.17	0.15	*	0.28	0.28	0.63
IT—GDP nowcast error first rel YoY	0.58	0.55	0.26	0.36	0.34	0.28	*	0.91	0.30
IT—GDP nowcast error first rel. QoQ	0.63	0.59	0.30	0.38	0.36	0.28	0.91	*	0.31
IT—Infl. nowcast error first rel. YoY	0.30	0.31	0.43	0.01	− 0.00	0.63	0.30	0.31	*

Sample 2003Q2–2019Q4

B SVAR Analysis

See Appendix Figs. 14, 15 and 16.

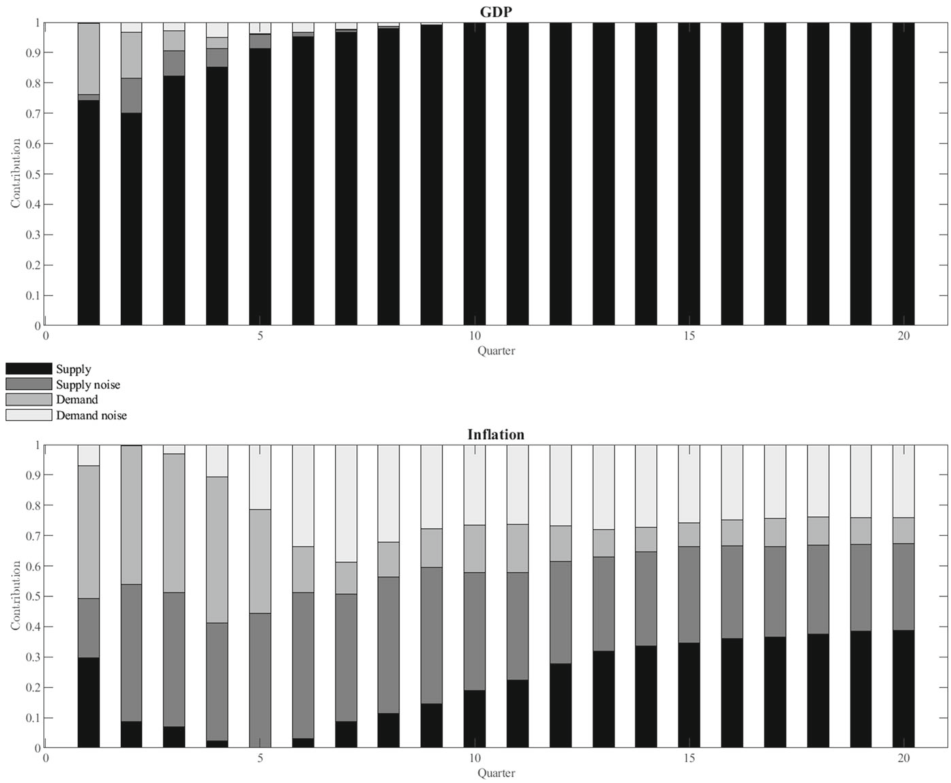

Fig. 14 Conditional variance decomposition of real GDP and inflation—France

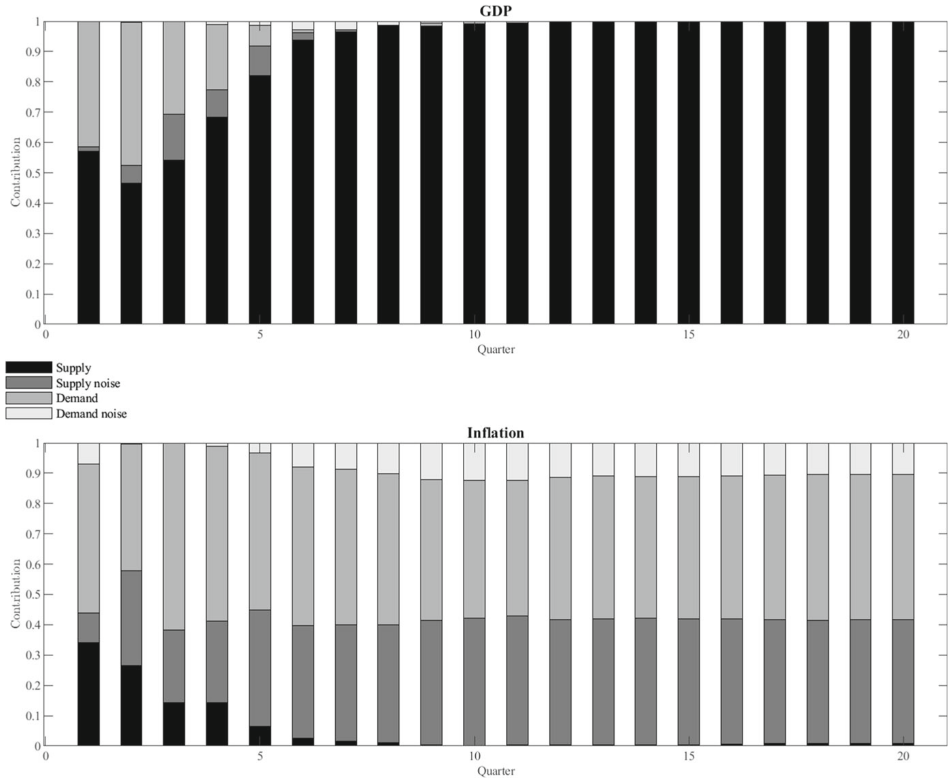

Fig. 15 Conditional variance decomposition of real GDP and inflation—Germany

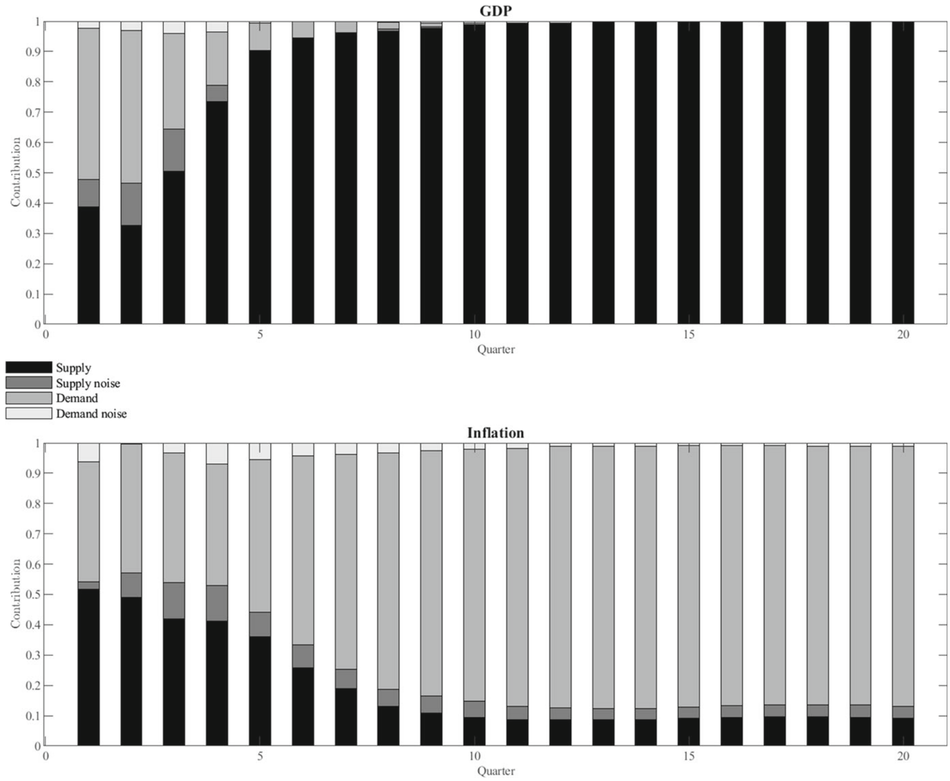

Fig. 16 Conditional variance decomposition of real GDP and inflation—Italy

C Robustness

C.1 Robustness: GDP quarter-on-quarter nowcast errors

See Appendix Figs. 17, 18 and 19 and Table 9.

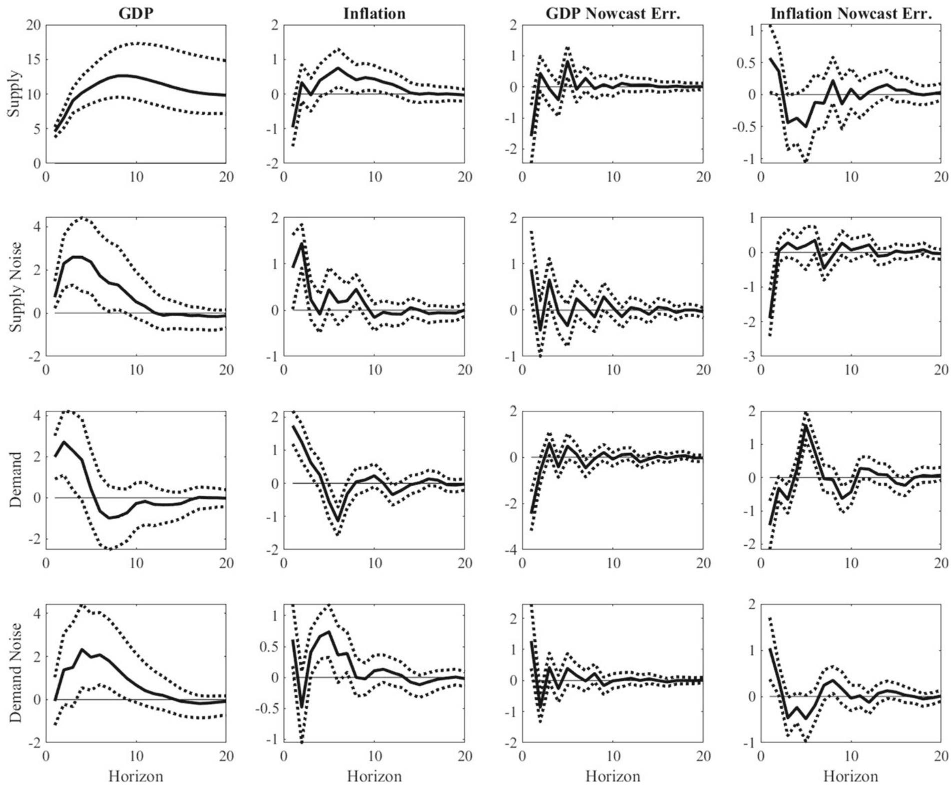

Fig. 17 IRF Robustness—France. The nowcast error of GDP is calculated from the quarter on quarter nowcast and the quarter on quarter first release estimate of the national statistical office. The solid lines depict the median impulse responses function. The 16th and 84th percentile confidence regions are marked by the dotted lines

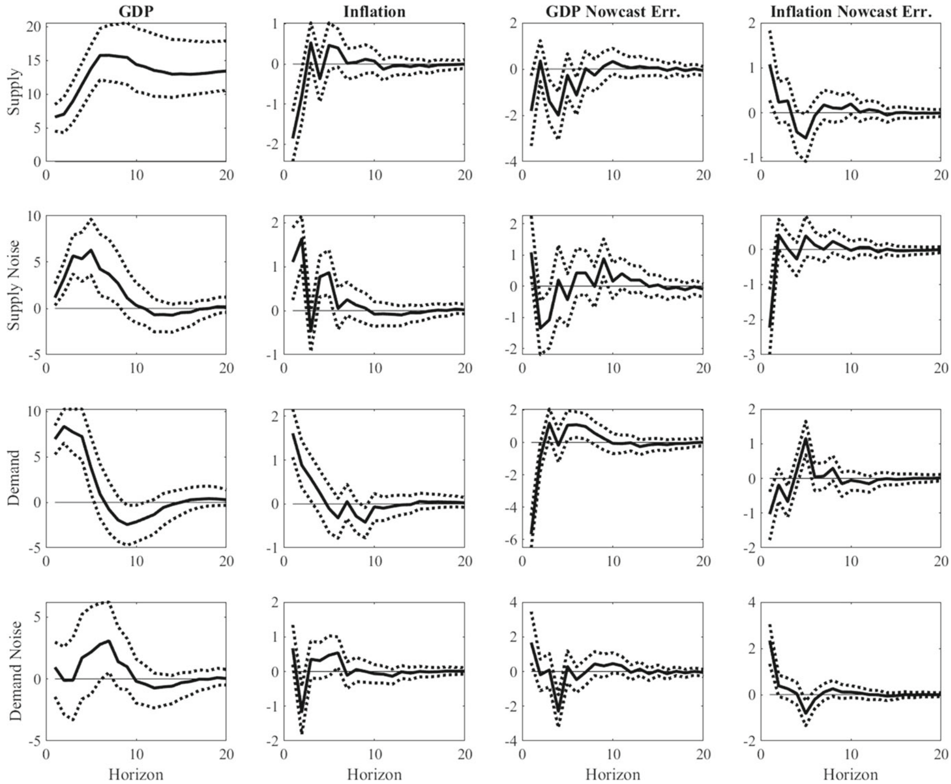

Fig. 18 IRF Robustness—Germany. The nowcast error of GDP is calculated from the quarter on quarter nowcast and the quarter on quarter first release estimate of the national statistical office. The solid lines depict the median impulse responses function. The 16th and 84th percentile confidence regions are marked by the dotted lines

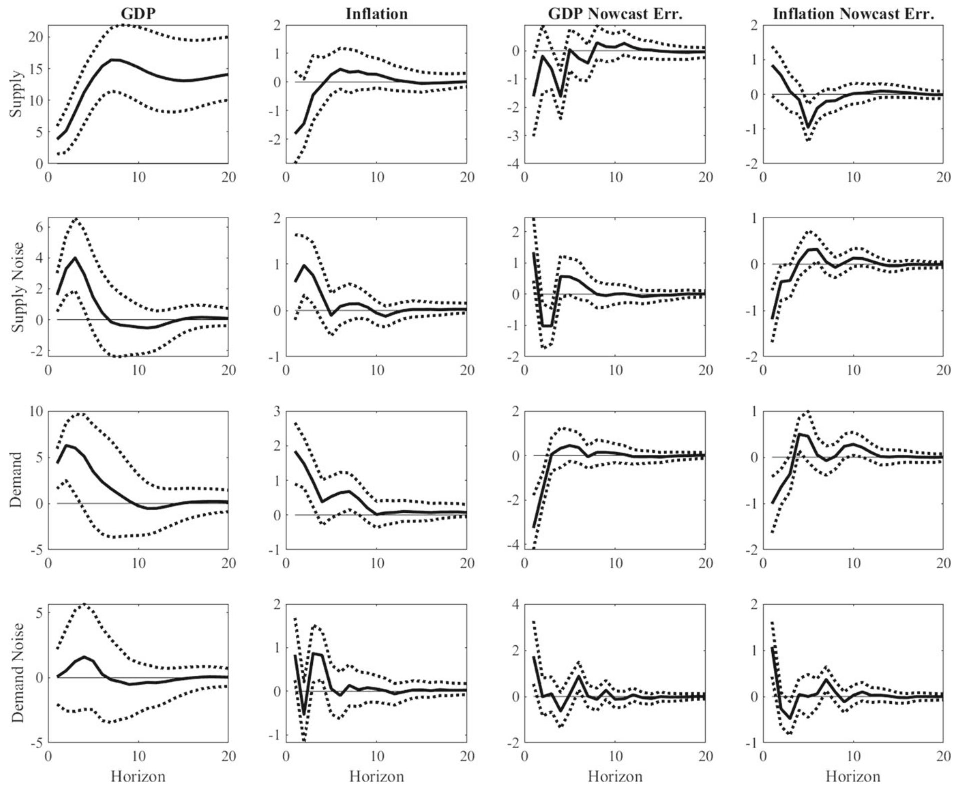

Fig. 19 IRF Robustness—Italy. The nowcast error of GDP is calculated from the quarter on quarter nowcast and the quarter on quarter first release estimate of the national statistical office. The solid lines depict the median impulse responses function. The 16th and 84th percentile confidence regions are marked by the dotted lines

Table 9 Unconditional variance decomposition

	Supply	Supply noise	Demand	Demand noise
France				
GDP growth	0.57 [0.43, 0.71]	0.10 [0.05, 0.19]	0.18 [0.09, 0.30]	0.10 [0.05, 0.19]
Inflation	0.22 [0.13, 0.35]	0.21 [0.13, 0.32]	0.37 [0.24, 0.50]	0.15 [0.10, 0.22]
GDP Nowcast err	0.23 [0.12, 0.37]	0.15 [0.08, 0.24]	0.37 [0.23, 0.52]	0.19 [0.10, 0.34]
Inflation Nowcast err	0.14 [0.08, 0.23]	0.26 [0.15, 0.40]	0.40 [0.26, 0.55]	0.16 [0.08, 0.27]
Germany				
GDP growth	0.33 [0.23, 0.46]	0.15 [0.08, 0.23]	0.36 [0.26, 0.46]	0.12 [0.07, 0.20]
Inflation	0.26 [0.16, 0.38]	0.29 [0.19, 0.40]	0.23 [0.15, 0.34]	0.18 [0.12, 0.26]
GDP Nowcast err	0.20 [0.13, 0.29]	0.14 [0.08, 0.21]	0.46 [0.33, 0.57]	0.18 [0.10, 0.28]
Inflation Nowcast err	0.14 [0.07, 0.25]	0.28 [0.13, 0.46]	0.20 [0.11, 0.32]	0.32 [0.16, 0.49]
Italy				
GDP growth	0.46 [0.31, 0.61]	0.11 [0.05, 0.24]	0.27 [0.13, 0.43]	0.09 [0.04, 0.19]
Inflation	0.36 [0.18, 0.58]	0.10 [0.04, 0.26]	0.30 [0.15, 0.49]	0.14 [0.07, 0.24]
GDP Nowcast err	0.25 [0.15, 0.39]	0.16 [0.09, 0.25]	0.36 [0.21, 0.50]	0.18 [0.09, 0.31]
Inflation Nowcast err	0.31 [0.15, 0.46]	0.20 [0.10, 0.34]	0.24 [0.13, 0.42]	0.19 [0.12, 0.29]

Robustness: GDP quarter-on-quarter nowcast errors

For each successful draw, the unconditional variance decomposition is computed. The upper number reports the median value and the numbers in brackets are the 16th and 84th percentile values of the variance decomposition distribution

C.2 Robustness: lag length 8 quarters.

See Appendix Figs. 20, 21, 22, 23, 24, and 25 and Table 10.

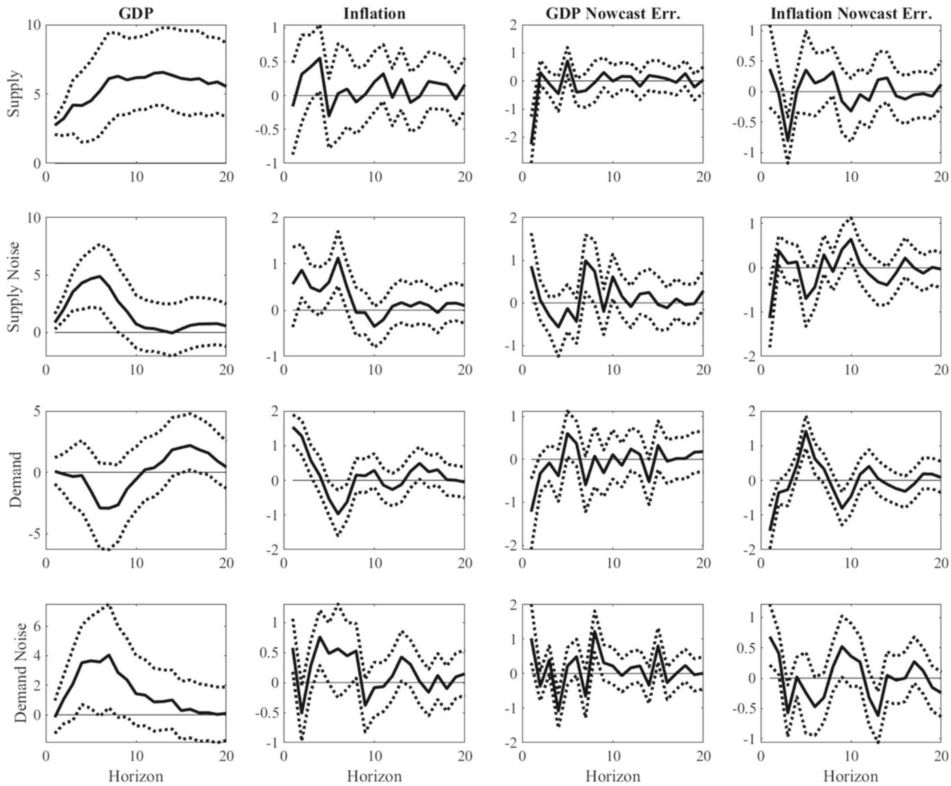

Fig. 20 IRF Robustness: 8 Lags—France. The solid lines show the median impulse responses function. The 16th and 84th percentile confidence regions are marked by the dotted lines

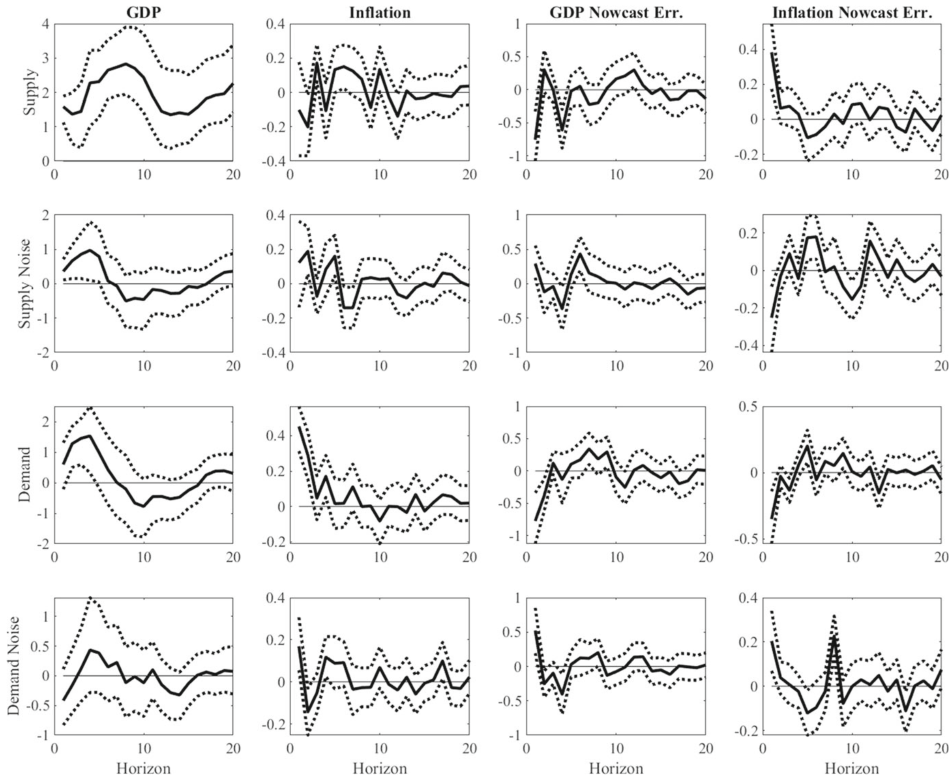

Fig. 21 IRF Robustness: 8 Lags—Germany. The solid lines show the median impulse responses function. The 16th and 84th percentile confidence regions are marked by the dotted lines

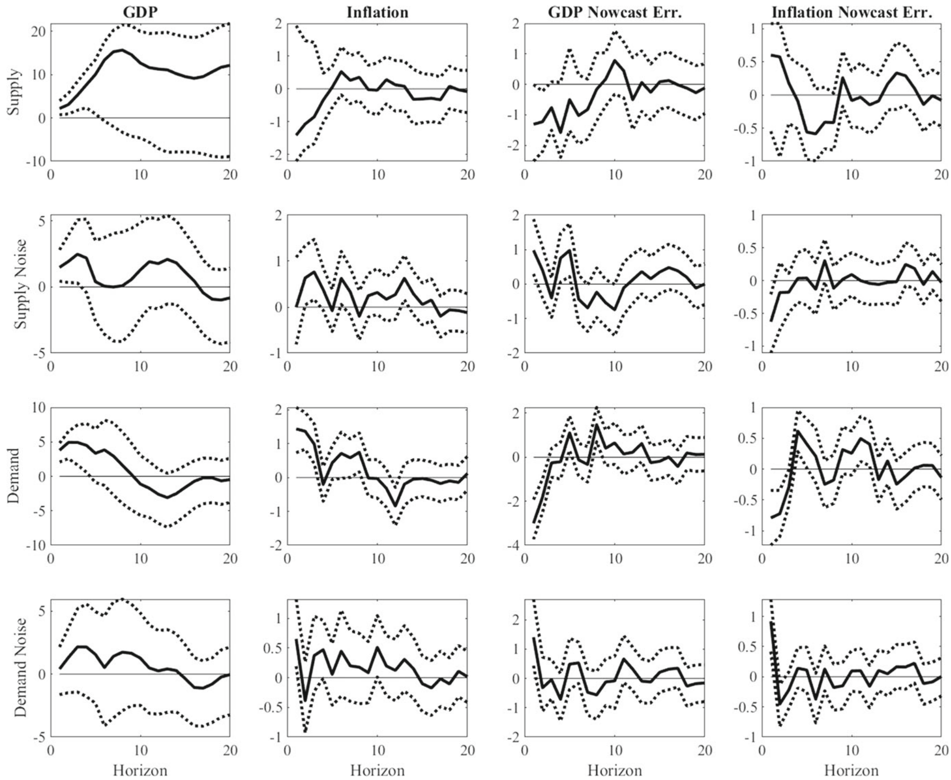

Fig. 22 IRF Robustness: 8 Lags—Italy. The solid lines show the median impulse responses function. The 16th and 84th percentile confidence regions are marked by the dotted lines

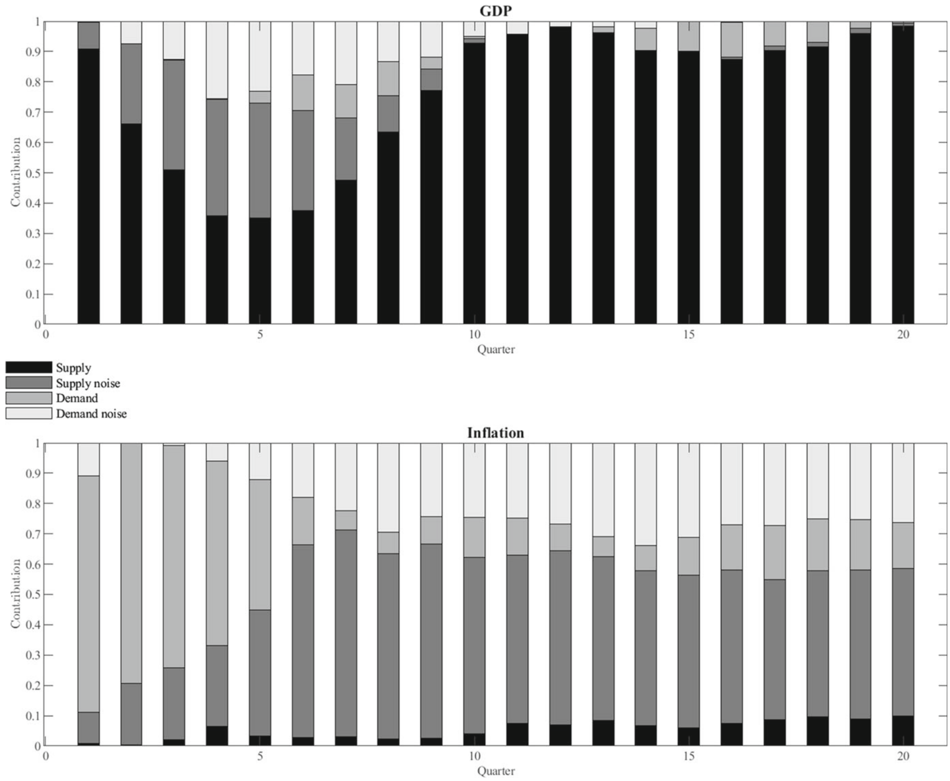

Fig. 23 Conditional variance decomposition of real GDP and inflation for Lag length 8—France

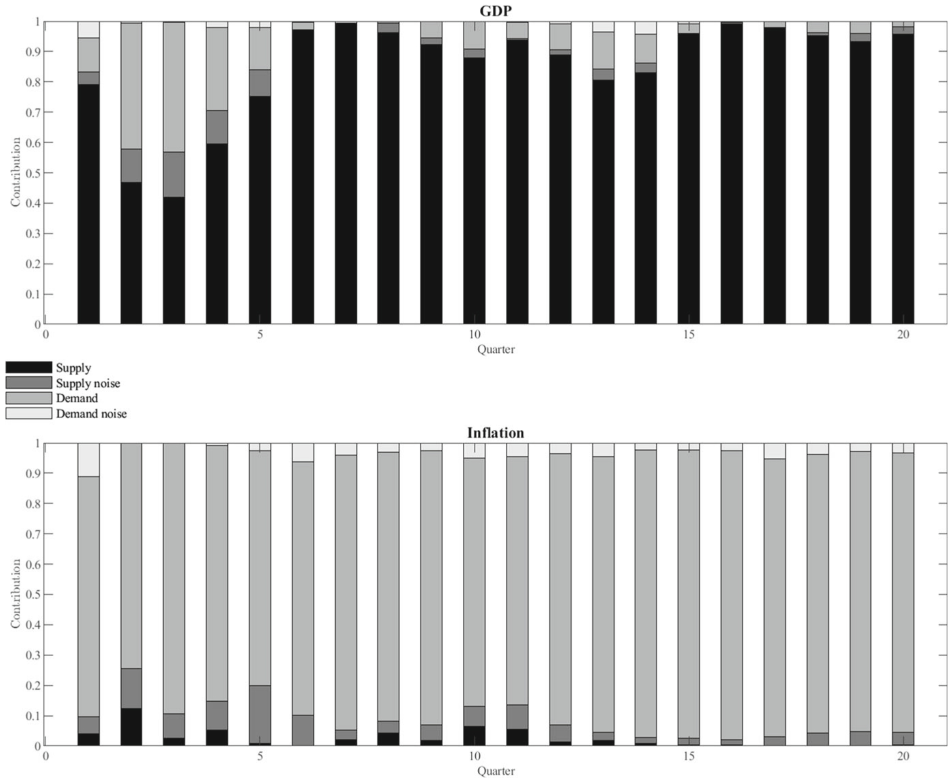

Fig. 24 Conditional variance decomposition of real GDP and inflation for Lag length 8—Germany

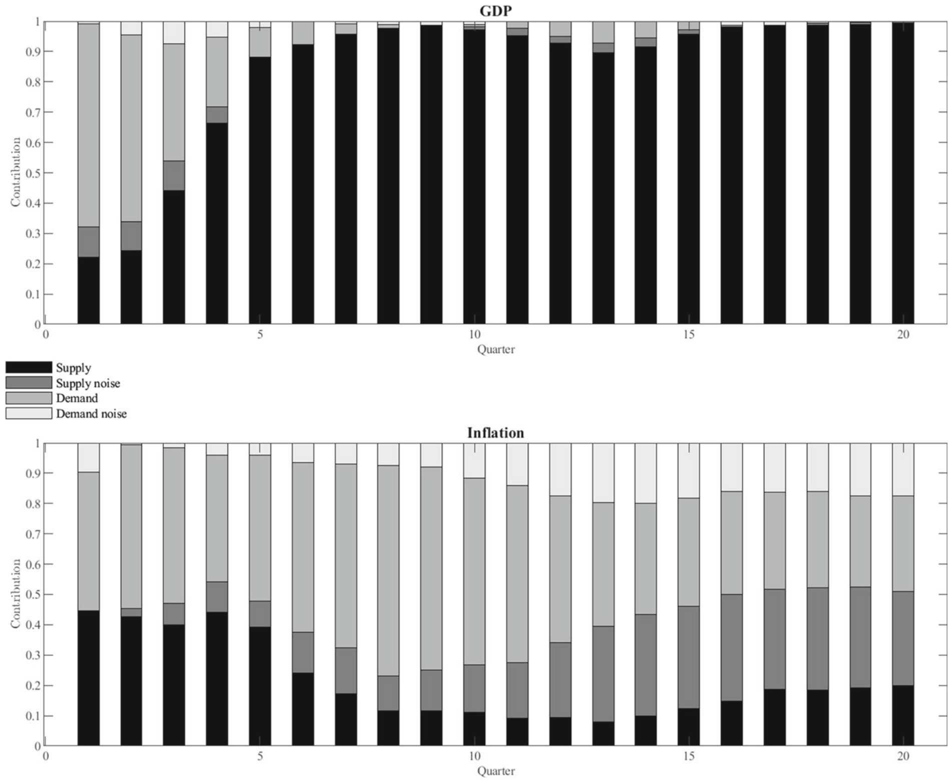

Fig. 25 Conditional variance decomposition of real GDP and inflation for Lag length 8—Italy

Table 10 Unconditional variance decomposition

	Supply	Supply noise	Demand	Demand noise
France				
GDP growth	0.25 [0.17, 0.36]	0.23 [0.13, 0.37]	0.25 [0.15, 0.37]	0.21 [0.12, 0.34]
Inflation	0.17 [0.10, 0.29]	0.24 [0.15, 0.36]	0.32 [0.21, 0.44]	0.20 [0.12, 0.32]
GDP Nowcast err	0.26 [0.17, 0.37]	0.22 [0.13, 0.32]	0.22 [0.13, 0.32]	0.26 [0.17, 0.37]
Inflation Nowcast err	0.18 [0.10, 0.29]	0.24 [0.15, 0.35]	0.33 [0.21, 0.45]	0.20 [0.12, 0.32]
Germany				
GDP growth	0.36 [0.26, 0.48]	0.20 [0.11, 0.32]	0.26 [0.16, 0.37]	0.14 [0.08, 0.22]
Inflation	0.29 [0.18, 0.42]	0.22 [0.13, 0.33]	0.29 [0.18, 0.42]	0.15 [0.09, 0.23]
GDP Nowcast err	0.30 [0.22, 0.41]	0.21 [0.12, 0.31]	0.28 [0.19, 0.37]	0.18 [0.10, 0.27]
Inflation Nowcast err	0.26 [0.15, 0.40]	0.24 [0.15, 0.36]	0.26 [0.15, 0.40]	0.18 [0.11, 0.27]
Italy				
GDP growth	0.39 [0.26, 0.54]	0.15 [0.08, 0.24]	0.26 [0.15, 0.38]	0.15 [0.08, 0.26]
Inflation	0.35 [0.21, 0.54]	0.15 [0.08, 0.27]	0.27 [0.15, 0.41]	0.15 [0.08, 0.26]
GDP Nowcast err	0.30 [0.19, 0.45]	0.15 [0.09, 0.24]	0.31 [0.19, 0.44]	0.18 [0.10, 0.29]
Inflation Nowcast err	0.32 [0.20, 0.47]	0.15 [0.09, 0.25]	0.27 [0.16, 0.40]	0.20 [0.12, 0.30]

Robustness: 8 Lags

For each successful draw, the unconditional variance decomposition is computed. The upper number reports the median value, and the numbers in brackets are the 16th and 84th percentile values of the variance decomposition distribution

C.3 Robustness: final release nowcast errors.

See Appendix Figs. 26, 27, 28, 29, 30, and 31 and Table 11.

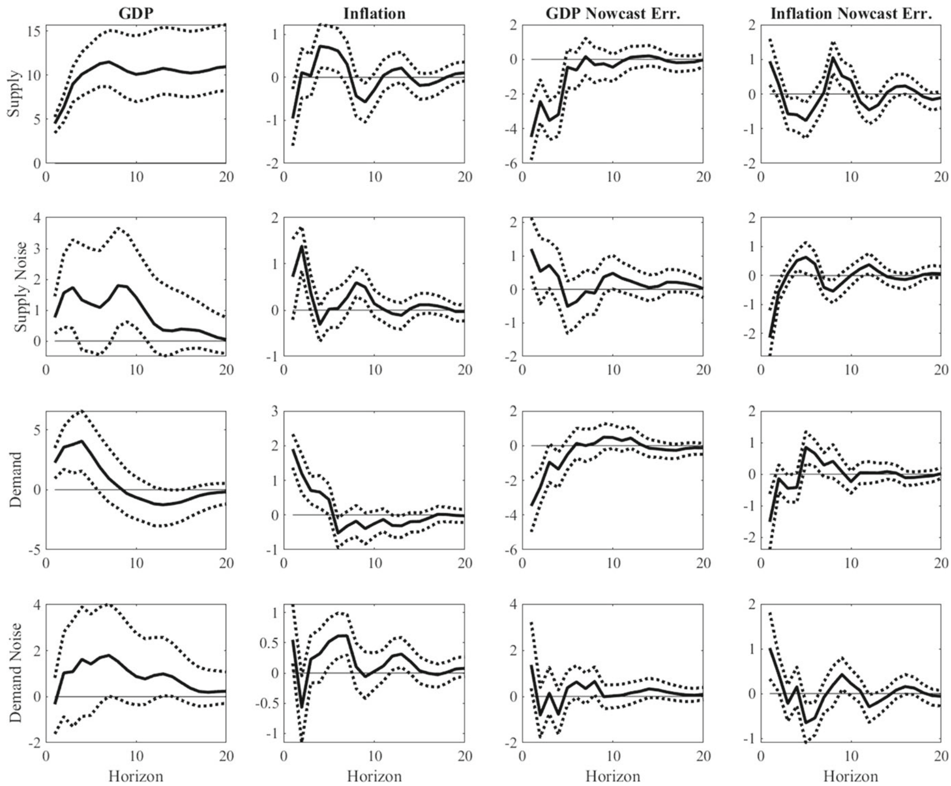

Fig. 26 IRF Robustness: Final release Nowcast Errors—France. The solid lines show the median impulse responses function. The 16th and 84th percentile confidence regions are marked by the dotted lines

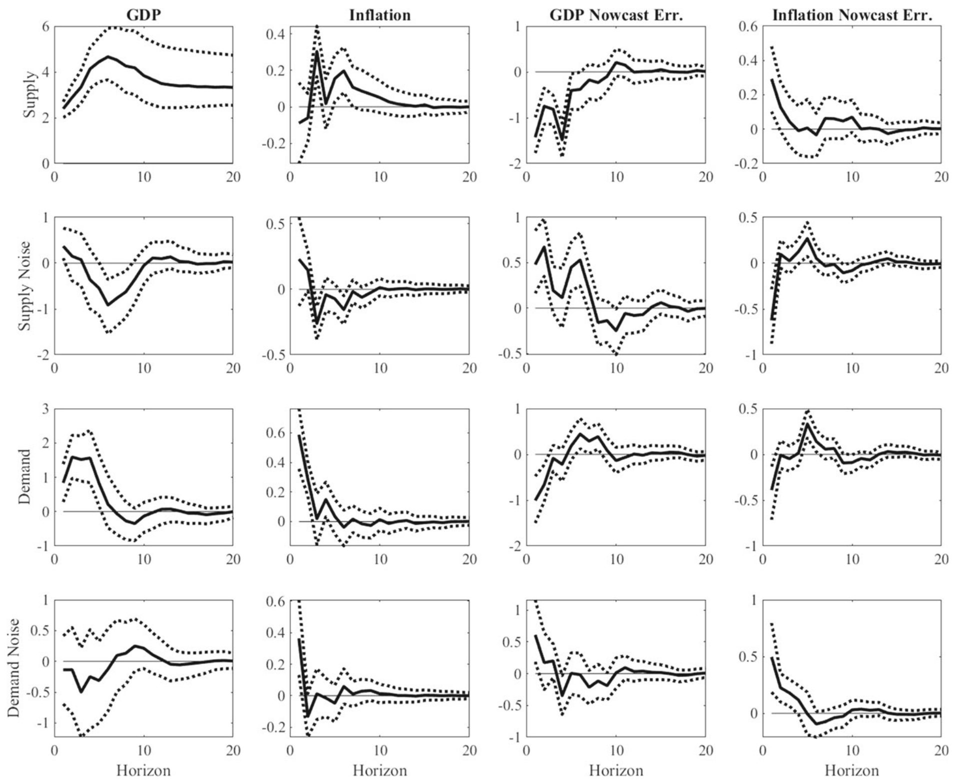

Fig. 27 IRF Robustness: Final release Nowcast Errors—Germany. The solid lines show the median impulse responses function. The 16th and 84th percentile confidence regions are marked by the dotted lines

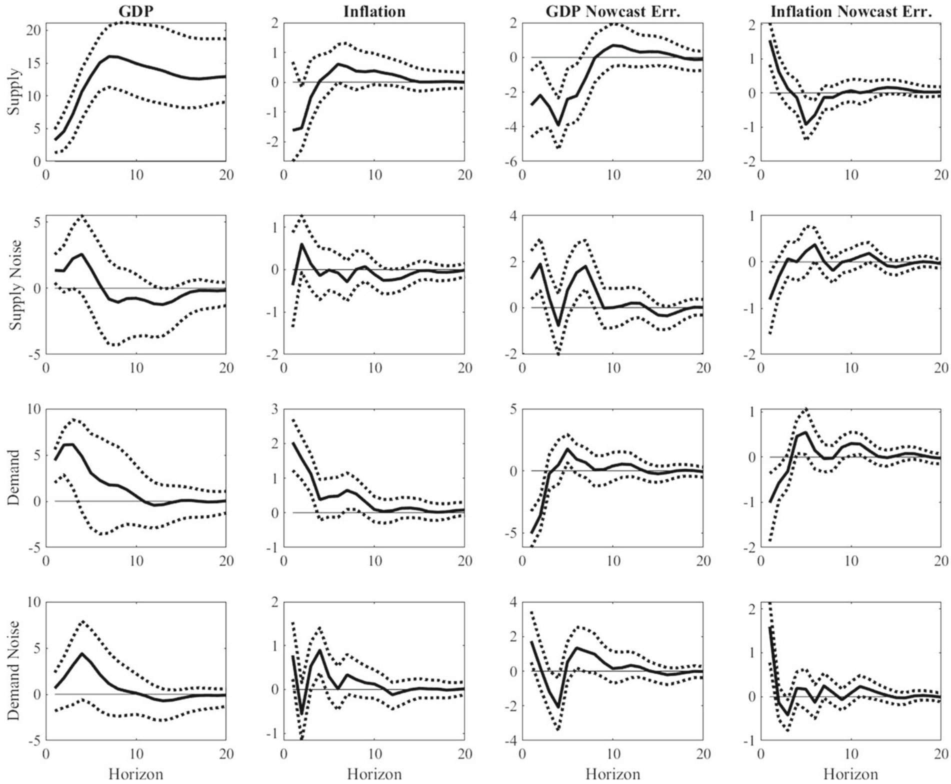

Fig. 28 IRF Robustness: Final release Nowcast Errors—Italy. The solid lines show the median impulse responses function. The 16th and 84th percentile confidence regions are marked by the dotted lines

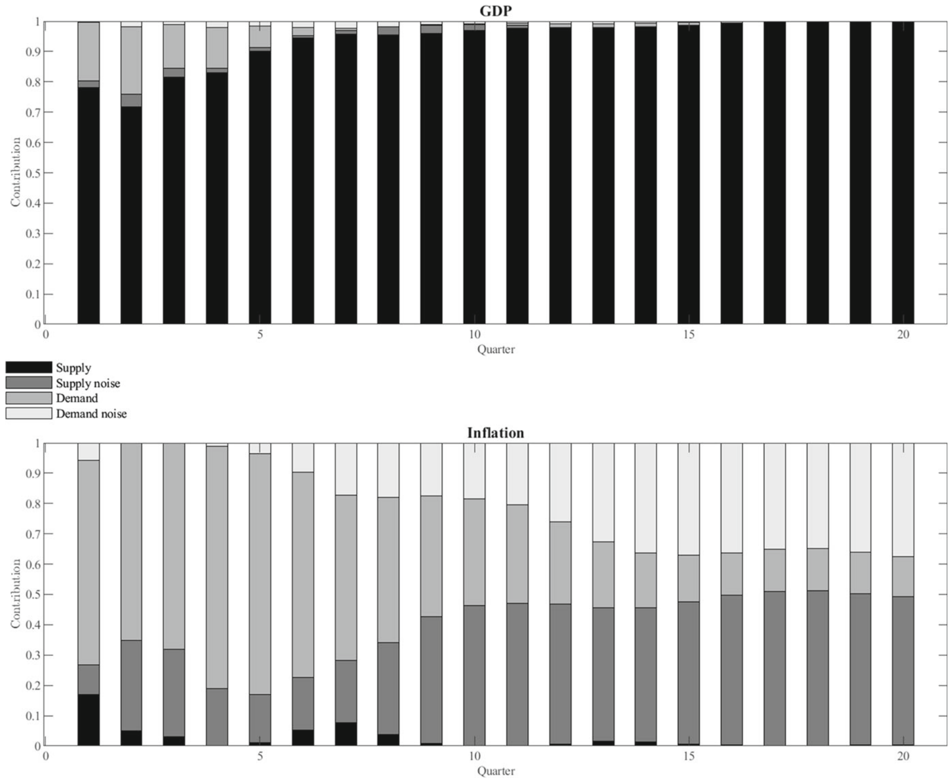

Fig. 29 Conditional variance decomposition of real GDP and inflation based on final release data—France

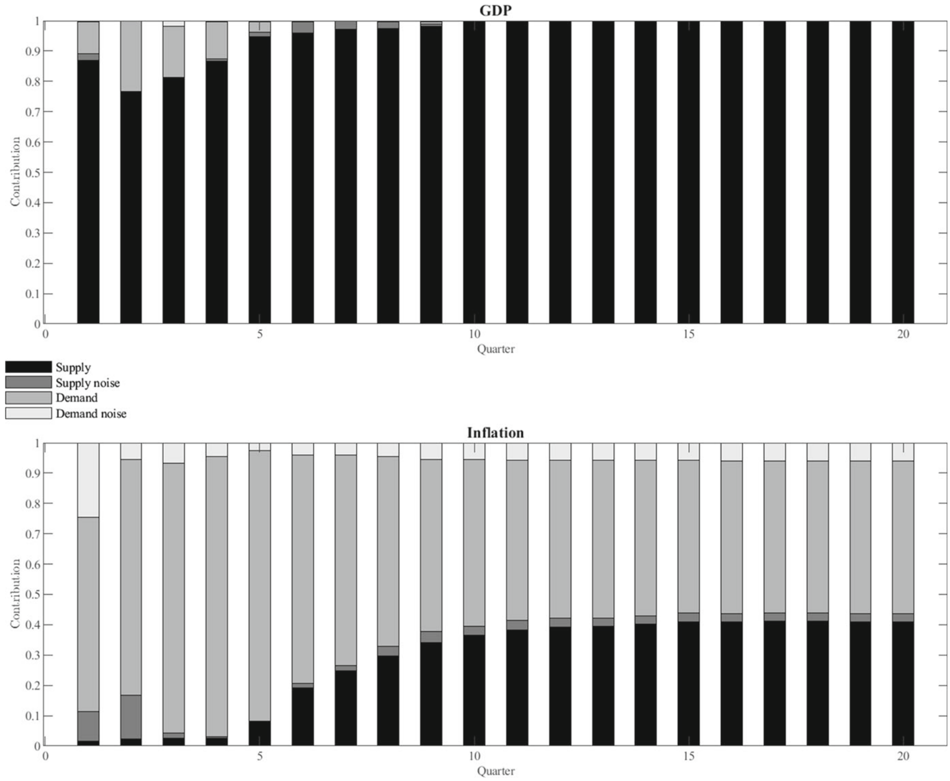

Fig. 30 Conditional variance decomposition of real GDP and inflation based on final release data—Germany

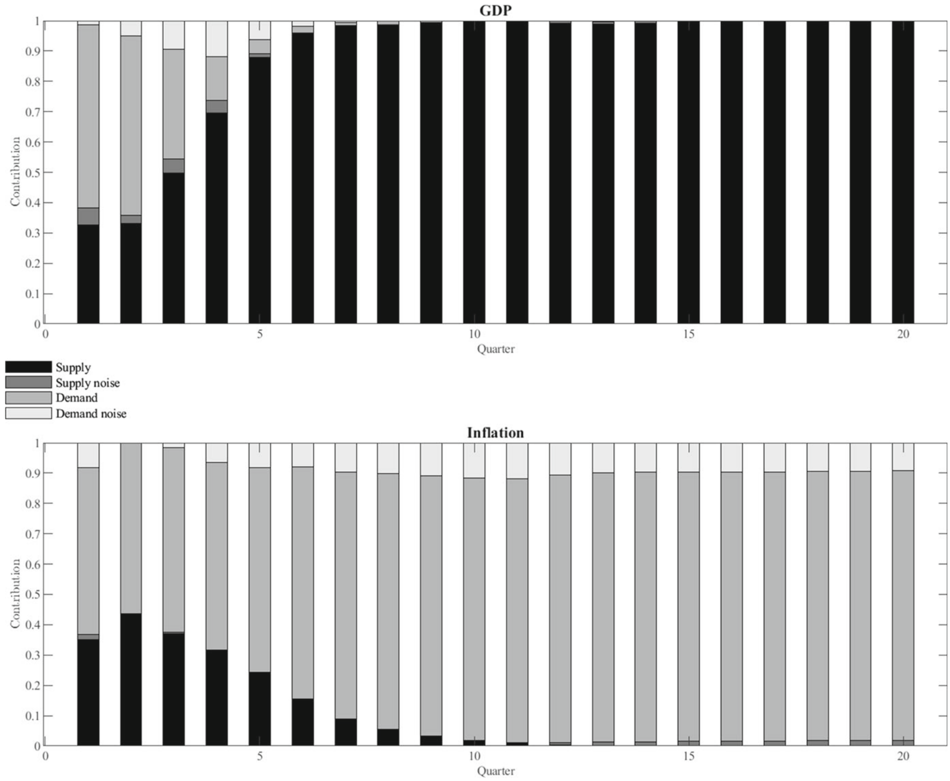

Fig. 31 Conditional variance decomposition of real GDP and inflation based on final release data—Italy

Table 11 Unconditional variance decomposition

	Supply	Supply noise	Demand	Demand noise
France				
GDP growth	0.56 [0.39, 0.72]	0.08 [0.04, 0.14]	0.21 [0.10, 0.38]	0.10 [0.05, 0.18]
Inflation	0.25 [0.16, 0.35]	0.20 [0.12, 0.32]	0.35 [0.24, 0.47]	0.16 [0.10, 0.23]
GDP Nowcast err	0.51 [0.29, 0.70]	0.08 [0.04, 0.14]	0.25 [0.12, 0.45]	0.10 [0.06, 0.19]
Inflation Nowcast err	0.26 [0.16, 0.37]	0.29 [0.13, 0.48]	0.23 [0.12, 0.39]	0.15 [0.07, 0.29]
Germany				
GDP growth	0.53 [0.40, 0.66]	0.12 [0.07, 0.19]	0.22 [0.13, 0.34]	0.09 [0.05, 0.16]
Inflation	0.22 [0.13, 0.33]	0.20 [0.11, 0.36]	0.34 [0.20, 0.49]	0.17 [0.09, 0.29]
GDP Nowcast err	0.49 [0.34, 0.63]	0.15 [0.09, 0.23]	0.20 [0.11, 0.34]	0.11 [0.06, 0.20]
Inflation Nowcast err	0.14 [0.07, 0.24]	0.31 [0.13, 0.51]	0.23 [0.11, 0.44]	0.23 [0.12, 0.41]
Italy				
GDP growth	0.43 [0.30, 0.58]	0.11 [0.05, 0.22]	0.27 [0.17, 0.39]	0.13 [0.06, 0.25]
Inflation	0.36 [0.20, 0.56]	0.11 [0.05, 0.21]	0.33 [0.18, 0.50]	0.13 [0.07, 0.23]
GDP Nowcast err	0.38 [0.25, 0.53]	0.13 [0.07, 0.22]	0.30 [0.19, 0.42]	0.15 [0.07, 0.24]
Inflation Nowcast err	0.36 [0.22, 0.48]	0.14 [0.07, 0.27]	0.20 [0.10, 0.37]	0.23 [0.13, 0.36]

Robustness: Nowcast errors based on final release data

For each successful draw, the unconditional variance decomposition is computed. The upper number reports the median value, and the numbers in brackets are the 16th and 84th percentile values of the variance decomposition distribution

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Appendix 3

Publication III
Nicolas Reigl and Lenno Uusküla (2021). "Alternative Frameworks for Measuring Credit Gaps and Setting Countercyclical Capital Buffers". *Journal of Financial Economic Policy* 13.2, pp. 161–179

The current issue and full text archive of this journal is available on Emerald Insight at:
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Alternative frameworks for measuring credit gaps and setting countercyclical capital buffers

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Abstract

Purpose – This paper aims to complement to standard Basel countercyclical capital buffer framework by suggesting additional measures for credit gaps that can be used to measure the financial cycle and to decide on countercyclical capital buffers for banks.

Design/methodology/approach – The paper concentrates on European Union countries with the data starting from 1970. The authors check whether the newly suggested buffers are in place and sizable before financial distress periods.

Findings – The new measures are: the change in the credit-to-GDP ratio over two years; the growth in credit compared to the eight-year moving average of growth in nominal GDP over two years; the growth in credit compared to annual nominal growth of 5% over two years; and growth in credit relative to the nominal GDP trend value over two years. They behave similarly to the gaps calculated with the standard Basel one-sided Hodrick–Prescott filter in long samples.

Originality/value – The main contribution of the paper is to suggest new alternative measures of credit cycles that can be used in short samples and in case of structural breaks. New measures correlate well with actual countercyclical capital buffers in place in 2018.

Keywords Financial markets and the macroeconomy, Macroeconomics and monetary economics, Macroeconomic policy, Credit gaps, Countercyclical capital buffer, Basel III

Paper type Research paper

1. Introduction

After the financial crisis that started in 2007 in the USA, there has been a lot of discussion about what type of policies should be put in place to avoid such negative events occurring in the future. Basel III introduced a framework for evaluating the state of the financial cycle and how to set countercyclical capital buffers (Basel Committee, 2011; Drehmann *et al.*, 2010; Drehmann and Yetman, 2018). The key in setting the buffer is to understand the cyclical

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nature of credit and to calculate the underlying credit gap that is used in deciding on the size of the buffer.

The original framework has been the subject of much discussion. Several papers have questioned the practical use of the original approach and shown potential weaknesses in it (Drehmann and Tsatsaronis, 2014; Edge and Meisenzahl, 2011; Lang *et al.*, 2019). Discussion about ways to measure credit cycles and how to set countercyclical capital buffers continues to be active as countries are setting up the systems for monitoring and deciding on policy actions.

This paper suggests additional approaches for measuring excessive credit growth that can be used in setting countercyclical capital buffers. The European Systemic Risk Board that performs macro prudential oversight of the entire European Union (EU) financial system allows for alternative rules. In fact, EU members are required to measure and calculate additional credit-to-GDP gaps if the standard Basel measurement is judged to inaccurately reflect the national financial cycle (ESRB – European Systemic Risk Board, 2014a). The purpose of this paper is to complement the standard Basel approaches at the times when it may require additional information.

This study offers new background information for understanding the dynamics of credit [1] gaps and buffers in the historical context in Europe and the strengths and weaknesses of the standard Basel framework. It then suggests alternative measures that can be used in calculating credit gaps and setting the size of the countercyclical buffer. The objective is to find measures that pick up financial cycles that may or may not correlate with the business cycle. Leaning against financial cycles is an objective on its own for the policy measures. Early warning properties of financial distress and crises is welcomed property, but the evaluation should not be down on the noise to signal ratios as not every financial cycle needs to lead to problems in the financial sector.

The new additional measures for credit gaps are: the change in the credit-to-GDP ratio over two years; the growth in credit compared to the eight-year moving average of growth in nominal GDP over two years; the growth in credit compared to annual nominal growth of 5% over two years; and growth in credit relative to the nominal GDP trend value over two years. Buffer rates can be set following the original Basel suggestions for all the proposed new measures.

The main value of the paper is to suggest alternative measures of credit cycles that work well in short data samples and are robust enough to resist to structural changes. The new measures have properties that are at least as good in offering positive countercyclical capital buffers before and after the crisis for short data samples than standard measures under long samples. In addition, the new measures correlate well with actual countercyclical capital buffers, which were in place in 2018, especially when the suggested values are compared to the standard Basel approach. We hope that the new measures are especially useful for countries that have relatively short time-series available or that may have witnessed strong structural breaks in the past two decades.

The paper contributes to the body of literature that suggests various solutions for selected countries or country groups. Alessandri *et al.* (2015) suggest new measures for Italy, Castro *et al.* (2016) for Spain and Lang *et al.* (2019) for a selected group of EU countries. None of them concentrates specifically on countries that have relatively short time-series available. Out of the 22 countries that Lang *et al.* (2019) study, 8 have effective samples that start in 2005 or later and 6 have data going back to 1983 or earlier. It is likely the estimates capture more the dynamics of the countries with longer samples than those of the shorter sample.

The paper first explains the Basel framework and suggests additional ways of calculating gaps in Section 2. Section 3 suggests different gaps that can be used for understanding the credit cycle. Section 4 then shows how these gaps have behaved in European countries. Section 5 suggests a way to calculate buffers and demonstrates how the buffers would have evolved over time. Section 6 concludes the paper.

2. Basel framework

The main Basel framework [2] uses the debt-to-GDP ratio, which is calculated using quarterly data:

$$Debt\text{–}to\text{–}GDP_t = \frac{100 \times Debt_t}{nGDP_t + nGDP_{t-1} + nGDP_{t-2} + nGDP_{t-3}},$$

where $Debt_t$ is the nominal value of debt at quarter t, and $nGDP_t$ is nominal GDP. The summation of the current and last quarters of the GDP gives the value of the annual GDP.

The Basel credit gap is calculated as the difference between the debt-to-GDP ratio and the one-sided Hodrick–Prescott (HP) trend:

$$Gap_t^{Basel} = Debt\text{–}to\text{–}GDP_t - HP^{os}(Debt\text{–}to\text{–}GDP_t),$$

where Gap_t^{Basel} is the benchmark Basel credit gap, and $HP^{os}(Debt\text{–}to\text{–}GDP_t)$ is the filtered trend value with a smoothing parameter of 400,000.

A positive gap opens whenever the actual value of the debt-to-GDP ratio is higher than the calculated value of the trend. The main strength of this method is that it has been shown to produce gaps that can be used to set capital buffers that can be in place when a financial crisis erupts (Drehmann *et al.*, 2010; Drehmann and Yetman, 2018).

The Basel framework also explains how the capital buffer could be set using the credit gap. Figure 1 shows the buffer size graphically as a function of the gap size. The buffer is zero when the credit gap is smaller than 2 percentage points and it increases linearly to reach 2.5% of the capital [3] when the credit gap hits 10 percentage points. The suggested buffer size increases by 0.3125% with each additional credit gap percentage point. The buffer size for the banks is then rounded to the buffer step size of 0.25%.

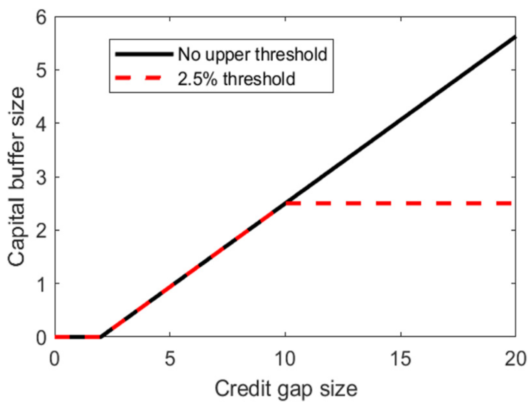

Figure 1.
Buffer rate as a function of the credit gap

There are two possible versions of the buffer settings that have not been fully tested in practice. In the first version, the buffer rate is increased linearly as the credit gap increases (the solid black line in Figure 1), and in the second version, there is an upper limit of 2.5% for the buffer rate (the dashed red line). In this scenario, either the national authority does not increase capital buffers above that value or other countries do not have to recognise levels that exceed that threshold (in the EU, a "comply or explain" procedure would then follow according to the ESRB Recommendation [4]).

The main weakness of the Basel framework for calculating credit gaps is that it requires long data-series to pick up the trend values for financial deepening from the early periods. Only after the initial years have set the trend can a change in the debt-to-GDP ratio signal a possible credit cycle. The literature on discussing various problems with HP filter and other techniques is growing fast [5]. There are also many papers discussing the measurement of financial cycles [6].

A second weakness is that the approach requires long data-series for it to be able to estimate the trend value, but the early data that are used in the calculations might have become uninformative about the current state of the economy. For example, Baltic states started with a very low level of financial depth that is not likely to return in the near future.

Thirdly, periods with long credit cycles become equilibrium phenomena as the trend catches up with the actual values. Moreover, if these long cycles are followed by stabilisation of the credit level as a ratio to GDP, it would automatically be picked up as a negative credit gap [7], although the accumulated risks might be on the balance sheets of banks. Therefore, long periods must be sufficiently homogeneous and should not include structural changes. Fourthly, the approach is also less useful after sharp declines in aggregate output or periods of deleveraging following credit booms. Declining GDP raises the debt-to-GDP ratio but is clearly not a sign of a credit boom emerging.

Figure 2 shows the Basel credit gaps and benchmark buffer rates for countries that have relatively long time-series that are more likely to fit the long and stable periods of financial sector dynamics. We use a broad credit measure in the calculations. Data from Eurostat and

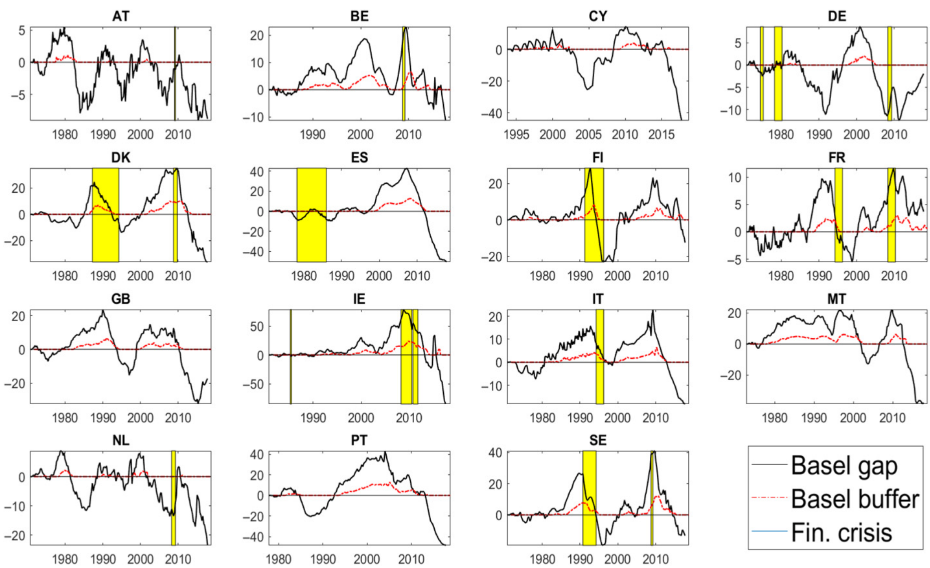

Figure 2.
Basel gaps and benchmark buffer rates for the countries for which longer time-series are available

public and internal European Central Bank (ECB) sources was combined to increase the sample period. Further details of the data are presented in the Appendix. Additional information can be obtained from the authors.

The buffer rate is calculated under the assumption that the authority setting it knows the current values of nominal credit and GDP. It uses the framework to set the buffer exactly one year ahead, which is a compromise between two aspects of the policy. One is that the actual implementation lag includes data publication lags and the time needed for evaluating the quality of the data and covering administrative procedures, and so it is likely to be a few quarters longer. Equally though, the capital buffers can also be set with shorter notice in extraordinary circumstances, and so a year seems an appropriate time lag for such ex-post technical analysis. It is easy to see if the buffer is also different from zero a year before the period observed, so as to take account of longer implementation periods.

Figure 2 shows clearly the strengths of the standard approach. The solid black line shows the credit gap and the red dashed line shows the buffer size. The yellow vertical regions are the financial crises dates of the ECB heads of research data set (Babecký *et al.*, 2012). The gaps and buffers are positive for many of the episodes of financial crisis, which confirms the finding of Drehmann *et al.* (2010) that the standard framework could indeed be used in these countries to set capital buffers for the period.

However, Figure 2 also shows the weakness of this approach. The gap and buffer values are zero in the late 1970s and again in the 1980s, when a lot of the financial liberalisation took place in Europe. There were not many financial crises, maybe because the financial sector was still much more regulated and so was different from what it has been in recent years. A good measure of the financial cycle should pick up the wave of credit deepening in Europe.

Even though some of the countries do have longer series, most have credit gaps deep in negative territory after the financial and economic crisis, and those gaps are unlikely to close in the near future. The negative gaps are even large enough in some countries such as Denmark, Spain, Malta or Portugal that a strong boom phase of a financial cycle would fit in the data without the gap closing.

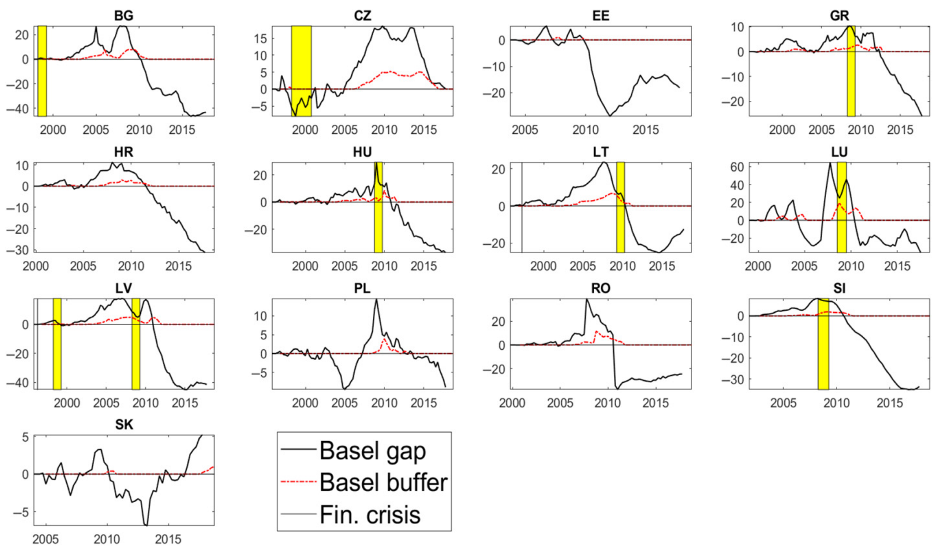

Figure 3.
Basel gaps and benchmark buffer rates for the countries with shorter time-series available

All these problems are much more severe in countries where only relatively short time-series are available, as shown in Figure 3. Building up the trend estimate up to the financial crisis takes time, and only a few countries that experienced unusual dynamics see credit gaps opening before the 2007–2008 financial crisis early enough so that the authorities would have had time to react to it. These dynamics included credit dynamics that showed a short increase in the debt-to-GDP ratio just before the crisis, where stable growth in the debt-to-GDP ratio was picked up as an equilibrium financial deepening. Another case of a positive gap was when the country had a stable debt-to-GDP ratio for a relatively long period at the beginning of the sample that would make the trend growth much smaller.

The negative gap in Estonia, for example in 2012, was wide enough that it would have allowed for a credit boom similar to that witnessed from 2004 to 2008 without the gap closing and buffers being set. The credit gap remains in negative territory because of a combination of the strong boom, falling GDP, the subsequent deleveraging in 2009–2014 and the shorter time-series. Lang and Welz (2017) demonstrate how credit booms influence the estimated credit gaps more than a decade after the initial event, making the standard measures uninformative.

Similar examples are Latvia and Lithuania, which had a low debt-to GDP ratio for longer than Estonia and saw credit growth at a later stage and at a much higher rate than Estonia did. Poland started off with a negative credit gap in 2005, so that the measure allowed for much higher change in the debt-to GDP ratio than, for example, it would have allowed for Croatia that had a credit gap close to zero in 2005.

Figure 3 also demonstrates that even if the credit gaps opened before the crisis, there was very little time to set capital buffers, and several countries that did witness financial market distress would have been able to set capital buffers only at a fairly late stage on the grounds of extraordinary circumstances, rather than with the standard one-year warning.

3. New gaps

The paper suggests four additional measures for the gap alongside the standard Basel framework:

(1) Change in the debt-to-GDP ratio, over a two-year period (2-year change).

(2) Nominal debt growth minus average nominal GDP growth over eight years, over a two-year period (8 year average).

(3) Nominal debt growth minus 5% annually, over a two-year period (5% rule).

(4) Change in the ratio of nominal debt to the nominal GDP trend, over a two-year period, where trend GDP is an exponent of the one-sided HP filtered (with the smoothing parameter $\lambda = 400{,}000$) log of nominal trend GDP (GDP trend).

These measures are selected because they have simple rules that do not require expert judgement in the calculations, and so they can all be used directly by anyone who has the underlying data. They should also be free of the main weaknesses of the HP filter, as they do not require long time-series to extract the cycles, they do not depend on credit developments as long as 15 years ago, and they pick up long cycles and are informative at times when GDP is decreasing and in periods of deleveraging.

This allows the future situation to be analysed using current knowledge, and the result is less sensitive to the potential psychological biases that come from accepting the current situation as equilibrium dynamics. Using different measures also recognises explicitly that no single measure is likely perfect, so different measures pick up possible scenarios in different economic environments.

3.1 Change in the debt-to-GDP ratio

The change in the debt-to-GDP ratio over two years picks up the type of credit cycle where credit growth is stronger than nominal GDP growth within the two-year period. The exact formula is:

$$Gap_t^{2y\ change} = 100 * \left(\frac{Debt\text{–}to\text{–}nGDP_t}{Debt\text{–}to\text{–}nGDP_{t-8}} - 1 \right).$$

The main strength of this is that it does not depend on events from the distant past. With this approach, every change in the debt-to-GDP ratio, which lasts for two years, opens up a gap that could be a sign of a financial cycle. The two-year period is a compromise between measuring the deepness of a financial boom and early warning properties. Somewhat longer periods would capture better longer cycles. However, they would fail to give advance warnings of forthcoming problems as longer periods can mask the build up of rapidly emerging imbalances. On the contrary, the use of an even shorter period could lead to situations where one-off fast-lived events would open up gaps but miss problems that accumulate over longer horizons. Aikman *et al.* (2014) discuss the length of the credit cycles and conclude that standard cycles last for 4.5 or 13 years [8], so this measure would comfortably capture the shorter cycles.

Several papers show that the change in credit-to-GDP ratio is a sound leading indicator for distress in the financial sector. Lang *et al.* (2019) use many variables as predictors for financial crises and they conclude that the change in the debt-to-GDP ratio to be among the top indicators. Aikman *et al.* (2014) use the change of credit in a logistic regression set-up and show that the changes in the debt-to-GDP ratio – lagged two and three years – are the strongest predictors for crises. Therefore, also the other measures concentrate on the change of credit over a period of two years.

The main weakness is that it can miss a credit boom that is accompanied by a nominal GDP boom that may or may not be caused by credit developments. It would also show positive credit gaps when nominal GDP falls faster than credit aggregate, though this should not be interpreted directly as a credit boom. Next measures tackle the issues that may arise from strong economic booms that may be caused by the credit cycle.

3.2 Nominal debt growth relative to average GDP growth

The second approach compares the nominal credit growth over two years with the average GDP growth rate over eight years. The number of years is selected to cover a sufficiently long window so that business cycle developments can be picked up without data that might have become irrelevant being included. The exact formula for the calculations is:

$$Gap_t^{8y\ window} = 100 * \left(\frac{Debt_t}{Debt_{t-8}} - 1 \right) - 100 * aGDPgrowth_t,$$

where the average growth of the 32 quarters is taken to the power of 8 to get the accumulated change in GDP over an 8-quarter period:

$$aGDPgrowth_t = \left[1 + \frac{1}{32}\sum_{i=0}^{31}\left(\frac{nGDP_{t-i}}{nGDP_{t-i-1}} - 1\right)\right]^8 - 1.$$

The main strength of the approach is that it does not depend on long time-series. Another is that it recognises shorter credit booms that the change in the debt-to-GDP ratio cannot pick up as it uses averages over longer periods. It also is free of the problem of sudden drops in GDP increasing the gap. Repullo and Saurina (2011) show how policy that is solely decided on the information in the debt-to-GDP ratio can lead to pro-cyclical instead of counter-cyclical regulation. They demonstrate that changes in debt have more favourable properties. Equally importantly, the recent GDP data tends to be revised several times and therefore the debt-to-GDP ratio is subject to strong revisions. Here, the use of eight-year average growth rate in GDP downplays the importance of recent revisions and lets the credit measure to give stronger signals.

The main weakness is that it does not pick up booms when they are long and possibly driven by credit growth. This might happen because average nominal growth becomes similar to nominal credit growth and the gaps remain close to zero.

3.3 Nominal debt growth relative to 5% nominal growth

This approach uses a fixed denominator of 5% growth annually. The 5% rule could be interpreted as annual real GDP growth of 2% and the annual growth of the GDP deflator inflation rate of 2% with an extra margin of 1% to compensate for possible adjustments after the financial and economic crises in the EU average during the coming years. The exact formula is given by:

$$Gap_t^{5\%\,rule} = 100 * \left(\frac{Debt_t}{Debt_{t-8}} - 1\right) - 100 * \left(1.05^2 - 1\right).$$

Unlike the measure that uses the eight-year period, it is not sensitive to credit-driven booms that result in either high real GDP growth or strong GDP inflation rates. It is also easy to calculate and intuitive to understand. Ideally, the growth rate of the underlying unobservable potential nominal GDP could be used instead. However, real-time estimates of potential real GDP are not very reliable and tend to be biased towards realised growth rates, and there is no standard methodology for calculating the growth rate of the equilibrium GDP deflator.

The main benefit of comparing the debt growth rate to a constant is that the measure becomes free from the need to evaluate the cyclical fluctuations of output. The lengths of the business cycles are very uneven and so are the lengths of the financial cycles (Aikman *et al.*, 2014; Schularick and Taylor, 2012). Bordo *et al.* (2001) demonstrate that financial crises have become more frequent since the 1980s and the rules suggested in the paper only use credit growth data. The value of the constant that is subtracted could also be considered to be compared to the measure above, which considers average GDP growth rate that varies over the cycle.

The problem is that the 5% rule of thumb does not fit for all periods, such as those when there is low equilibrium nominal growth, and historically many countries have had high levels of growth or periods of high inflation that were followed by exchange rate adjustments.

3.4 Nominal debt relative to trend GDP

This final measure compares the level of debt to a trend value for GDP. The measure is close to the first alternative of the change in the debt-to-GDP ratio over a two-year period, but the ratio is calculated relative to the GDP trend value. The equation used in the calculations is:

$$Gap_t^{GDP\,trend} = 100 \times \left(\frac{Debt\text{–}to\text{–}nGDP_t^{tr}}{Debt\text{–}to\text{–}nGDP_{t-8}^{tr}} - 1 \right),$$

where the level values of GDP are used to calculate trend GDP:

$$nGDP_t^{tr} = \exp(HP^{os}(ln(nGDP_t))),$$

where, in turn, the trend GDP is summed over the previous four quarters as in the original Basel framework [9].

The main strength of this compared to Basel framework is that it opens positive gaps when credit booms are accompanied by GDP booms. The trend estimation should take growth potential into account over longer periods. Equally, it does not open negative gaps during periods of negative nominal GDP growth.

Castro *et al.* (2016) calculate the credit gaps also against potential GDP. This measure has worked in certain episodes in Spain during past 50 years. GDP growth can also be a separate indicator for crises prediction as high economic growth leads to lower probabilities of distress as in Alessandri *et al.* (2015). Jokivuolle *et al.* (2015) show how strong output loss exacerbates bank loan losses during financial distress. But of course strong output losses can sometimes be traced back to preceding booming economies. The use of trend GDP would be in line with the recommendations of Lang and Welz (2017), who show how output cycle can cause misleading estimates of credit gap.

The main weakness is that it requires a good estimate of the trend GDP, and the approach suggested is only one way to calculate the trend value. It is also less transparent, more complicated and less intuitive to understand, compared to other suggested measures.

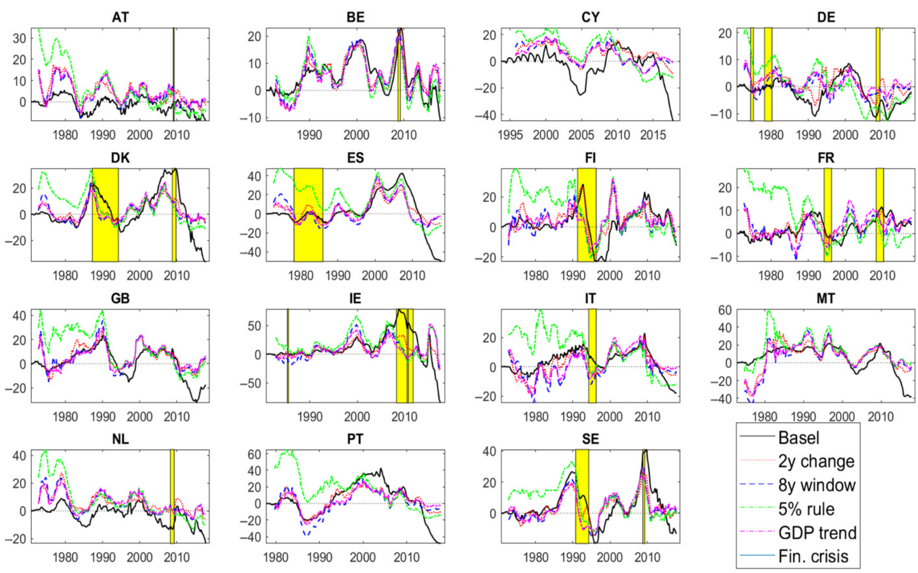

Figure 4.
New credit gaps for countries with longer time-series

4. New gaps in European countries in a historical perspective

This section shows how the new credit gaps have evolved in European countries. Figure 4 shows all four new gaps together with the same Basel credit gap as in Figure 2 for comparison for countries with longer time-series [10].

For most of the periods, all the calculated gaps behave quite similarly. Credit cycles in Belgium, for example, look similar in frequency and size for all the measures. There are, however, several noticeable differences between the standard Basel gap and the new gaps suggested here.

Firstly, the new gaps do not show substantial negative gaps for the years after the financial crisis, as some are still slightly negative but some are in positive territory. This shows that the new gaps do not depend on the availability of long data like the Basel benchmark does. Secondly, the early periods of the sample in the 1970s and 1980s do not have zero gaps in many countries, including Austria, Cyprus and Germany.

As expected, the 5% rule behaves very differently in the countries that witnessed strong nominal GDP growth rates in the 1970s and 1980s. It opens positive gaps that are much larger than those from other measures. This means that in these countries, banks and other institutions giving credit provided larger and larger numbers of loans at that time. Europe did not face many financial crises during that period, but general economic conditions, the performance of the financial sector and regulations governing the financial sector were different from what they were in the 2000s. It is likely that such a rule of thumb for monitoring cycles would not have been put in place at that time as the particular value is set for looking to the future, but it gives a picture of how the rules would have evolved.

The overall conclusion is that the variability of the new measures is fairly similar to that for the Basel credit gap in the middle of the sample, which is the period where the Basel gap measures cycles well. This is taken as a sign of the strength of the new gap measures.

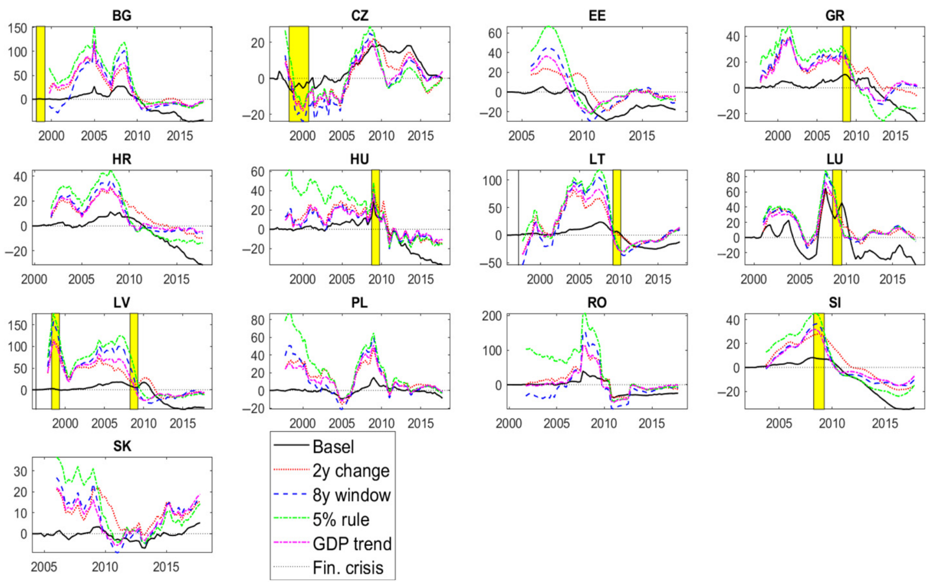

Figure 5.
New credit gaps for countries with shorter time-series

Differences in the early and late periods are also to be expected and taken as a positive sign rather than a negative one.

Figure 5 shows that the variability of the new measures for countries with shorter samples is often very different from that for the Basel measures. This happens because in broad terms, the sample consists of two periods, an early period when the Basel gap is close to zero because of the initialisation of the trend, and the post-2008 crisis period where the Basel framework has become less informative.

The new gap measures show the financial boom of the 2004–2007 much more strongly and open gaps at the right time, before the financial crisis hit. Many of the countries that went through a period of strong financial deepening and have been deleveraging show gaps close to zero where the Basel rule would predict strongly negative gaps. A more detailed analysis of the new measures is postponed to the next chapter that covers suggested buffer rates. The most valuable information to decide on the usefulness of the new measures depends on the timely signals that allow to decide on sufficiently large capital buffers for banks.

5. New buffer rates

This section first recommends that the standard Basel buffer setting framework can be used with the new gaps. Then it shows how the new buffer rates look in historical perspective.

The Basel capital buffer framework can be used in the same way for the new suggested gaps. The new gaps produce similar variability to the Basel framework in the countries and periods where it is good for measuring financial cycles, but they are mostly more intuitive in terms of the relative distance between various cycles within countries and in the size and length of cycles across countries. Using the Basel framework makes the system transparent and simplifies communication.

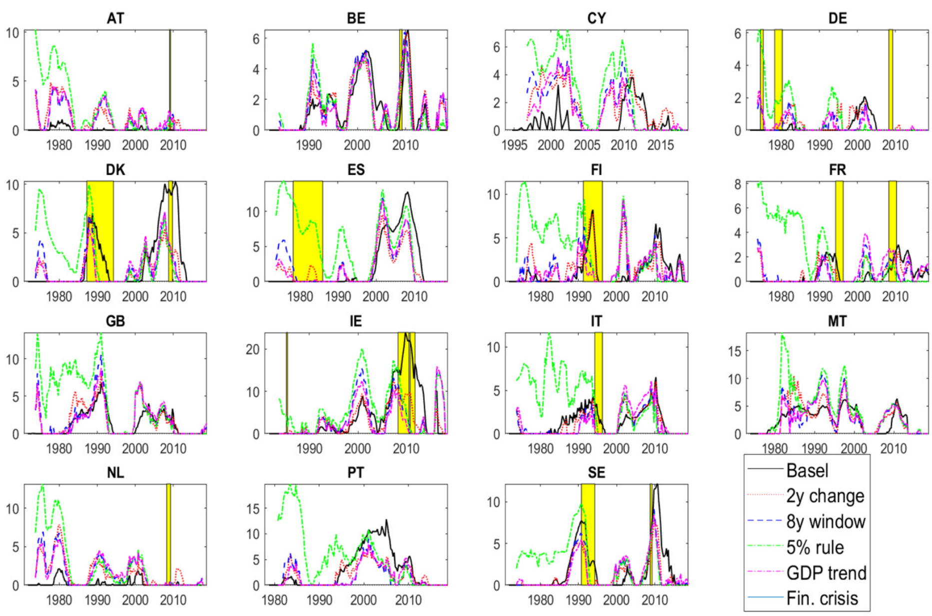

Figure 6.
New buffer rate calculations for countries with longer time-series

The buffer rates demonstrated are part of the technical exercise. It is important to stress again that the actual decision to set a buffer requirement depends on many other conditions. The authority can take account of the development of different loan aggregates, including ones based only on bank lending data, or it may keep the buffer requirement for longer periods, decide to increase the buffer rate with a different lag than was assumed in the exercise or release the buffer requirement before the gaps close. However, as the objective of the current exercise is to look at how the credit gaps would suggest buffer sizes and to evaluate their usefulness in the historical perspective, it is instructive to look at the predicted buffer rates.

Figure 6 demonstrates how the five new buffer rates have evolved over time when the upper limit of 2.5% would not be applied. Apart from the dynamics of the 5% gap rule, which differ in the early periods of the sample, most gaps show fairly similar dynamics, as seen in, for example, the developments in Belgium, Denmark and Italy.

It is remarkable that the new suggested buffer rates pick up periods of financial crisis in Germany in the 1970s. There are also several cases where the gaps would be zero before financial crises such as in Germany and The Netherlands in 2008. These countries probably did not have a financial crisis because of the earlier boom in the local financial sector.

Clearly, the 5% rule behaves quite differently from several others, but this is to be expected as it should pick up different types of reasons for accumulating risks. The other measures behave fairly similarly, but when looked at closely, the actual suggested buffer rates differ economically, for example in France or Ireland.

Continuing with the countries where shorter time-series are available, Figure 7 shows how the dynamics of the suggested new measures differ, most obviously from those of the Basel framework, but also among themselves.

The 5% rule is especially good benchmark at the times when economic growth is high or prices increase a lot during longer periods of time. As the measure naturally brings out

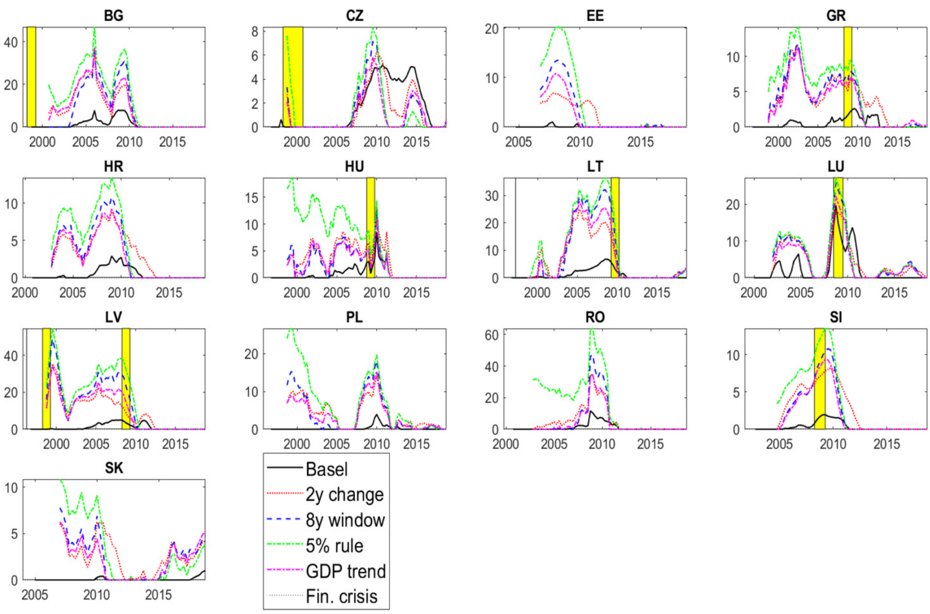

Figure 7.
New buffer rate calculations for countries with shorter time-series

moments of credit growth that are stronger than nominal growth in normal times, it may naturally capture the ability of the financial sector to assess new loan projects with stable quality. The 5% rule suggests the highest buffer rates for almost all Eastern European countries.

The measures built on the two-year change, the eight-year window and the GDP trend offer more balanced views on the suggested buffer rates, but very different picture from the Basel measure that either suggests very minimal buffers or suggest to implement them too late.

The buffer setting framework is relatively new and many countries have only just started to implement the policy, and a few have raised the buffer rate above zero only recently. It is instructive to see which countries have actual buffer rates currently above zero and to compare them to the group of countries where at least one of the suggested gaps is above zero.

The current and predicted new buffer rates are shown in Table 1 only for those countries where one of the measures suggests a gap above zero or which have set a buffer rate above zero. Other countries have not been reported. The suggested buffer rate levels are rounded up to the nearest 0.25% and the maximum point of the past two years is used.

The maximum buffer rate suggested by the trend GDP approach for Germany was 0.03%, but because of rounding, it is included in the table. There are only two countries where the Basel framework suggests a buffer rate that is higher than zero, France and Slovakia (see the first column of Table 1). Slovakia has already set the countercyclical capital buffer above zero and France has announced that it will increase the buffer to 0.25% in 2019 (see the last column of Table 1).

Several other countries have set buffer rates above zero, and these are the Czech Republic, the UK, Lithuania and Sweden. For all these countries, at least one of the measures suggested a credit gap and a corresponding buffer rate above zero. Sweden has had a higher buffer rate than predicted by the model in recent years because it previously had larger gaps and the authority has decided to keep the buffer requirement, as the risks are still on the balance sheets of the banks as real estate prices have only recently stabilised after increasing substantially over the past years.

Lithuania targets setting the buffer at 1% as the neutral stance, but with current measures, it could also need to increase the buffer rate because of the credit market situation.

Country	Basel	2-year change	8-year window	5% rule	GDP trend	Actual
BE		2.00	2.25	0.75	2.50	
CY					0.25	
CZ			0.50		0.75	1.25
DE					0.25	
FR	1.50	1.25	1.25		1.75	0.25*
GB		0.75	1.00	0.25	1.50	1.00
GR			0.25		0.50	
IE			7.75	8.75	7.25	
LT		2.75	2.50	3.50	4.00	0.50
LU		2.00	1.00	0.75	0.75	
PL		1.25	0.75	0.75	1.00	
SE			0.50		1.00	2.00
SK	1.25	4.50	5.00	4.00	5.50	1.25

Notes: Predicated buffer rates of zero are not shown in the table; *signifies planned buffer rate in 2019 as in 2018

Table 1. Actual and predicted buffer rates in 2018

The UK has a buffer rate similar to the one that the models predict and the Czech Republic has one slightly above the level that is predicted by the model.

There are several countries that have not set a buffer requirement, though the model would predict that they should. Ireland, for example, is closely monitoring credit developments, and the Irish central bank's decision (Central Bank of Ireland, 2018) of 20 March 2018 explains carefully why the authority has decided against setting a buffer even if the growth rates of credit are strong. Countries such as Cyprus and Germany have very small suggested buffer sizes that are more indicative of a neutral stance.

The main objective of the countercyclical capital buffer is to have sufficient capital at the time any financial crisis starts. However, this is not the only capital requirement that banks have to follow. The countercyclical capital buffer aims to foster resilience against losses from credit booms, but not every financial crisis is caused by developments in the credit market. It is not easy to show one particular cause for each financial crisis and the role of credit developments cannot be measured exactly. Therefore, each case should be discussed separately, but this leaves room for a lot of judgment, which is not the objective of this exercise. Having buffers before episodes of financial crisis is certainly positive, but missing some financial crises should not be an argument against using the measures for these reasons.

Table 2 shows the snapshot from Figures 6 and 7 for the time when the financial crisis starts. As could be observed from the graphical representation, many of the crisis episodes started when the models would have suggested having a capital buffer ready. This also

Table 2.
Predicted buffer rates at the beginning of banking crises

Country	Beginning	Basel	2-year change	8-year window	5% rule	GDP trend
AT	2008 Q3		0.50	1.50	1.25	1.75
BE	2008 Q2		1.25	2.00	1.75	2.00
CZ	1998 Q1	0.50				
DE	1974 Q2		2.00	1.75	6.00	2.25
DE	1978 Q1				1.00	
DE	2008 Q1					
DK	1987 Q1	2.00	3.00	3.00	6.75	2.50
DK	2008 Q3	9.00	3.25	4.00	3.50	4.00
ES	1978 Q1		0.50	2.25	11.75	0.50
FI	1991 Q1	1.00	2.00	3.75	7.75	3.25
FR	1994 Q1	2.25	1.00			
FR	2008 Q1	0.75	1.25	1.50	1.00	2.50
GR	2008 Q1	0.75	6.00	6.50	8.00	5.75
HU	2008 Q3	1.50	4.50	3.50	7.00	3.75
IE	1985 Q1				4.25	
IE	2008 Q1	15	10.75	11.75	15.75	9.50
IE	2010 Q3	21.75	8.75	2.25	1.50	0.25
IT	1994 Q1	3.75	3.75	2.25	5.00	1.50
LT	2009 Q1	6.25	17.50	29.25	34.00	22.25
LU	2008 Q2	8.50	8.75	13.25	15.25	12.25
LV	1998 Q1					
LV	2008 Q1	4.75	13.50	30.25	38.25	21.00
NL	2008 Q1				0.25	0.25
SE	1990 Q3	7.50	5.00	6.00	9.50	5.00
SE	2008 Q3	3.75	2.75	4.00	4.00	4.50
SI	2008 Q1	0.25	5.50	5.50	8.50	5.50

Note: *Predicated buffer rates of zero are not shown in the table holds true for the Basel framework for the countries that have data for longer time periods available.

The level of the buffer calculated with the new measures is often higher than the Basel framework suggests for countries with shorter series such as Latvia and Lithuania. Looking back, the rate of credit growth was very high and this is unlikely to be repeated in the coming years. Although the level of the buffers looks high, it is not completely outside the boundaries of the standard Basel framework. For example, Ireland did have longer data samples available and the Basel framework also suggested a buffer of 15% at the time when the financial crisis started in 2008 Q1. Even the 5% rule gaps do not exceed the maximum values of the other rules even at the times when nominal GDP growth was high in local currency in some of the countries in the 1970s.

Our paper confirms the finding that the growth rate of credit is a good early warning indicator. There are many papers discussing different data periods and country groups. Alessi and Detken (2014) and Detken *et al.* (2014) find that changes in debt-to-GDP ratio and growth rates of credit perform well as early warning indicators. Bonfim and Monteiro (2013) find that although the standard Basel gap works well for Portugal, there are several other indicators that work equally well and should be considered when deciding about the countercyclical capital buffers.

The results show clearly the problems that Lang and Welz (2017) discussed. Strong economic and financial crises cause the standard gaps to give misleading information. The recent financial crisis has left many countries in situations where the standard gap would not close soon even if the credit market would develop fast. In case the credit developments bring a boom in output, the situation is even worse and alternative measures have to be used to set countercyclical capital buffers.

Lang *et al.* (2019) find that many variables are likely to offer sound early warning properties and the combination of those can lead to more precise estimates. Their approach requires large amounts of data and is not transparent as calculations are hard to replicate. Their main conclusion is that the change in the two-year change in the debt-to-GDP ratio is one of the strongest indicators. Our results also confirm the findings of Alessandri *et al.* (2015) that demonstrate the importance of credit market and output separately for Italian data.

This paper stresses the importance of measuring potential output rather than relying on current cyclical estimates. Potential outputs, when treated with care, are less prone to mistakes that come from statistical revisions. Even if potential output is estimated to be pro-cyclical, the dynamics are with smaller amplitude and the use of it leads to earlier detection of credit gaps and also earlier release of the buffers when positive cycle turns. The results in this paper are in line with the findings of Castro *et al.* (2016) for Spain that show that in certain episodes, the potential output would have given a clearer signal even with the standard Basel approach.

The properties of the new measures are equally good for different measures of financial distress of the ECB database of Lo Duca *et al.* (2017). Of course, not all financial problems are caused by financial cycles and different models of early warning should be used to anticipate financial crises.

6. Summary

The Basel framework for calculating credit gaps and corresponding rates for the countercyclical capital buffer suffers from several weaknesses. Many of them have materialised since the financial crisis of 2007 and the great recession that followed.

Following the European Systemic Risk Board's policy framework recommendations, this paper proposes four alternative ways of measuring credit gaps and suggests a way to set capital buffers that is free from the main weaknesses of the original rule but retains the desired property that the benchmark buffer rates are sizable at the time when a financial crisis hits. The new measures are shown to be as good as the standard Basel framework for countries with stable and long time periods but offers gaps and buffers that are more in line with the current countercyclical capital buffer stance in many countries. The new measures behave well also in short time horizons and do not depend on the changes of the availability of the data, making them ideal for countries with short time-series and potential structural breaks.

The paper does not cover theoretical properties of the newly suggested cyclical decomposition measures. It would be interesting to look how they behave on simulated data and which frequencies do the new filters captures. Equally, it would be beneficial to test the behaviour of the new measures on countries outside of the EU as many countries outside may face the problem with short data samples available for the broad credit measures and may witness similar problems with the standard Basel framework.

Notes

1. Credit, loans and debt are used interchangeably in the text as they have the same meaning in the current context.
2. The first description of the rules is available in Basel Committee (2011), and they have been updated several times over the years.
3. The buffer size is calculated as a percentage of the capital; for space flow reasons, the buffers are referred to as per cents without reference to the capital.
4. Recommendation of the European Systemic Risk Board of 18 June 2014 on guidance for setting countercyclical buffer rates (ESRB – European Systemic Risk Board, 2014b).
5. See for example, Harvey and Jaeger (1993), King and Rebelo (1993), Burnside (1998), Canova (1998), Pedersen (2001), A'Hearn and Woitek (2001), Murray (2003) and Hamilton (2017).
6. Claessens *et al.* (2011), Claessens *et al.* (2012), Hiebert *et al.* (2015) and Schüler *et al.* (2017).
7. If the initial credit-to-GDP growth is sufficiently strong and long, negative gaps could even occur when debt-to-GDP ratio is increasing.
8. The length of the financial cycle depends on the sample and periods. For example, Drehmann *et al.* (2012) find average length of the financial cycle to be 16 years over the whole sample.
9. The exact formula is: $Debt_t o_n GDP_t^{tr} = \frac{Debt_t}{nGDP_t^{tr}+nGDP_{t-1}^{tr}+nGDP_{t-2}^{tr}+nGDP_{t-3}^{tr}}$.
10. Excel file for the replication of the results for Estonia, a country for which the data is public, can be found in https://drive.google.com/drive/folders/1o7GNqsZYDz3zpZHRv68hoVEe0ew9wJNK?usp=sharing
11. Data availability for different countries depends on individual data sources. The final data set contains a smaller sample of countries as not every country is represented in every data source.

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Appendix. Data sources

This section briefly presents the data used to calculate the measures of debt-to-GDP ratios. Multiple data sources, including the Macro-prudential Research Network (MaRs) data set, Eurostat and information from the Statistical Data Warehouse (SDW) of the ECB (ecb.sdw) [11] are used so a longer time-series can be obtained for debt and nominal GDP. Data from the sources are combined by harmonising the latest available value from the *older* data set with the first available value from the up-to-date data source (ecb.sdw and Eurostat).

The main debt series is "CTN", which is total nominal credit to HHS and HFS, billion in local currency from the MaRs data file. The full data set is downloaded on quarterly financial and non-financial sector accounts from ecb.sdw (QSA: ESA2010). To calculate debt, the paper follows the Basel III suggestions and constructs two filters, one for reference sectors and the other for instruments and asset classification (presented in Table A1).

The filtered values are aggregated by country and date and then seasonally adjusted. In the next step, the MaRs data set and the aggregated credit data from the ECB's SDW are harmonised and combined. For the harmonisation, an algorithm first searches for intersections of available observations in the two data sets. An intersection is found when an observation exists for country i date t in the MaRs data set for which there is also an observation for the same date t from the previously calculated credit data from the ECB's SDW. Should there be more than one intersection, the first observation value of the credit data from the ECB's SDW is used to calculate a harmonisation factor. The intersection observations are filtered and a harmonisation factor is calculated for each country (harmonisation factor$_{i,t} = \frac{ecb.sdw_{i,t}}{MaRs_{i,t}}$). After the harmonisation factor has been calculated, every observation of the MaRs data prior to the first observation of the ECB's SDW data is multiplied by the harmonisation factor. The new debt series is then created by stacking the harmonised MaRs series and the ECB's SDW together. The dynamics and magnitude of credit are comparable for most of the countries in the sample with very few exceptions where the coverage of the two data sets on debt differs.

For GDP, the quarterly data from Eurostat (namq10gdp) are used, and the data set is filtered for GDP at market prices (B1GQ) and chain linked volumes (2010), million euro, current prices and million units of national currency (CPMNAC). Nominal GDP is extracted from the MaRs data set, and the values are in billion of local currency (GDPN). The data sets are merged and the harmonisation factor is calculated in the same way as with the debt series and the harmonised nominal GDP data are stacked together. The debt-to-GDP ratio is calculated using the first equation. The four-quarter moving sum of GDP is used as the denominator for the ratio.

Series ID	Description
S1M	Households and non-profit institutions serving households
S15	Non-profit institutions serving households
S11	Non-financial corporations
F3	Debt securities
F4	Loans
F7	Financial derivatives and employee stock options

Table A1. Reference sectors and classifications of instruments and assets of the SDW of the ECB

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Appendix 4

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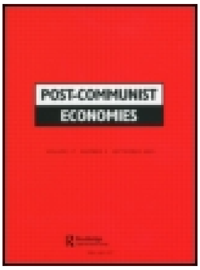

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Banking sector concentration, competition and financial stability: the case of the Baltic countries

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Banking sector concentration, competition and financial stability: the case of the Baltic countries

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ABSTRACT

This paper empirically assesses the potential nonlinear relationship between competition and bank risk for a sample of commercial banks in the Baltic countries over the period 2000–2014. Competition is measured by two alternative indexes, the Lerner index and the market share, while we consider the Z-score and loan loss reserves as proxies for bank risk. In line with the theoretical predictions, we find an inverse U-shaped relationship between competition and financial stability. This then means that above a certain threshold, the lack of competition is likely to exacerbate the individual risk-taking behaviour of banks, and could be detrimental to the stability of the banking sector in the Baltic countries. The threshold is around 0.60 for the Lerner index, and close to 50% for market share in terms of assets. The policy implications are that the existence of such a threshold suggests that the future evolution of the structure of the banking industry in these countries is of critical importance. Specifically, this implies that policy-makers should place greater emphasis on mergers and acquisitions to avoid any significant increase of banking sector concentration.

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1. Introduction

After the collapse of Lehman Brothers in the US in 2008, and the consequent need for a number of European banks to be bailed out, there has been concern recently about the relationship between banking sector concentration and financial stability within a country. According to Schinasi (2004), financial stability is a combination of three important characteristics. First, a stable financial system is capable of efficiently facilitating the spatial and intertemporal allocation of economic resources. Second, financial risks are assessed and priced reasonably accurately and are also relatively well managed. Third, the financial system is in such a condition that it can effectively absorb financial and real economic shocks. If any one or a combination of these characteristics is not maintained, then it is likely that the financial system exhibits instability. In such periods of financial instability, asset prices deviate excessively from their intrinsic values, banks are reluctant to finance profitable projects, and payments may not arrive on time.

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A number of studies have attempted to answer whether highly concentrated banking markets have an impact on financial stability. However, the results are far from conclusive since they vary with the period and countries analysed. The importance of a healthy banking sector for the successful functioning of an economy makes this subject topical for academics and policy-making institutions alike. Proper analysis of the degree of causality from banking concentration to banking sector stability can help institutions deploy the right measures to enhance stability, while it is a priority for academics to investigate how to measure banking competition and financial stability, and how to help policy-making promote stability and economic growth. Basic industrial organisation theory assumes that competition in markets tends to reduce the prices paid by consumers and increases efficiency, as only the most efficient firms could survive in a perfect competitive market. However, this prevailing assumption might be misguided for the banking sector, since fierce competition among banks can result in increased instability in the banking sector, leading to a financial crisis with fatal consequences for the banks. In this scenario, pro-competition policies that are targeted to enhance the efficiency of the financial sector might have strong adverse effects for the whole economy. Whether they do or not depends on whether tight competition enhances or reduces financial stability. The empirical literature does not provide a clear answer to this question, and theoretical papers do not reach a consensus either. This highlights the importance of establishing what the effect of bank competition on the risk-taking behaviour of financial institutions is, and then what its effect on financial stability is.

The literature offers two opposing views of the relationship between competition in the banking sector and financial stability (see, for instance, Beck, 2008). These views are the traditional 'competition-fragility' view, and the 'competition-stability' view.

The competition-fragility view argues that high levels of competition in the banking sector may increase financial instability and the fragility of banks. In a highly competitive banking sector, bank managers may have an incentive to take on high-risk operations in the search to make big profits quickly to meet profit objectives. This may lead them to put together a riskier portfolio of assets, which may end up in bankruptcies if there is a case of financial distress (see Keeley, 1990 amongst others for a theoretical model). In contrast, a less competitive environment where banks can afford higher capital buffers and less aggressive operations means the incentive to take increased unnecessary risk diminishes, enhancing the stability of the banking sector overall. Bergantino and Capozza (2013) say that bigger banks can afford to give low interest rates to new start-ups and share future profits. In addition, it is easier for the financial authorities to monitor a banking sector with fewer and bigger banks. Finally, bigger banks with a higher level of market concentration can access better conditions in international markets than they can find in domestic ones, making them able to lend more cheaply and reducing the cost of capital for firms and households (Beck, Demirgüc-Kunt, & Levine, 2006).

The competition-stability view claims, on the contrary, that if a reduced number of banks have greater market power, it may increase the risks to their portfolios, as they will tend to set higher margins on loan interest rates. In this case, clients will have to pay a higher cost for borrowing, which may make non-performing loans more likely to increase in number. Linked to this, increased competition may affect the cost of capital, giving firms and individuals access to lower interest rates, which would boost the profitability of investment projects, thus reducing credit risks and ultimately enhancing financial stability. In addition, big banks may believe that they are ‘too big to fail’, which comes from the moral hazard effect of the authorities providing bailouts when problems arise (Mishkin, 1999). In this case a lack of competition may give banks an incentive to engage in riskier operations.

Our analysis in this paper focuses on the relationship between the competition and concentration in the banking sector and financial stability in the Baltic countries, which are Estonia, Latvia and Lithuania. The Baltic countries are a textbook example of an area with a highly concentrated banking sector, with a small number of large, mostly foreign, banks. In Figure 1 we illustrate the share of assets held by the three largest banks in the Baltic countries and in other Central and Eastern European Countries (CEECs). Estonia and Lithuania stand out for the high degree of concentration in their banking sectors, as it is significantly higher than in Latvia or the other CEECs. The three largest banks in Lithuania had around 80% of total banking-sector assets in 2013, and in Estonia the three largest had more than 96%. Most of the larger financial institutions in Estonia, Latvia, and Lithuania are Nordic banks. This high level of banking sector concentration in the Baltic countries is a result of privatisation and mergers following the banking crises in Estonia (1992–1994), Latvia (1995) and Lithuania (1995–1996). During this period, some banks were liquidated, while others were recapitalised, and the primary outcome was that the Baltic banking sector has become highly concentrated and largely foreign-owned because the governments encouraged bank mergers and foreign takeovers for fear of bank runs and credit contraction.

Since the empirical literature does not seem to provide a clear answer as to which view holds empirically, this paper addresses this well-worn debate for this group of countries. Understanding whether the high concentration levels in the banking sector in the Baltic countries affect the risk-taking behaviour of banks, and consequently the stability of the banking sector, is of key importance for regulation and competition policies.

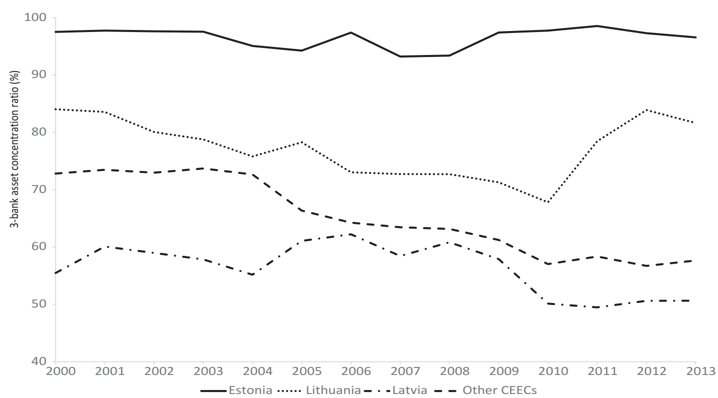

Figure 1. Concentration of banking sector assets: Baltic countries and other CEECs.

Source: Authors’ calculations, Global Financial Development Database, The World Bank. Other CEECs: Albania, Bulgaria, Croatia, Czech Republic, Hungary, Poland, Romania, Slovak Republic, Slovenia.

This paper investigates empirically at bank level the relationship between competition and risk for a sample of forty commercial banks in the Baltic countries from 2000 to 2014. Rather than simply analysing the potential trade-off between competition and financial stability in a linear fashion though, we follow the recent theoretical predictions from Martinez-Miera and Repullo (2010), and allow for the possibility of an inverse U-shaped relationship between competition and financial stability. The most recent literature on banking sector competition and concentration and financial stability highlights the importance of accounting for a U-shaped relationship between both measures. Doing so could let us identify an optimal degree of concentration and competition, and may indicate that both the competition-stability and the competition-fragility views are appropriate, depending on the level of concentration and competition.[1]

Martinez-Miera and Repullo (2010) establish that there may indeed be two separate effects in operation. One is the risk-shifting effect found by Boyd and De Nicoló (2005) where risk is reduced as competition increases, provided that there is a negative correlation between loan interest rates and competition, as this reduces the risk of loan defaults. The second effect is the margin effect, which implies that greater bank competition reduces interest payments, reducing the buffer against losses. According to Martinez-Miera and Repullo (2010) the risk-shifting effect dominates in less competitive banking markets, so the marginal effect of a new bank entry is negative for financial stability, whereas in more competitive markets the margin effect overwhelms the risk-shifting effect, so a new entry increases financial risk.

In the empirical literature, U-shaped relationships are usually tested by including a quadratic term in a standard regression model. If the estimated coefficient associated with this term is statistically significant and the estimated extremum point is within the data range, then it is common to conclude that there is a U-shaped relationship. In our paper, we go a step further and test the existence of a U-shaped relationship between bank competition and financial stability formally with the U-shape test developed by Lind and Mehlum (2010). This procedure also gives us a confidence interval for the optimal point. Such a confidence interval can be very useful for policy making, as it lets the regulatory authorities assess whether any financial institution has passed the upper bound, given the existence of a U-shaped relationship. It can be particularly useful for assessing whether the entry of new financial institutions or mergers could exacerbate financial instability.

We do this using balance-sheet data taken from the Bankscope database and we consider two types of bank risk proxy, the Z-score and the loan loss reserves. We also consider two different measures of competition, a structural measure derived from market share, and a non-structural measure from the Lerner index. As we will show in this paper, these two alternative measures of banking competition are not necessarily highly correlated, and they seem to capture different aspects of competition.

The remainder of the paper is organised as follows. Section 2 reviews the theoretical and empirical literature the on link between banking competition and financial (in) stability. Section 3 presents the data and the measures of competition and bank risk used. Section 4 presents the methodology and discusses the results. Section 5 concludes and gives some policy recommendations.

2. Literature review

A number of empirical papers have investigated the relationship between banking sector competition and concentration and financial stability. However, the empirical findings do not all lead to the same conclusion. Indeed, while some cross-country analyses (see, for instance, Beck et al., 2006) argue that banking crises are less likely in economies with more concentrated banking systems, others show on the contrary that competitive banking sectors are less prone to systemic banking crises and exhibit increased time to crisis (see, for instance, Schaeck, Čihák, & Wolfe, 2009). The recent empirical investigation by Diallo (2015) seems to support the competition-fragility view, as it considers a large sample of emerging and industrial economies and uses different measures of bank competition and finds the opposite results to those of Schaeck et al. (2009). Diallo (2015) shows that bank competition increases the probability of a systemic banking crisis occurring and that it is also positively related to the duration of the crisis.

More recent evidence from studies with a European perspective also offers mixed results. The first paper to study the link between banking sector concentration and financial stability in Europe is that of Uhde and Heimeshoff (2009). They use an aggregate z-score as a measure of banking sector fragility for 25 European countries and show that banking market concentration that has a significant negative effect on financial stability. Their results suggest this negative relationship between concentration and stability may be explained by the higher volatility of the returns of larger banks in concentrated markets. In a recent paper, IJtsma, Spierdijk, and Shaffer (2017) re-investigate this issue for the same sample of countries, but unlike Uhde and Heimeshoff (2009), they analyse them at both country level and bank level. Indeed, they show that if returns on assets of the banks are not perfectly correlated, the aggregated and bank-level z-scores measure different aspects of financial stability. Notably, the aggregate z-score accounts for systemic risk. In line with Uhde and Heimeshoff (2009), the results that they obtain suggest that concentration has a significant negative effect on stability. However, their findings also indicate that this effect is economically small at both levels of analysis. A similar result is obtained by Cifter (2015) for Central and Eastern European Countries (CEECs), as no robust relationship is found between bank concentration and non-performing loans.

Finally, a focus on empirical studies that investigate the competition-stability nexus using bank-level data also finds conflicting results.[2] For instance, results obtained by Agoraki, Delis, and Pasiouras (2011) for a sample of CEECs suggest that a weak competitive environment is not necessarily synonymous with financial instability. Indeed, they find that banks with relatively high market power tend to take on lower credit risk and have a lower probability of default. The opposite is found by Schaeck and Čihák (2014), who show that competition in the banking sector enhances financial stability. They say that efficiency is the transmission mechanism through which competition contributes to stability. Using the Boone index as a proxy for banking sector competition and considering a large sample of European banks, Schaeck and Čihák (2014) find that competition is stability-enhancing, but that this effect of competition on stability is greater for efficient banks than for inefficient ones.

However, Leroy and Lucotte (2017) show from a large sample of European listed banks that bank competition can have opposite effects on individual risk and systemic risk, which they proxy using the SRISK measure. Indeed, the results that they obtain suggest that competition encourages banks to take risks and then increases individual bank fragility, but tends to enhance financial stability by decreasing systemic risk. We also find two further studies for individual countries in the papers of Kick and Prieto (2015) and Jimenez, Lopez, and Saurina (2013), who analyse the relationship between competition and concentration and stability for the cases of Germany and Spain respectively. In the German case, the authors find evidence pointing towards the competition-fragility view, while for Spain nonlinear effects are found, which is in line with the theoretical predictions of Martinez-Miera and Repullo (2010).

Although most of the existing literature indicates that the competition-fragility hypothesis seems to hold empirically, we focus in our paper on the Baltic countries, which have not been studied much, and where concentration is among the highest in Europe. In addition, we also look at the potential nonlinear relationship between competition and bank risk.

3. Data and stylised facts

3.1. Data, measures of competition, concentration and risk

We consider all the commercial banks in the Baltic countries for which we have balance-sheet data over the period 2000–2014, giving an unbalanced panel data of 40 banks. Table 1 shows the list of banks, with their country and the period available. Our sample contains 21 banks in Latvia, 10 banks in Lithuania, and 9 banks in Estonia. All the data are taken from Bankscope, which is a database computed by Bureau Van Dijk.

Since our analysis aims to investigate the relationship between banking competition and risk-taking by banks, we first need to choose a bank-level measure of competition. The literature traditionally distinguishes two types of measure of competition: structural and non-structural measures. As Northcott (2004) argued however, there is no consensus in the literature about the best indicator for gauging competition. Moreover, a number of empirical studies (see e.g. Bikker & Haaf, 2002; Carbó, Humphrey, Maudos, & Molyneux, 2009; Claessens & Laeven, 2004; Lapteacru, 2014) show that the existing indicators of competition give conflicting predictions across countries, within countries, and over time, even if they seem to provide similar rankings.

Against this background, we adopt a conservative approach and choose to use both a structural measure of bank-level competition and a non-structural one. The structural measure we consider is market share, and the non-structural measure is the Lerner index. The market share corresponds to the amount of assets held by each bank divided by the total assets of the national banking sector. This ratio is comprised between 0 and 100%. It is an inverse proxy for bank competition. A low value indicates a high degree of competition and vice versa.

The Lerner index is also an inverse proxy for competition. It is designed to measure the pricing power of firms and corresponds to the mark-up of price over marginal cost. The Lerner index is bounded between 0 and 1, with the extreme value of zero corresponding to perfect competition, and the value of one to a pure monopoly. As stated by

Table 1. List of commercial banks located in the Baltic countries.

Bank Name	Country code	Period	Bank Name	Country code	Period
Swedbank AS[sub]	LV	2001–2014	Swedbank AS[sub]	EE	2000–2014
ABLV Bank AS[cor]	LV	2002–2014	SEB Pank[sub]	EE	2000–2014
SEB banka AS[sub]	LV	2000–2014	Danske Bank A/S Estonia Branch[bra]	EE	2000–2007
Rietumu Bank Group-Rietumu Banka[cor]	LV	2000–2014	DNB Pank AS[sin]	EE	2011–2014
AS Citadele Banka[sub]	LV	2010–2014	AS LHV Pank[sub]	EE	2012–2014
AS DnB Banka[sub]	LV	2004–2014	BIGBANK AS[cor]	EE	2006–2014
Norvik Banka AS[sub]	LV	2006–2014	Estonian Credit Bank-Eesti Krediiidipank[sub]	EE	2000–2014
Latvijas Kraj Banka AS-Latvian Savings Bank[sub]	LV	2005–2010	Versobank AS[sub]	EE	2011–2014
As PrivatBank[sub]	LV	2004–2014	Tallinn Business Bank Ltd-Tallinna Äripanga AS[cor]	EE	2010–2013
Baltikum Bank AS[sub]	LV	2005–2014	AB SEB Bankas[sub]	LT	2000–2014
Regionala investiciju banka-Regional Investment Bank[sub]	LV	2003–2014	Swedbank AB[sub]	LT	2003–2014
Trasta Komercbanka-Trust Commercial Bank[cor]	LV	2000–2014	AB DNB Bankas[sub]	LT	2000–2014
Baltic International Bank- Baltijas Starptautiska Banka[sub]	LV	2009–2014	AB Bankas Snoras[ide]	LT	2000–2010
AS Expobank[bra]	LV	2012–2014	Danske Bank A/S[bra]	LT	2000–2014
Danske Bank A/S[sub]	LV	2000–2007	Siauliu Bankas[cor]	LT	2000–2014
Jsc Latvian Development Financial Institution Altum[sin]	LV	2003–2013	Citadele Bankas AB[sub]	LT	2006–2014
Meridian Trade Bank AS[ind]	LV	2003–2014	UAB Medicinos Bankas[sub]	LT	2000–2014
AS Reverta[sub]	LV	2000–2014	AB Bankas FINASTA[sub]	LT	2009–2014
Bank M2M Europe AS[sub]	LV	2005–2009, 2013–2014	Skandinaviska Enskilda Banken AB; Vilniaus Filialia[sin]	LT	2009–2014
JSC Latvijas Pasta banka[sub]	LV	2009–2014			
GE Capital Latvia[sub]	LV	2004–2012			

Source: Bankscope, Bureau Van Dijk. Type of bank entity: sub - controlled subsidiary, cor - corporate group, bra - branch, sin - single location, ind - independent, ide - not identified.

Leroy and Lucotte (2017), the main advantage of the Lerner index is that it is the only time-varying non-structural measure of competition that can be computed at the disaggregated level of the firm. This certainly explains why the Lerner index has been used as a proxy for firm-level competition by a number of recent empirical studies in the banking literature (see Table A1 in the Appendix).

Formally, the Lerner index corresponds to the difference between price and marginal cost as a percentage of price. It can be written as follows:

$$Lerner_{it} = \frac{p_{it} - mc_{it}}{p_{it}} \tag{1}$$

with p_{it} the price and mc_{it} the marginal cost for the bank i in period t. Under the assumption that the heterogeneous flow of services produced by a bank is proportional to its total assets, the price p_{it} is calculated as the ratio of total revenue (the sum of interest and non-interest income) to total assets.

To obtain the marginal cost, we adopt an approach that is conventional in the literature (see, e.g., Berger, Klapper, & Turk-Ariss, 2009 or Beck, Jonghe, & Schepens, 2013) and model the total operating cost of running the bank as a function of a single, aggregate output proxy, Q_{it}, and three input prices, $W_{1,it}$, $W_{2,it}$, and $W_{3,it}$. More precisely, we estimate the following translog cost function:

$$\begin{aligned} lnC_{it} = \beta_0 + \beta_1 lnQ_{it} + \frac{\beta_2}{2} lnQ_{it}^2 + \sum_{k=1}^{3} \gamma_k lnW_{k,it} + \sum_{k=1}^{3} \phi_k lnQ_{it} lnW_{k,it} \\ + \sum_{k=1}^{3} \sum_{j=1}^{3} \frac{\rho_{kj}}{2} lnW_{k,it} lnW_{j,it} + \delta_1 T + \frac{\delta_2}{2} T^2 + \delta_3 T lnQ_{it} + \sum_{k=4}^{6} \delta_k T lnW_{k,it} + \varepsilon_{it} \end{aligned} \tag{2}$$

in which C_{it} measures the total operating costs from interest expenses, personnel costs, and other administrative and operating costs for bank i at the period t, and Q_{it} represents a proxy for bank output and corresponds to the total assets. $W_{1,it}$, $W_{2,it}$ and $W_{3,it}$ are the prices of inputs. $W_{1,it}$ is the ratio of interest expenses to total assets, $W_{2,it}$ is the ratio of personnel expenses to total assets, and $W_{3,it}$ is the ratio of administrative and other operating expenses to total assets. T is a trend that is included to capture technical changes and potential movements in the cost function over time. Furthermore, to reduce the influence of outliers, all variables are winsorised at the 1st and 99th percentile levels (see, e.g., Berger et al., 2009 or Anginer, Demirguc-Kunt, & Zhu, 2014). Following Turk-Ariss (2010) and Liu, Molyneux, and Wilson (2013), we also scale cost and input prices by W_3 to correct for heteroscedasticity and scale biases. We further impose the following restrictions on regression coefficients to ensure homogeneity of degree one in input prices: $\sum_{k=1}^{3} \gamma_{k,t} = 1$, $\sum_{k=1}^{3} \phi_k = 0$ and $\sum_{k=1}^{3} \sum_{j=1}^{3} \rho_k = 0$.

Because there are a relatively low number of observations, the Equation (2) is not estimated separately for each Baltic country. We estimate the translog cost function on the whole sample of commercial banks in the Baltic countries, and we include country fixed effects in the regression to control for potential differences in technology across economies. The coefficient estimates from Equation (2) are then used to calculate the marginal cost for each bank i at each period t:

$$mc_{it} = \frac{\partial C_{it}}{\partial Q_{it}} = \frac{C_{it}}{Q_{it}} \left(\hat{\beta}_1 + \hat{\beta}_2 lnQ_{it} + \sum_{k=1}^{3} \hat{\theta}_k lnW_{k,it} + \hat{\delta}_3 T \right) \tag{3}$$

However, as argued by Turk-Ariss (2010), one important problem associated with the estimation of the conventional Lerner index is that it implicitly assumes full bank efficiency and does not consider the possibility that banks may not exploit the pricing opportunities that result from market power. Indeed, banks with a large amount of market power could choose the quiet life and reduce their cost efficiency (Hicks, 1935 or Berger & Hannan, 1998).[3] Alternatively, efficiency could also lead to the market being concentrated in the hands of the most efficient banks (Demsetz, 1973; Peltzman, 1977). Consequently, as shown by Koetter, Kolari, and Spierdijk (2012), not controlling for inefficiency is problematic because it can affect the difference between price and marginal cost, and this then biases the estimation of the Lerner index.

We account for this bias by not proxying the market power of banks using the conventional Lerner index, but instead by considering the efficiency-adjusted Lerner index proposed by Koetter et al. (2012), defined as:

$$AdjustedLerner_{it} = \frac{(\hat{\pi}_{it} + \hat{C}_{it}) - \hat{m}c_{it}}{(\hat{\pi}_{it} + \hat{C}_{it})} \tag{4}$$

where $\hat{\pi}_{it}$ is the estimated profit, $\hat{C}_{it}$ the estimated total cost, and $\hat{m}c_{it}$ the estimated marginal cost.

To calculate this adjusted Lerner index, we follow Koetter et al. (2012) and first estimate the translog cost function (Equation 2) using a Stochastic Frontier Analysis (SFA). We then obtain $\hat{C}_{it}$ and $\hat{m}c_{it}$. This an approach has the advantage of taking into account banks' cost inefficiency, defined as the distance of a bank from a cost frontier accepted as the benchmark. Second, we specify an alternative profit function (Berger & Hannan, 1998), that we estimate using a SFA to obtain $\hat{\pi}_{it}$.

Finally, we evaluate financial stability at the firm-level by considering two alternative proxies for bank risk: the Z-score and the loan loss reserves as a percentage of gross loans. The loan loss reserves are a measure of credit risk, while the Z-score is a commonly-used accounting-based measure of bank stability. Financial stability is usually defined as the absence of system-wide episodes in which the banking and financial system fails to function. In particular, according to the Federal Reserve Bank of St. Louis (2002), financial stability can be simply defined as the smooth and uninterrupted operation of both credit and payment mechanisms. Balance sheet disturbances faced by banks can then be viewed as a source of risk and vulnerability that might threaten the maintenance of financial stability. Consequently, even if these two measures evaluate the fragility of each financial institution separately, they give an idea of the vulnerability of the banking sector as a whole.

The Z-score explicitly compares the buffers of capitalisation and returns with risk from the volatility of returns to measure how far a bank is from insolvency. It is defined as:

$$Zscore_{it} = \frac{E_{it}/A_{it} + \mu_{ROA_{it}}}{\sigma_{ROA_{it}}} \tag{5}$$

where $\mu_{ROA_{it}}$ is the expected return on assets, E_{it}/A_{it} is the equity to total assets ratio, and $\sigma_{ROA_{it}}$ is the standard deviation of the return on assets.

The Z-score is inversely related to the probability of a bank becoming insolvent. A higher Z-score implies a lower probability of this happening. Because a bank becomes insolvent when the value of its assets drops below that of its debt, the Z-score can be interpreted as the number of standard deviations that a bank's return must fall below its expected value by to wipe out all the equity in the bank and render it insolvent (Boyd & Runkle, 1993). This study opts for the approach used by Beck et al. (2013) to compute the standard deviation of ROA.[4] This approach uses a three-year rolling time window to compute the standard deviation of ROA rather than the full sample period, whereas the return on assets and the equity to total assets ratio are contemporaneous. As argued by Beck et al. (2013), this approach has two main advantages. First, it avoids the variation in the Z-score within banks that is exclusively driven over time by variation in the levels of capital and profitability. Second, given the unbalanced nature of our panel dataset, it avoids the denominator being computed at different window lengths for different banks.

3.2. Stylised facts

Before turning to the econometric analysis, we present the main cross-sectional and times series features of the Lerner index and the market share variable, and analyse whether they are linked to our proxies for bank risk. Table 2 reports the mean of the Lerner index and the bank market share for the Baltic countries for different sub-periods and for the overall period. We can observe in all the Baltic countries that the market power of commercial banks seems to have decreased between 2000 and 2014. This evolution is the most pronounced for Latvia, where the average of the Lerner index went from 0.72 in 2000–04 to 0.33 in 2010–14, and the average market share went from 13.73% in 2000–04 to 5.63% in 2010–14. We find that, in any case, Estonia is the Baltic country with the highest values for the Lerner index and the bank market share, which is consistent with the findings reported in Figure 1.

In Table 3 we report the value of the Lerner index and of the market share in 2014 for all the commercial banks considered in our sample. For the market share, we can see that the distribution of activity across banks is relatively more homogeneous in Latvia than in Lithuania and Estonia. Indeed two banks in Lithuania, AB SEB Bankas and Swedbank AB, have a market share of more than 30%, while in Latvia Swedbank AS had the largest market share at 18.75% in 2014. More importantly, fewer than one quarter of the banks in Latvia had a market share of more than 10%. In Estonia, the

Table 2. Evolution of the Lerner index and the market share in Baltic countries.

	Lerner index (mean)			Market share in% (mean)		
Sub-periods	Estonia	Lithuania	Latvia	Estonia	Lithuania	Latvia
2000–2004	0.652	0.512	0.716	25.00	15.718	13.73
2005–2009	0.608	0.428	0.532	22.95	12.358	5.964
2010–2014	0.562	0.35	0.334	14.268	10.888	5.628
Overall period						
2000–2014	0.6	0.41	0.48	19.26	12.61	7.01

Source: Authors' calculation based on the Bankscope database. Note: The Lerner index refers to the adjusted Lerner index proposed by Koetter et al. (2012).

Table 3. Lerner index and market share of commercial banks located in Baltic countries in 2014.

	Latvia			Lithuania			Estonia	
	Lerner index	Market share		Lerner index	Market share		Lerner index	Market share
ABLV Bank AS	0.76	15.78	AB Bankas FINAST	0.05	0.30	AS LHV Pank	0.61	3.13
AS Citadele Banka	0.66	10.55	AB Bankas Snoras	n.a.	n.a.	BIGBANK AS	0.21	1.88
AS DNB Banka	0.64	8.73	AB DNB Bankas	0.42	17.97	DNB Pank AS	0.68	3.75
AS Expobank	0.61	1.81	AB SEB Bankas	0.73	32.21	Danske Bank A/S	n.a.	n.a.
AS Reverta	−0.04	0.85	Citadele Bankas AB	0.01	2.04	Estonian Credit Bank	0.31	1.48
Baltic International Bank	0.03	1.96	Danske Bank A/S	0.66	8.44	SEB Pank	0.90	30.03
Baltikums Bank AS	0.57	2.31	Siauliu Bankas	0.45	7.83	Swedbank As	0.91	54.00
Bank M2M Europe AS	0.31	0.57	Skandinaviska Enskilda Banken AB	0.09	0.01	Tallinn Business Bank Ltd	0.60*	1.12*
Danske Bank A/S	n.a.	n.a.	Swedbank AB	0.71	30.02	Versobank AS	0.65	1.48
GE Capital Latvia	0.01**	0.46**	UAB Medicinos Bankas	−0.01	1.17			
JSC Latvijas Pasa Banka	0.27	0.52						
Jsc Latvian Dev. Fin. Inst. Altum	−0.01*	1.17*						
Latvijas Krajbanka	n.a.	n.a.						
Meridian Trade Bank AS	0.02	0.93						
Norvik Banka AS	0.02	4.28						
PrivatBank	0.54	2.51						
Regionala Investiciju Banka	0.02	2.19						
Rietumu Bank Group	0.73	12.86						
SEB Banka AS	0.72	13.29						
Swedbank AS	0.76	18.75						
Trasta Komercbanka	0.01	2.12						

Source: Authors' calculation based on the Bankscope database. Note: The Lerner index refers to the adjusted Lerner index proposed by Koetter et al. (2012). Due to data availability, *refers to the Lerner index and the market share in 2013, and **to the Lerner index and the market share in 2012. N.A. means that balance sheet data are not available for those years.

banking industry is dominated by two foreign banks, SEB Pank and Swedbank AS, which between them hold nearly 85% of the banking sector assets. Furthermore, these two banks are also notable for the high values they recorded for the Lerner index in 2014 at 0.90 or more, which would indicate that our two proxies for market power give similar patterns. However, the picture for small banks is less clear, since four of them, AS LHV Pank, DNB Pank AS, Tallinn Business Bank Ltd and Versobank AS, had a Lerner index above 0.60 in 2014.

The low correlation between our two proxies for market power in Estonia is confirmed by Figure 2. In contrast to the results for Latvia and Lithuania, the Estonian data suggest a non-significant correlation between market share and the Lerner index for the Estonian banking sector. This reinforces our decision to consider two alternative measures of bank market power.

Finally, in Figure 3 we plot the Lerner index (x-axis) against the Z-score and the loan loss reserves (y-axis), while in Figure 4 we plot market share (x-axis) against our alternative measures of bank risk-taking. In each case, we consider both linear and nonlinear fitted values. The R-squared are obtained by regressing each measure of risk on the Lerner index or the market share, and by considering a linear or a quadratic function. The result shows that a relatively tight relationship exists between the Lerner index and the risk measures, while the link is less clear when we consider the market share of the banks. This relationship is negative with loan loss reserves, and positive with the Z-score, which is an inverse proxy for bank-individual risk. This preliminary result is in line with the competition-fragility view. More importantly, bottom scatter plots reported in Figure 3 indicate a potential nonlinear relationship between the Lerner index and the Z-score, and between the Lerner index and the loan loss reserves. The next section provides an in-depth assessment of this issue.

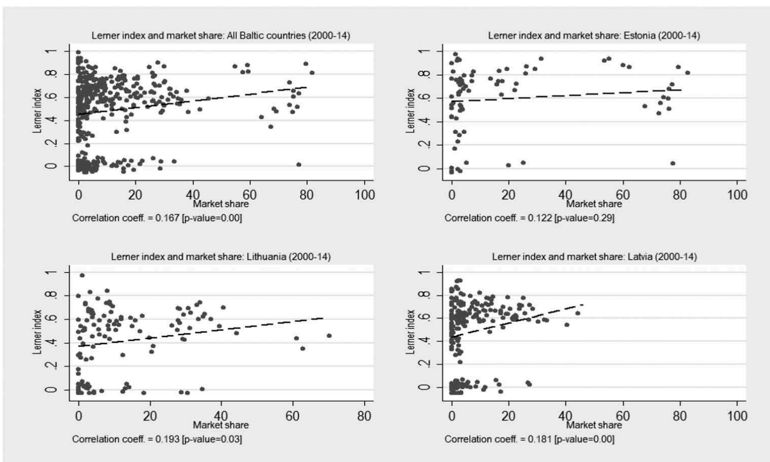

Figure 2. Correlation between the market share and the Lerner index.

Note: The Lerner index refers to the adjusted Lerner index proposed by Koetter et al. (2012).

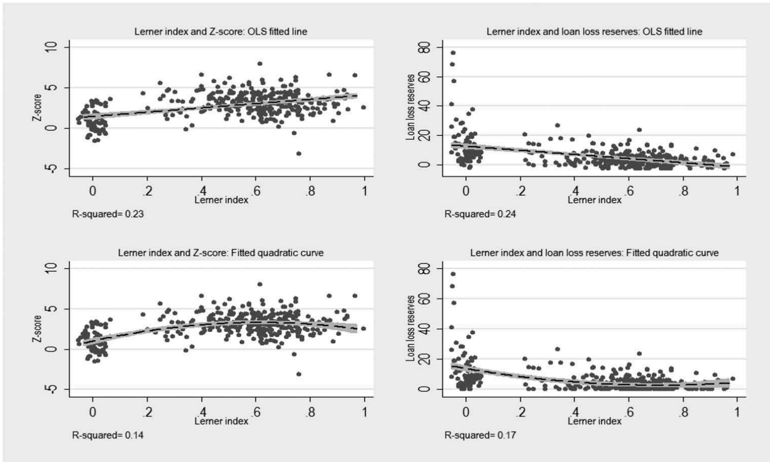

Figure 3. Scatterplots between the Lerner index and alternative measures of risk.

Note: The shaded area represents the 95% confidence interval. The Lerner index refers to the adjusted Lerner index proposed by Koetter et al. (2012).

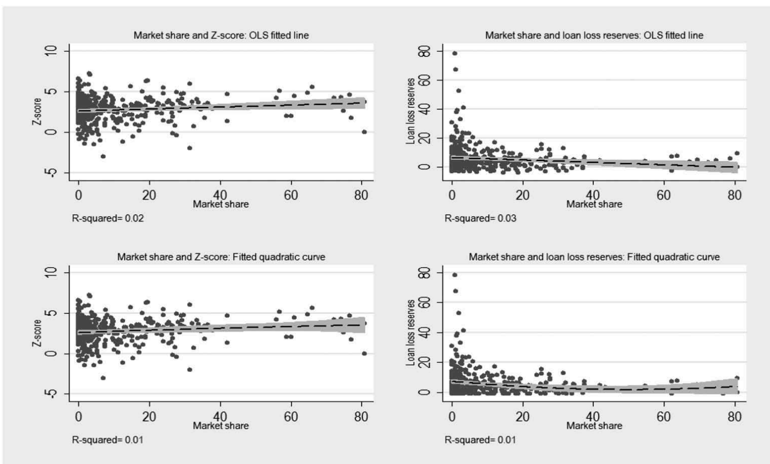

Figure 4. Scatterplots between market share and alternative measures of risk.

Note: The shaded area represents the 95% confidence interval.

4. Methodology and results

4.1. Econometric approach

Following the theoretical results from Martinez-Miera and Repullo (2010), we examine whether nonlinear causality exists between the proxies for concentration and competition and our alternative measures of risk. To this end, we include the squared term of the Lerner index or of the market share. Such a nonlinear investigation is useful from a policy point of view, as it allows an optimal threshold to be identified beyond which bank competition, or inversely a lack of competition, becomes dangerous for the stability of the banking sector. Our analysis is based upon the following regression:

$$risk_{it} = \alpha + \beta_1 Comp_{it-1} + \beta_2 Comp_{it-1}^2 + \beta_3 Crisis_t + \sum_{k=4}^{n} \beta_k X_{it-1} + \mu_i + \gamma_t + \varepsilon_{it} \quad (6)$$

where i and t are respectively the bank and time period indicators, $risk_{it}$ represents one or another of our of our measures of risk, $Comp_{it-1}$ represents one or another of our measures of market power, either the Lerner index or the bank market share, $Crisis_t$ is a dummy variable capturing the subprime crisis episode, equal to 1 from 2008 to 2012 and zero otherwise, and X_{it-1} is the vector of control variables (See Table 3 and Table 4). The term μ_i is an individual specific effect, γ_t is an unobserved time effect included to capture common time-varying factors, and ε_{it} is the random error term. This specification is similar in many ways to that considered by recent studies that have investigated the competition-stability trade-off (see, for instance, Leroy & Lucotte, 2017). Equation (6) is estimated using the fixed effects (FE) estimator.

However, examining whether market power influences risk-taking by banks raises the question of endogeneity bias. Indeed, Schaeck and Čihák (2008) argued that the level of risk-taking could affect the competitiveness of banks, which could then impact our measures of market power. Banks might have an incentive to gamble in the hope of resurrection when they face a high probability of default. They may even be more inclined to change the price of their products so as to access new financial resources and attract new customers, thus affecting the existing market power. To address this potential endogeneity issue, we lag our proxies for market power by one period and do the same for all the control variables. We further consider an instrumental variable approach using the two-stage least squares (2SLS) estimator. We consider three instrumental variables, which are the first lag of the market power proxy considered, and two variables proxying cost inefficiency, these being the ratio of overhead expenses to total assets and the cost-to-income ratio.

4.2. Baseline estimates

The results obtained are reported in Tables 4 and 5 when we consider the Lerner index as right-hand side variable, and in Tables 6 and 7 when we consider the market share as a proxy for competition. For each specification, we report the turning point, representing the optimal threshold, when the U-shape test developed by Lind and Mehlum (2010) indicates a statistically significant nonlinear relationship between our proxies for bank market power and our alternative measures of risk. In

Table 4. Market power and bank risk-taking: The nonlinear relationship between the Lerner index and the Z-score.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Z-score FE	Z-score FE	Z-score FE	Z-score 2SLS	Z-score 2SLS	Z-score 2SLS
Lerner	5.014***	5.031***	5.056***	13.924***	14.067***	14.922***
	(1.102)	(1.135)	(1.212)	(3.490)	(3.523)	(3.310)
Lerner*Lerner	−4.306***	−4.368***	−4.344***	−10.916***	−10.906***	−12.088***
	(1.258)	(1.327)	(1.439)	(3.140)	(3.218)	(3.182)
Inflation		0.033	0.006		−0.027	−0.059
		(0.065)	(0.063)		(0.077)	(0.080)
GDP growth		−0.027	−0.025		−0.038	−0.021
		(0.049)	(0.050)		(0.056)	(0.055)
Crisis dummy	−2.743***	−1.263**	−1.367	−1.621***	−1.397**	−1.529***
	(0.438)	(0.551)	(0.858)	(0.462)	(0.597)	(0.529)
Size			0.023			−0.171
			(0.132)			(0.215)
Non-interest income/ total income			−0.577			−0.566
			(0.600)			(0.919)
Fixed assets/total assets			4.767			3.974
			(8.028)			(6.083)
Loans/total assets			2.122			2.672
			(1.464)			(1.723)
Liquidity			0.005			0.007
			(0.011)			(0.011)
U-shape test	2.30	2.21	2.00	2.44	2.27	2.69
	[0.013]	[0.016]	[0.026]	[0.007]	[0.011]	[0.003]
Turning point	0.582	0.576	0.582	0.638	0.645	0.617
95% confidence interval, Fieller method	[0.485; 0.862]	[0.474; 0.889]	[0.478; 0.983]	[0.540; 0.838]	[0.541; 0.877]	[0.533; 0.789]
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	350	350	346	343	343	339
R-squared	0.430	0.431	0.447	0.187	0.171	0.188
Number of banks	40	40	39	40	40	39
Hansen J-OverID test [p-value]	–	–	–	0.0980	0.130	0.162

Note: Constant included but not reported. Robust standard errors clustered at bank level are reported below their coefficient estimates. The Hansen test evaluates the joint validity of instruments used. *, ** and ***indicate statistical significance at the 10%, 5% and 1% levels, respectively. The Lerner index refers to the adjusted Lerner index proposed by Koetter et al. (2012). The U-shape test is based on Lind and Mehlum (2010) and the p-value of the test statistic is reported between square brackets.

this case, we also report the confidence interval for the extreme point, using the Fieller method.[5]

Table 4 reveals that the results for each specification show an inverse U-shaped relationship between the Lerner index and the Z-score. The turning points vary between 0.57 and 0.64, suggesting that market power tends to increase the fragility of the banking sector beyond this threshold. The results that we obtain between the Lerner index and loan loss reserves are more mixed. Indeed, the results reported in Table 5 only indicate a U-shaped relationship between these two variables when we estimate Equation (6) using a 2SLS estimator. In this case, the turning points vary between 0.66 and 0.70.

We do not find a significant nonlinear relationship between the market share and the Z-score (see Table 6). More interestingly, the results reported in Table 7 suggest a U-shaped relationship between the market share of the bank and its loan loss reserves.

Table 5. Market power and bank risk-taking: the nonlinear relationship between the Lerner index and loan loss reserves.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Loan loss FE	Loan loss FE	Loan loss FE	Loan loss 2SLS	Loan loss 2SLS	Loan loss 2SLS
Lerner	−28.659	−29.232	−19.250**	−59.703***	−58.714***	−51.906***
	(17.547)	(17.495)	(8.709)	(21.534)	(20.474)	(15.712)
Lerner*Lerner	24.365	26.052	13.090	42.663**	42.568**	39.232**
	(18.393)	(18.689)	(9.821)	(19.790)	(19.187)	(15.614)
Inflation		−0.774*	−0.842*		−0.169	−0.102
		(0.398)	(0.419)		(0.309)	(0.280)
GDP growth		−0.116	−0.036		−0.185	−0.175
		(0.124)	(0.163)		(0.143)	(0.138)
Crisis dummy	4.666***	4.822	13.002	4.593***	5.824***	6.439***
	(1.391)	(4.095)	(8.514)	(1.608)	(2.256)	(1.888)
Size			−3.585			1.035
			(2.901)			(1.133)
Non-interest income/total income			−3.860*			4.861**
			(2.069)			(1.955)
Fixed assets/total assets			23.219			19.324
			(20.720)			(22.169)
Loans/total assets			6.614			−4.208
			(10.228)			(5.203)
Liquidity			0.036			−0.035
			(0.055)			(0.023)
U-shape test	1.00	1.11	0.53	1.29	1.33	1.56
	[0.162]	[0.137]	[0.301]	[0.099]	[0.091]	[0.060]
Turning point	–	–	–	0.699	0.689	0.661
95% confidence interval, Fieller method	–			[0.585; 2.478]	[0.571; 2.057]	[0.552; 1.321]
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	349	349	349	341	341	341
R-squared	0.462	0.484	0.553	0.035	0.084	0.306
Number of banks	38	38	38	38	38	38
Hansen J-OverID test [p-value]	–	–	–	0.286	0.299	0.215

Note: Constant included but not reported. Robust standard errors clustered at bank level are reported below their coefficient estimates. The Hansen test evaluates the joint validity of instruments used. *, ** and ***indicate statistical significance at the 10%, 5% and 1% levels, respectively. The Lerner index refers to the adjusted Lerner index proposed by Koetter et al. (2012). The U-shape test is based on Lind and Mehlum (2010) and the p-value of the test statistic is reported between square brackets.

For each specification, the coefficient estimates associated with the market share and the interaction term appear statistically significant at the conventional levels. The turning points vary between 44% and 52% (See Figure A1).

Consequently, our nonlinear analysis suggests that a low degree of bank competition is likely to exacerbate risk-taking by banks and then be detrimental to the stability of the banking sector in the Baltic countries. In line with the theoretical predictions of Martinez-Miera and Repullo (2010), we find a very stable and statistically significant inverse U-shaped relationship between the Lerner index and the Z-score, a measure of solvency risk. This means that banking sector fragility is higher in either very competitive or very monopolistic markets, and lowest when there are moderate levels of competition.

If we now compare each commercial bank in the Baltic countries in 2014 with the average optimal thresholds for the Lerner index and the market share, we can see from Figure A2 that only one financial institution, Swedbank AS in Estonia, lies above both threshold values. The situation is more mixed for Lithuania and Latvia,

Table 6. Market power and bank risk-taking: the nonlinear relationship between the market share and the Z-score.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Z-score FE	Z-score FE	Z-score FE	Z-score 2SLS	Z-score 2SLS	Z-score 2SLS
Market share	−0.006	−0.005	0.028	0.005	0.006	0.065
	(0.071)	(0.068)	(0.069)	(0.086)	(0.084)	(0.075)
Market share*Market share	0.000	0.000	0.000	0.000	0.000	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Inflation		0.050	0.012		0.049	0.006
		(0.070)	(0.065)		(0.069)	(0.065)
GDP growth		−0.048	−0.042		−0.041	−0.037
		(0.047)	(0.048)		(0.044)	(0.045)
Crisis dummy	−2.121***	−0.263	−0.579	−1.038***	−1.061***	−1.108***
	(0.639)	(0.793)	(1.292)	(0.297)	(0.405)	(0.411)
Size			0.019			−0.070
			(0.162)			(0.180)
Non-interest income/total income			−0.504			−0.558
			(0.644)			(0.607)
Fixed assets/total assets			3.239			4.030
			(9.939)			(9.518)
Loans/total assets			3.616*			3.467*
			(1.865)			(1.796)
Liquidity			0.012			0.012
			(0.014)			(0.013)
U-shape test	0.09 [0.464]	0.08 [0.47]	Ext. outside interval	Ext. outside interval	Ext. outside interval	Ext. outside interval
Turning point	–	–	–	–	–	–
95% confidence interval, Fieller method	–	–	–	–	–	–
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	370	370	366	369	369	365
R-squared	0.329	0.333	0.362	0.330	0.333	0.364
Number of banks	40	40	39	40	40	39
Hansen J-OverID test [p-value]	–	–	–	0.236	0.251	0.178

Note: Constant included but not reported. Robust standard errors clustered at bank level are reported below their coefficient estimates. The Hansen test evaluates the joint validity of instruments used. *, ** and ***indicate statistical significance at the 10%, 5% and 1% levels, respectively. The U-shape test is based on Lind and Mehlum (2010) and the p-value of the test statistic is reported between square brackets. *Ext. outside interval* means that the extremum point (i.e. the turning point) is outside the interval, then we cannot reject the null hypothesis of a monotone relationship.

as a number of banks in Latvia exhibit a Lerner index that is higher than the optimal threshold but have market shares of between 10% and 20%, which appears relatively low next to the shares seen in Estonia and Lithuania.[6]

4.3. Robustness checks

We test the robustness of our results in several ways. First, we consider two additional proxies for bank risk. Then, following Soedarmono, Machrouh, and Tarazi (2011), we use a Z-score measure based on the return on equity (*ZROE*). We also replace the loan loss reserves as a percentage of gross loans with impaired loans as a percentage of gross loans. The results obtained with these two alternative left-hand side variables are presented in Table 8. To save space, we do not report the coefficient estimates associated with the control variables, and we only focus on the results obtained with the FE

Table 7. Market power and bank risk-taking: the nonlinear relationship between the market share and loan loss reserves.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Loan loss FE	Loan loss FE	Loan loss FE	Loan loss 2SLS	Loan loss 2SLS	Loan loss 2SLS
Market share	−1.649**	−1.611**	−1.557***	−0.798**	−0.752**	−0.694***
	(0.686)	(0.676)	(0.568)	(0.317)	(0.310)	(0.204)
Market share*Market share	0.016**	0.016**	0.015***	0.009***	0.008***	0.007***
	(0.007)	(0.007)	(0.006)	(0.003)	(0.003)	(0.002)
Inflation		−0.604**	−0.679**		−0.396*	−0.276
		(0.286)	(0.332)		(0.215)	(0.203)
GDP growth		0.072	0.053		−0.058	−0.026
		(0.158)	(0.143)		(0.108)	(0.098)
Crisis dummy	−1.699	−4.874	−1.811	2.296*	3.897**	4.407***
	(3.032)	(3.352)	(4.072)	(1.302)	(1.602)	(1.513)
Size			−0.583			0.730
			(1.180)			(0.687)
Non-interest income/total income			−4.438*			5.093**
			(2.560)			(2.350)
Fixed assets/total assets			16.946			30.684*
			(33.153)			(16.915)
Loans/total assets			−3.592			−4.805
			(5.070)			(4.134)
Liquidity			−0.041			−0.047**
			(0.029)			(0.022)
U-shape test	2.40	2.36	2.66	2.52	2.43	3.40
	[0.010]	[0.011]	[0.005]	[0.006]	[0.007]	[0.000]
Turning point	50.90	51.58	51.50	45.69	47.15	47.21
95% confidence interval, Fieller method	[44.48; 57.35]	[44.68; 59.89]	[46.16; 58.70]	[31.89; 50.88]	[31.54; 52.58]	[38.04; 53.08]
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	368	368	368	365	365	365
R-squared	0.583	0.594	0.608	0.582	0.593	0.633
Number of banks	38	38	38	38	38	38
Hansen J-OverID test [p-value]	–	–	–	0.196	0.194	0.0799

Note: Constant included but not reported. Robust standard errors clustered at bank level are reported below their coefficient estimates. The Hansen test evaluates the joint validity of instruments used. *, ** and ***indicate statistical significance at the 10%, 5% and 1% levels, respectively. The U-shape test is based on Lind and Mehlum (2010) and the p-value of the test statistic is reported between square brackets.

Table 8. Market power and bank risk-taking: results obtained with alternative measures of risk.

	(1)	(2)	(3)	(1)	(2)	(3)
Dependent variable	ZROE FE	ZROE FE	ZROE FE	Imp. Loans FE	Imp. Loans FE	Imp. Loans FE
Lerner	4.866***	4.817***	5.054***	−33.889	−38.433	−22.507*
	(1.223)	(1.234)	(1.308)	(23.139)	(23.563)	(13.142)
Lerner*Lerner	−3.930***	−3.874***	−4.020**	19.313	27.620	6.435
	(1.372)	(1.407)	(1.511)	(23.235)	(24.324)	(15.164)
U-shape test	1.77	1.67	1.58	0.16	0.62	Ext. outside
	[0.042]	[0.051]	[0.061]	[0.438]	[0.27]	interval
Turning point	0.619	0.621	0.628	–	–	–
95% confidence interval, Fieller method	[0.500; 1.133]	[0.498; 1.232]	[0.504; 1.349]	–	–	–
Observations	304	304	299	253	253	253
R-squared	0.428	0.428	0.466	0.479	0.506	0.574
Number of banks	40	40	39	34	34	34
Market share	−0.022	−0.020	0.036	−2.354**	−2.270**	−1.918**
	(0.058)	(0.055)	(0.056)	(0.944)	(0.931)	(0.737)
Market share*Market share	0.001	0.001	0.000	0.023**	0.021**	0.018**
	(0.001)	(0.001)	(0.001)	(0.009)	(0.009)	(0.007)
U-shape test	0.37	0.37	Ext. outside	2.49	2.42	2.60
	[0.355]	[0.356]	interval	[0.009]	[0.010]	[0.007]
Turning point	–	–	–	52.30	53.32	51.85
95% confidence interval, Fieller method	–	–	–	[43.39; 59.06]	[43.61; 63.64]	[41.91; 60.66]
Observations	321	321	316	264	264	264
R-squared	0.324	0.332	0.372	0.529	0.539	0.553
Number of banks	40	40	39	34	34	34

Note: Constant included but not reported. Year fixed effects included. Robust standard errors clustered at bank level are reported below their coefficient estimates. *, ** and ***indicate statistical significance at the 10%, 5% and 1% levels, respectively. Specification (1) includes crisis dummy as control variable, specification (2) includes crisis dummy, inflation, and GDP growth as control variables, while specification (3) includes all control variables. Control variables are lagged one period. The Lerner index refers to the adjusted Lerner index proposed by Koetter et al. (2012). The U-shape test is based on Lind and Mehlum (2010) and the p-value of the test statistic is reported between square brackets. *Ext. outside interval* means that the extremum point (i.e. the turning point) is outside the interval, then we cannot reject the null hypothesis of a monotone relationship.

estimator. Detailed results are available upon request. The results that we obtain are very similar to those reported above, and we still find an inverse U-shaped relationship between the Lerner index and our *ZROE* measure of bank stability, and a statistically significant U-shaped relationship between market share and our proxy for credit risk, which is impaired loans as a percentage of gross loans. Consistent with our previous findings, the turning points are close to 0.62 for the Lerner index and between 51% and 54% for the market share.

We also test the sensitivity of our results by considering three alternative measures of the Lerner index and one alternative measure of market share. The first alternative measure of the Lerner index uses a three-year moving average. This measure aims to smooth the cyclical fluctuations of the Lerner index because the market power of a bank is not likely to change radically in the short-run, as argued by Leroy and Lucotte (2017). Second, we follow Maudos and de Guevara (2007) and Turk-Ariss (2010) by re-estimating the translog cost function (Equation 2) with funding costs excluded. It may be expected that banks with a high level of market power, especially those with a high level of deposit market power, are able to raise funds at a cheap cost. In this case, as Maudos and de Guevara (2007) argue, including financial costs and consequently the price of deposits in the cost function captures the effect of market power in banking and may bias the results. By excluding funding costs, we are likely to get a clean proxy for pricing power that is not distorted by deposit market power (Turk-Ariss, 2010). As before, the two-input cost function is estimated using an SFA, and we apply the correction proposed by Koetter et al. (2012) to compute the funding-adjusted Lerner index. In a very few cases values can be obtained empirically for the Lerner index that are outside the 0 to 1 range. In our case, we have a total of 29 observations below zero, and no observations above one (see Figure A3 and Table A2 in Appendix). Rather than treating these observations as outliers and dropping them, we code them equal to zero, and then consider a left-censored Lerner index. Finally, we use an alternative measure of market share that does not only look at bank assets, but also considers deposit and loan market power. This index is called global market share and is equal for each bank to the average of its market shares for assets, loans, and deposits. Correlations between our different proxies for market power for each Baltic country are illustrated in Figure A5. The results are reported in Tables 9 and 10. As previously, we only report the coefficient estimates of our variables of interest. The results we obtain confirm our previous findings.

Third, we re-estimate our benchmark nonlinear specification (Equation 6) by considering a robust regression approach. The idea behind the robust regression is to down-weight the influence of high leverage data points and outliers to provide a better fit of the data.[7] Our results, reported in Table 11, confirm the substance of the previous results. We find a very significant nonlinear relationship between the Lerner index and our two proxies for bank risk, though this relationship appears not to be statistically significant when we consider market share and its squared term as right-hand side variables. This last result could nonetheless easily be explained by the distribution of the market share series, where there is consistently a large left tail (see Figure A4), which implies that banks with a large market share are down-weighted.

Table 9. Market power and the Z-score: results obtained with alternative proxies for market power.

	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Dependent variable	Z-score FE	Z-score IV	Z-score FE	Z-score IV	Z-score FE	Z-score IV	Z-score FE	Z-score IV
Lerner 1	7.152***	9.565***						
	(1.534)	(2.212)						
Lerner 1*Lerner 1	−5.127***	−6.572***						
	(1.612)	(2.472)						
Lerner 2			5.370***	15.213***				
			(1.210)	(3.122)				
Lerner 2*Lerner2			−4.759***	−12.774***				
			(1.456)	(2.984)				
Lerner 3					5.202***	14.894***		
					(1.247)	(3.194)		
Lerner3*Lerner3					−4.478***	−12.323***		
					(1.473)	(3.085)		
Global Market share							0.078	0.133**
							(0.060)	(0.066)
Global Market share*Global market share							−0.000	−0.001
							(0.001)	(0.001)
U-shape test	1.51	1.12	2.26	3.19	2.04	2.91	0.01	0.30
	[0.069]	[0.131]	[0.014]	[0.001]	[0.024]	[0.002]	[0.494]	[0.381]
Turning point	0.697	–	0.564	0.595	0.580	0.604	–	–
95% confidence interval, Fieller method	[0.561; 1.182]	–	[0.472; 0.865]	[0.518; 0.725]	[0.480; 0.964]	[0.525; 0.755]	–	–
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	351	350	346	339	346	339	364	363
R-squared	0.444	0.497	0.451	0.218	0.448	0.228	0.375	0.381
Number of banks	39	39	39	39	39	39	39	39
Hansen J-OverID test [p-value]	–	0.104	–	0.0927	–	0.108	–	0.256

Note: Constant included but not reported. Robust standard errors clustered at bank level are reported below their coefficient estimates. *, ** and ***indicate statistical significance at the 10%, 5% and 1% levels, respectively. Specifications (1) and (2) includes all control variables. Specification (1) is estimated using the FE estimator, while specification (2) is estimated using the 2SLS estimator. Control variables are lagged one period. Lerner 1 corresponds to the 3-year moving average Lerner index, Lerner 2 to the funding-adjusted Lerner index, Lerner 3 to the left-censored Lerner index, and Global market share to the market share calculated by considering assets, loans and deposits. The U-shape test is based on Lind and Mehlum (2010) and the p-value of the test statistic is reported between square brackets.

Table 10. Market power and loan loss reserves: results obtained with alternative proxies for market power.

	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Dependent variable	Loan loss FE	Loan loss IV	Loan loss FE	Loan loss IV	Loan loss FE	Loan loss IV	Loan loss FE	Loan loss IV
Lerner 1	−54.098***	−50.048***						
	(17.699)	(12.095)						
Lerner 1*Lerner 1	41.918***	39.118***						
	(15.154)	(11.808)						
Lerner 2			−15.442**	−51.876***				
			(7.522)	(16.980)				
Lerner 2*Lerner2			8.634	38.018**				
			(9.385)	(16.209)				
Lerner 3					−16.570**	−51.129***		
					(7.892)	(16.748)		
Lerner3*Lerner3					9.712	37.320**		
					(9.466)	(16.092)		
Global Market share							−1.018**	−0.821***
							(0.407)	(0.194)
Global Market share*Global market share							0.010**	0.009***
							(0.004)	(0.002)
U-shape test	2.09	2.22	0.11	1.42	0.19	1.38	2.50	4.24
	[0.021]	[0.013]	[0.456]	[0.078]	[0.424]	[0.084]	[0.008]	[0.000]
Turning point	0.645	0.639	–	0.682	–	0.685	51.56	45.79
95% confidence interval, Fieller method	[0.543; 0.927]	[0.561; 0.871]	–	[0.568; 1.615]	–	[0.568; 1.721]	[45.59; 56.99]	[38.46; 51.86]
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	355	352	349	341	349	341	364	363
R-squared	0.645	0.684	0.543	0.271	0.546	0.301	0.606	0.638
Number of banks	38	38	38	38	38	38	38	38
Hansen J-OverID test [p-value]	–	0.202	–	0.168	–	0.156	–	0.0867

Note: Constant included but not reported. Robust standard errors clustered at bank level are reported below their coefficient estimates. *, ** and ***indicate statistical significance at the 10%, 5% and 1% levels, respectively. Specifications (1) and (2) includes all control variables. Specification (1) is estimated using the FE estimator, while specification (2) is estimated using the 2SLS estimator. Control variables are lagged one period. Lerner 1 corresponds to the 3-year moving average Lerner index, Lerner 2 to the funding-adjusted Lerner index, Lerner 3 to the left-censored Lerner index, and Global market share to the market share calculated by considering assets, loans and deposits. The U-shape test is based on Lind and Mehlum (2010) and the p-value of the test statistic is reported between square brackets.

Table 11. Market power and bank risk-taking: results obtained using a robust regression approach.

	(1)	(2)	(3)	(1)	(2)	(3)
Dependent variable	Z-score	Z-score	Z-score	Loan loss	Loan loss	Loan loss
Lerner	6.293***	6.251***	6.308***	−7.279***	−6.954***	−9.560***
	(0.754)	(0.762)	(0.714)	(1.571)	(1.535)	(1.532)
Lerner*Lerner	−5.780***	−5.709***	−5.888***	4.667**	4.183**	6.717***
	(0.854)	(0.872)	(0.822)	(1.811)	(1.785)	(1.790)
U-shape test	5.00	4.77	5.33	0.84	0.56	1.65
	[0.000]	[0.000]	[0.000]	[0.2]	[0.289]	[0.049]
Turning point	0.544	0.547	0.535	–	–	0.711
95% confidence interval, Fieller method	[0.494; 0.618]	[0.495; 0.627]	[0.488; 0.604]	–	–	[0.587; 1.071]
Observations	350	350	346	349	349	349
R-squared	0.442	0.443	0.520	0.650	0.660	0.713
Market share	0.008	0.007	−0.001	−0.003	−0.006	−0.079**
	(0.010)	(0.011)	(0.018)	(0.020)	(0.020)	(0.039)
Market share*Market share	0.000	0.000	0.000	−0.000	−0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
U-shape test	Ext. outside interval	Ext. outside interval	0.04 [0.483]	Ext. outside interval	Ext. outside interval	0.93 [0.176]
Turning point	–	–	–	–	–	–
95% confidence interval, Fieller method	–	–	–	–	–	–
Observations	370	370	366	368	368	368
R-squared	0.320	0.324	0.423	0.581	0.575	0.573

Note: Constant included but not reported. Year fixed effects included. Standard errors are reported below their coefficient estimates. *, ** and ***indicate statistical significance at the 10%, 5% and 1% levels, respectively. Specification (1) includes crisis dummy as control variable, specification (2) includes crisis dummy, inflation, and GDP growth as control variables, while specification (3) includes all control variables. Control variables are lagged one period. The Lerner index refers to the adjusted Lerner index proposed by Koetter et al. (2012). The U-shape test is based on Lind and Mehlum (2010) and the p-value of the test statistic is reported between square brackets. *Ext. outside interval* means that the extremum point (i.e. the turning point) is outside the interval, then we cannot reject the null hypothesis of a monotone relationship.

Table 12. Market power and bank risk-taking: results obtained with two proxies for competition in the same regression.

	(1)	(2)	(3)	(1)	(2)	(3)
Dependent variable	Z-score FE	Z-score FE	Z-score FE	Loan loss FE	Loan loss FE	Loan loss FE
Lerner	4.719***	4.742***	4.883***	−17.486**	−17.898**	−17.667**
	(1.139)	(1.167)	(1.213)	(6.639)	(6.808)	(6.513)
Lerner*Lerner	−3.898***	−3.970***	−4.144***	13.612*	14.713*	14.727*
	(1.273)	(1.330)	(1.435)	(8.003)	(8.194)	(8.297)
Market share	0.034	0.033	0.071	−1.633***	−1.588***	−1.551***
	(0.058)	(0.058)	(0.057)	(0.582)	(0.573)	(0.486)
Market share*Market share	−0.000	−0.000	−0.000	0.016**	0.015**	0.015***
	(0.001)	(0.001)	(0.001)	(0.006)	(0.006)	(0.005)
U-shape test (Lerner)	1.97	1.93	1.88	0.95	1.11	1.07
	[0.027]	[0.030]	[0.034]	[0.174]	[0.137]	[0.146]
Turning point (Lerner)	0.605	0.597	0.589	–	–	–
95% confidence interval, Fieller method (Lerner)	[0.497; 0.995]	[0.485; 1.021]	[0.477; 1.067]	–	–	–
U-shape test (Market share)	Ext. outside interval	Ext. outside interval	Ext. outside interval	2.60	2.52	2.82
				[0.006]	[0.008]	[0.003]
Turning point (Market share)	–	–	–	50.67	51.50	51.44
95% confidence interval, Fieller method (Market share)	–	–	–	[45.99; 60.21]	[46.07; 63.65]	[46.14; 61.73]
Observations	350	350	346	349	349	349
R-squared	0.435	0.436	0.457	0.646	0.656	0.665
Number of banks	40	40	39	38	38	38

Note: Constant included but not reported. Year fixed effects included. Robust standard errors clustered at bank level are reported below their coefficient estimates. *, ** and ***indicate statistical significance at the 10%, 5% and 1% levels, respectively. Specification (1) includes crisis dummy as control variable, specification (2) includes crisis dummy, inflation, and GDP growth as control variables, while specification (3) includes all control variables. Control variables are lagged one period. The Lerner index refers to the adjusted Lerner index proposed by Koetter et al. (2012). The U-shape test is based on Lind and Mehlum (2010) and the p-value of the test statistic is reported between square brackets. *Ext. outside interval* means that the extremum point (i.e. the turning point) is outside the interval, then we cannot reject the null hypothesis of a monotone relationship.

Finally, we investigate whether our results evolve when the same regression (Equation 6) includes our two proxies for bank competition, which are the Lerner index and market share. As argued by Carbó et al. (2009), structural and non-structural measures of competition tend to measure different things, and so they can be viewed as complementary proxies for competition. This is confirmed by the relatively low degree of correlation between the Lerner index and the market share for the Baltic countries (see Figure 2). The results that we obtain when we consider the Lerner index, market share, and their squared terms in the same regression are reported in Table 12. As is apparent, we still find a U-shaped relationship between bank competition and financial stability.

5. Conclusion

This paper is the first attempt to assess empirically the relationship between banking competition and financial stability in the Baltic countries. We do this using bank-level data and consider two alternative proxies for competition, the Lerner index and market share, with the Z-score and loan loss reserves as complementary measures of bank risk. We take a sample of 40 commercial banks in Estonia, Lithuania, and Latvia in 2000–2014, and our empirical results highlight an inverse and robust U-shaped relationship between the Lerner index and the Z-score, and a statistically significant U-shaped relationship between the Lerner index, market share and the loan loss reserves ratio. This means that a higher degree of market power arising from the low level of competition is associated with a decrease in risk-taking by banks and in the risk of insolvency for the banks up to a certain threshold, after which the relationship between competition and banking sector stability turns negative. We find that the optimal threshold for the Lerner index is 0.606 on average, and 49% is optimal for market share. The upper and lower values for the 95% confidence intervals are 0.508 and 0.873 for the Lerner index, and 39.46% and 55.41% for the market share.

The policy implications are that such a threshold implies that how the structure of the banking industry evolves is of critical importance for financial stability. This suggests that the policy-makers in charge of monitoring and regulating the banking industry should place greater emphasis on mergers and acquisitions, by encouraging them when competition is fierce, while preventing them in contrast in highly concentrated banking markets, at least for the largest banks.

This issue is especially important for the Baltic countries, which have a relatively high degree of concentration in the banking sector. As the low degree of correlation between the Lerner index and market share seems to suggest, permitting financial institutions to become larger might not necessarily lead to a lower degree of competition, but larger institutions might be encouraged to take more risk with their portfolios. Whatever the reason for financial institutions increasing risk, whether they are compensating for their improved diversification or exploiting their status as too big to fail, more attention should be devoted to the issue of the optimal size for them.

Notes

1. See, for instance, Berger et al. (2009), Fungáčová and Weill (2013), Jimenez et al. (2013), Liu et al. (2013), and Fu et al. (2014).
2. See Table A1 in the Appendix for an overview of bank-level analyses on the effect of bank competition on financial stability.
3. Note nonetheless that empirical results obtained by Maudos and de Guevara (2007) for a large sample of European banks do not confirm the quiet life hypothesis. On the contrary, they find a positive relationship between market power and the cost X-efficiency.
4. See Lepetit and Strobel (2013) for a review of different methodologies for computing the Z-score.
5. See Lind and Mehlum (2010) for more details concerning the U-shape test and the computation of the confidence interval. Please see Tables A2, A3 and A4 in the Appendix for more details concerning the control variables.
6. A graphical representation of the marginal effects is displayed in Figure A5 of the Appendix. Please see Figure A1 in the Appendix for a graphical representation of the conditional marginal effects.
7. A robust regression is an alternative approach used when the data contain some outliers or high leverage data points. It is a compromise between excluding these points entirely from the analysis and including all the data points and treating them all equally in the regression. In practice, robust regression works by assigning a weight to each data point. Weighting is done automatically and iteratively using a process called iteratively reweighted least squares. In the first iteration, each point is assigned an equal weight and model coefficients are estimated using ordinary least squares (OLS). At subsequent iterations, weights are recomputed so that points farther from the model predictions in the previous iteration are given a lower weight. The model coefficients are then recomputed using weighted least squares. The process continues until the values of the coefficient estimates converge within a specified tolerance.

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Appendix

Table A1. Overview of bank-level analyses on the effect of bank competition on financial stability.

Paper	Study area	Competition measure(s)	Dependent variable(s)	Effect of competition on financial stability
Agoraki et al. (2011)	CEECs	Lerner index	Z-score, Nonperforming loans (NPL)	Negative
Almarzoqi, Naceur, and Scopelliti (2015)	MENA	Lerner index	Z-score, NPL	Negative
Amidu and Wolfe (2013)	Emerging countries	Lerner index	Z-score, NPL, Capitalization ratio	Positive
Anginer et al. (2014)	Mixed	Lerner index	Systemic risk measures	Positive
Baselga-Pascual, Trujillo-Ponce, and Cardone-Riportella (2015)	Euro area	Industry concentration	Z-score, NPL	Negative
Beck et al. (2013)	Mixed	Lerner index	Z-score	Negative
Berger et al. (2009)	Industrialised countries	Lerner, Industry concentration	Z-score, NPL, Capitalization ratio	Non-linear
Buch, Koch, and Koetter (2013)	Germany	Lerner index	Measure of bank distress	Negative
Craig and Dinger (2013)	USA	Deposit market competition	NPL, ROA volatility, Stock price volatility	Positive
Fiordelisi and Mare (2014)	5 EU countries	Lerner index	Z-score	Positive
Forssbaeck and Shehzad (2015)	Mixed	Lerner index	Z-score	Negative
Fu, Lin, and Molyneux (2014)	Asia Pacific	Lerner, Industry concentration	Z-score, Probability of bankruptcy	Ambiguous
Fungáčová and Weill (2013)	Russia	Lerner index	Bank failure	Negative
IJtsma et al. (2017)	25 EU countries	Industry concentration	Z-score	Positive
Jeon and Lim (2013)	Korea	Boone index, Industry concentration	Z-score	Non-linear
Jimenez et al. (2013)	Spain	Industry concentration	NPL	Non-linear
Kasman and Kasman (2015)	Turkey	Lerner, Boone	Z-score, NPL	Non-linear
Kick and Prieto (2015)	Germany	Market share, Lerner, Boone	Bank distress, Bank default	Ambiguous
Kouki and Al-Nasser (2017)	Africa	Lerner index	Z-score	Negative
Leroy and Lucotte (2017)	Europe	Lerner index	Z-score, Distance-to-default (DD), SRISK	Negative: Z-score & DD, Positive: SRISK
Liu and Wilson (2013)	Japan	Lerner index	Z-score	Non-linear
Liu et al. (2013)	10 EU countries	Lerner index	Z-score	Non-linear
Mirzaei, Moore, and Liu (2013)	Mixed	Bank market share, Industry concentration	Z-score	Ambiguous
Saadaoui (2014)	Emerging countries	Lerner index	NPL	Negative
Schaeck and Čihák (2014)	10 EU countries	Boone index	Z-score	Positive
Soedarmono et al. (2011)	Asia	Lerner index	Z-score	Positive

(*Continued*)

Table A1. (Continued).

Paper	Study area	Competition measure(s)	Dependent variable(s)	Effect of competition on financial stability
Soedarmono, Machrouh, and Tarazi (2013)	Asia	Lerner index	Z-score	Positive
Tabak, Fazio, and Cajueiro (2012)	Latin America	Boone index	Measure of "stability efficiency"	Non-linear
Tabak, Fazio, and Cajueiro (2013)	Latin America	Industry concentration	Measure of "stability efficiency"	Positive
Tabak, Gomes, and Da Silva Medeiros (2015)	Brazil	H-statistic	Z-score, NPL	Negative
Turk-Ariss (2010)	Developing countries	Lerner index	Z-score, Risk-adjusted rates of return	Negative

Table A2. Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Lerner index	401	0.48	0.29	−0.05	0.97
3-year MA Lerner index	421	0.49	0.25	−0.05	0.96
Funding-adjusted Lerner index	401	0.48	0.28	0.00	0.97
Left-censored Lerner index	401	0.49	0.28	0.00	0.97
Market share	410	10.93	16.03	0.00	80.72
Global market share	400	11.21	16.14	0.06	80.36
Z-score	370	2.74	1.50	−2.99	7.27
ZROE	321	1.39	1.41	−4.27	6.86
Loan loss reserves	390	5.69	8.30	0.00	78.97
Impaired loans	273	13.04	15.34	0.07	89.05
Size	410	13.52	1.79	6.65	17.45
Non-interest income/total income	410	0.45	0.24	−0.67	2.73
Fixed assets/total assets	410	0.02	0.03	0.00	0.39
Loans/total assets	404	0.55	0.22	0.00	0.96
Liquidity	410	40.08	25.02	0.64	168.79
Annual inflation rate	600	3.79	3.57	−1.15	15.43
Annual GDP growth rate	600	4.24	6.39	−14.81	11.90

Table A3. Correlation matrix of bank-level variables.

	var1	var2	var3	var4	var5	var6	var7
Lerner (var1)	1						
Market share (var2)	0.1671*	1					
Size (var3)	0.0674	0.6271*	1				
Non-interest income/total income (var 4)	−0.1654*	−0.1098*	−0.1529*	1			
Fixed assets/total assets (var 5)	−0.0960	−0.0982*	−0.4610*	0.2992*	1		
Loans/total assets (var6)	0.1006*	0.3239*	0.4353*	−0.4343*	−0.1720*	1	
Liquidity (var7)	0.0529	−0.2554*	−0.4303*	0.3233*	0.2119*	−0.8161*	1

Note: *indicates statistical significance at the 5% level.

Table A4. Definition and source of variables.

Variable	Definition
Dependent variables	
Z-score	Accounting bank-level measure of individual bank risk. A larger value indicates a higher bank stability and less bank risk-taking. Source: Authors' calculations, Bankscope
ZROE	Return-on-equity based Z-score measure. A larger value indicates a higher bank stability and less bank risk-taking. Source: Authors' calculations, Bankscope
Loan loss reserves	Ratio indicating how much of the total portfolio of a bank has been provided for but not charged off. It is a reserve for losses expressed as percentage of total loans. Given a similar charge-off policy the higher the ratio the poorer the quality of the loan portfolio is. Source: Bankscope
Impaired loans	Impaired loans (or non-performing loans) are loans that are unlikely to be paid back for the full amount. The impaired loans to gross loans ratio is used to measure bank's asset risk. Source: Bankscope
Explanatory variables	
Lerner index	A bank-level measure of bank market power following the methodology proposed by Koetter et al. (2012). A higher value indicates more market power and less bank competition. Source: Authors' calculations, Bankscope
3-year MA Lerner index	A 3-year rolling time window is used to compute the Lerner index. A higher value indicates more market power and less bank competition. Source: Authors' calculations, Bankscope

(*Continued*)

Table A4. (Continued).

Variable	Definition
Funding-adjusted Lerner index	Following Maudos and de Guevara (2007), a two-input cost function is considered to estimate the translog costfunction. A higher value of the funding-adjusted Lerner index indicates more market power and less bank competition. Source: Authors' calculations, Bankscope
Left-censored Lerner index	Negative values of the Lerner index are truncated to zero. A higher value of the left-censored Lerner index indicates more market power and less bank competition. Source: Authors' calculations, Bankscope
Bank size	The log value of total assets. Source: BankScope
Non-interest income/ Total income	A bank-level measure of business diversification. Source: Bankscope
Fixed assets/Total assets	A bank-level measure of asset composition. Source: Bankscope
Liquidity	A bank-level liquidity indicator, which corresponds to the ratio of liquid assets over deposits and short term funding. A higher value indicates less liquidity risk. Source: Bankscope
Loans/Total assets	A bank-level measure of asset composition. Source: Bankscope
GDP growth	Annual real GDP growth. Source: World Development Indicators (WDI), World Bank
Inflation	Annual percentage change of consumer prices index. Source: World Development Indicators (WDI), World Bank

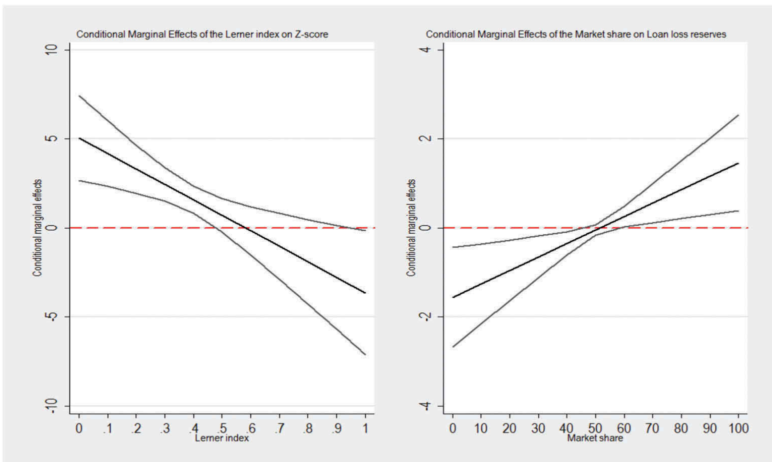

Figure A1. Conditional marginal effects.

Note: The conditional marginal effects are computed by considering our benchmark nonlinear specification estimated using the fixed effects (FE) estimator, i.e. the specification (3) in Table 4 for the Lerner index, and the specification (3) in Table 7 for the market share. The Lerner index refers to the adjusted Lerner index proposed by Koetter et al. (2012). The grey lines correspond to the 95% confidence interval.

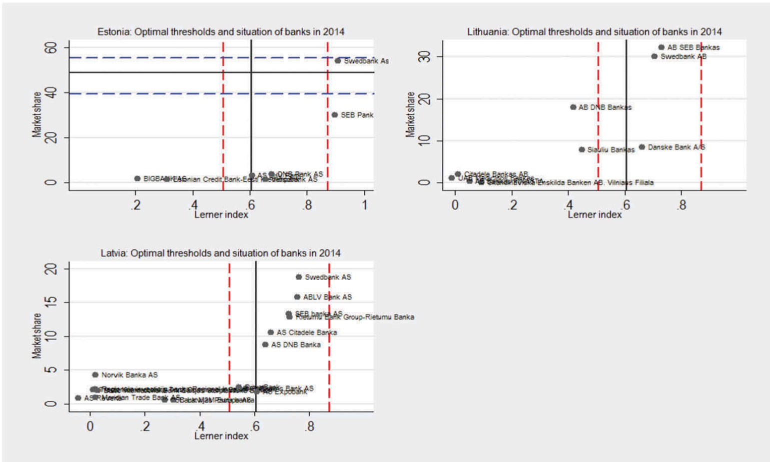

Figure A2. Average turning points and situation of banks in Baltic countries.

Note: The average turning point for the Lerner index and the market share is calculated by considering results obtained with our benchmark nonlinear specification, i.e. results reported in Tables 4–7. Also note that we only consider the specifications for which the U- shape test indicates a p-value below 0.05. The average 'optimal' threshold for the Lerner index is equal to 0.606, and to 49% for the market share. The Lerner index refers to the adjusted Lerner index proposed by Koetter et al. (2012). The red dash line corresponds to the 95% confidence interval for the Lerner index, while the blue dash line corresponds to the 95% confidence interval for the market share. More precisely, the confidence intervals reported in this graph correspond to the average of the upper and lower confidence bounds calculated by considering all specifications for which the U-shape test indicates a non-linear relationship statistically significant at the 5% level.

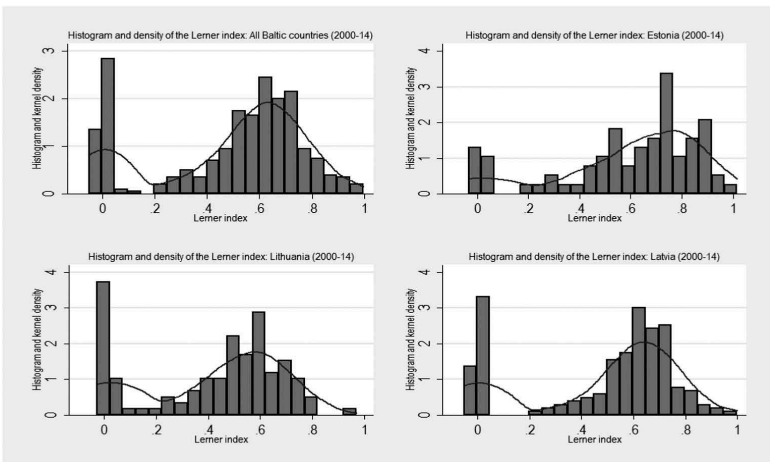

Figure A3. Histogram and kernel density plot of the Lerner index.

Note: The Lerner index refers to the adjusted Lerner index proposed by Koetter et al. (2012).

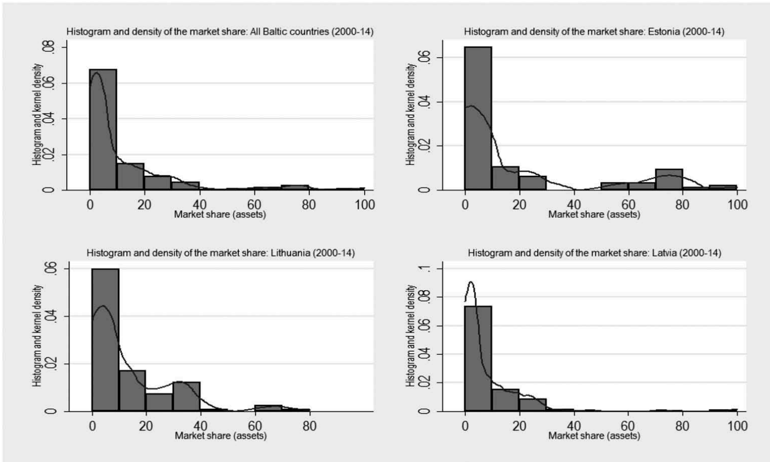

Figure A4. Histogram and kernel density plot of the market share.

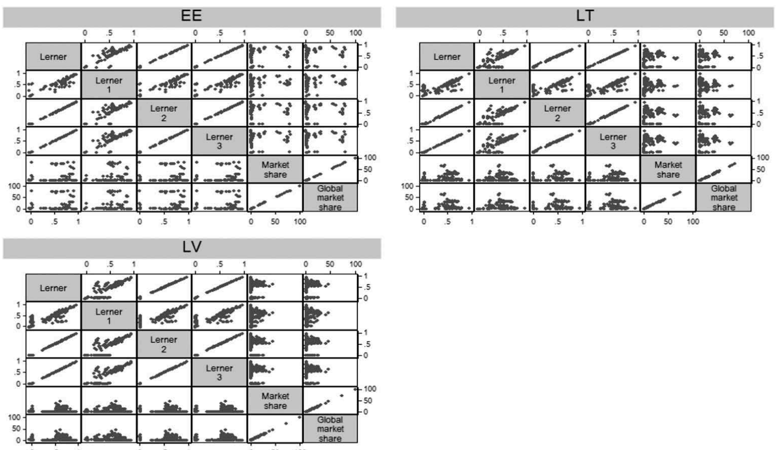

Figure A5. Correlation between alternative measures of market power for each Baltic country.

Note: EE: Estonia; LT: Lithuania; LV: Latvia. Lerner refers to the adjusted Lerner index proposed by Koetter et al. (2012). Lerner 1 to the 3-year moving average Lerner index, Lerner 2 to the funding-adjusted Lerner index, Lerner 3 to the left-censored Lerner index, Market share to the market share based on assets, and global market share to the market share calculated by considering assets, loans and deposits.

Appendix 5

Publication V

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RESEARCH ARTICLE

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The evolution and heterogeneity of credit procyclicality in Central and Eastern Europe

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Abstract

This article presents empirical estimates of bank credit procyclicality for a sample of 11 Central and Eastern European countries (CEECs) for the period 2000Q1–2016Q4. In the first step, we estimate a traditional-type panel vector autoregressive (VAR) model and analyse the evolution of credit procyclicality in the CEECs by comparing the impulse response functions for different business cycle periods. The results confirm the existence of credit procyclicality in the CEECs and show that procyclicality is higher during boom periods. Furthermore, we observe the heterogeneity of credit procyclicality in the different countries in our sample. To explain the cross-country heterogeneity in credit procyclicality we construct an interacted panel VAR model and analyse whether bank-level competition, proxied by the aggregate Lerner index, constitutes a driving force of credit procyclicality. Our findings indicate that bank competition affects credit procyclicality and explains the differences in credit dynamics across the CEECs. Specifically, we show that the reaction of credit to a gross domestic product shock is on average higher in a less competitive banking market.

KEYWORDS

bank competition, business cycle, CEEC, credit cycle, interacted panel VAR

JEL CLASSIFICATION

E32; E51; G20; D40; C33

1 | INTRODUCTION

In this article, we study how banking competition contributes to the procyclicality of credit for a group of Central and Eastern European countries (CEECs).

The strong growth in credit in the run up to the financial crisis in the CEECs has been called ‘one of the major pervasive developments’ of the time (Enoch & Ötker-Robe, 2007). Zdzienicka (2011) shows that even when the convergence process towards Western European standards and country-specific financial development indicators are accounted for, Bulgaria, the Czech Republic, Estonia, Latvia, Lithuania and Slovenia among the CEECs showed deviations in credit above the long-term equilibrium that can be determined from fundamentals. In Estonia, Latvia and Lithuania, those credit booms were followed by credit-to-GDP ratios that were not just below trend but well below credit crunch thresholds when the financial crisis reached its most severe stage in 2010.[1]

After the eruption of the financial crisis and the realisation of how necessary it was to improve the regulatory policies in the banking sector around the world, there has been increasing concern about how competition in the banking sector affects financial stability. Recent contributions are Cuestas, Lucotte, and Reigl (2017) for the CEECs and Leroy and Lucotte (2017) for Europe. These two articles, highlight the existence of an inverse U-shaped link between financial stability and competition, reconciling the competition-fragility view and the competition-stability view.

This line of research needs to be complemented by an analysis of how banking competition may affect the procyclicality of credit observed in Central and Eastern Europe. The procyclicality of credit needs to be understood because it can exacerbate the economic cycle by making booms unsustainable much faster, and busts too painful, because it causes economic recovery to be delayed for too long. During recessions potential borrowers may be seen as riskier as their creditworthiness may have been affected by the drop in economic activity, and this then reduces the amount of credit that is released, affecting investment and consumption negatively. The opposite may occur during booms (Berger, Demirgüç-Kunt, Levine, & Haubrich, 2004). A review of the most recent literature on the nexus between credit and the economic cycle can be found in Leroy and Lucotte (2019). As these authors point out, research in this area is moving towards identifying the factors that may contribute to the procyclicality of credit.

Following this recent strand of the literature, we aim to analyse how far the idiosyncratic reactions of credit to gross domestic product (GDP) innovations may be explained by differences in banking sector competition. Specifically, we look to answer the following three questions: (a) does the procyclicality of bank credit vary over the phases of the business cycle? (b) Can we observe differences in credit procyclicality across the CEECs? (c) Does bank competition in these countries condition the procyclicality of credit? The first question is motivated by Jordà, Schularick, and Taylor (2013), who show that countries with a higher level of private indebtedness tend to experience deeper recessions. More recently Cuestas et al. (2017) show that there is a bidirectional causality between foreign liabilities and private domestic credit in some European countries from the periphery.

The second and third questions relate, respectively, to testing the hypotheses of competition-fragility and competition-stability in the banking sector. The competition-fragility view claims that high levels of competition may encourage banks to take on greater risks and behave less responsibly by lending more during boom times but curbing lending excessively during recessions, which would increase the procyclicality of credit. However, the competition-stability view claims that high levels of competition may reduce lending rates, shifting the focus to borrowers with high credit ratings and reducing the moral hazard incentives to engage in riskier projects. This would mean that less credit is released during boom times and so the procyclicality of credit is reduced. High levels of competition may also reduce asymmetric information as banks may seek to establish long-term relationships with their clients, meaning they hold more information on the creditworthiness of those clients (Boot & Thakor, 2000). This may also give an incentive to banks to increase their screening and monitoring of borrowers by investing in technology that can produce more detailed information (Gehrig, 1998).

The previous literature on the issue has produced mixed results. Bouvatier, López-Villavicencio, and Mignon (2012) show that competition in the banking sector does not seem to clarify the issue, as different countries with different degrees of banking competition do not seem to experience different degrees of cyclicality of credit. Leroy and Lucotte (2019) apply a different methodology based on interactive panel VARs (IPVAR) and find that differences in banking sector competition in a group of western European countries can actually explain why countries may show different degrees of procyclicality. To this extent the authors show that banking competition reduces procyclicality.

In this article, we follow the macro analysis of Leroy and Lucotte (2019) and apply the IPVAR method to a group of banks from Central and Eastern Europe to answer the three main questions. To the best of our knowledge this is the first attempt to focus on this group of countries. In this article, we use a panel vector autoregressive (VAR) model to analyse the evolution of bank credit procyclicality in the CEECs, and to assess how this procyclicality evolved in the aftermath of the sub-prime crisis. We then extend our empirical investigation by evaluating the cross-country heterogeneity in credit procyclicality. To this end, we estimate a country-specific VAR model and compare the differences in credit procyclicality across the CEECs. Finally, we use an IPVAR framework to test whether the differences in credit procyclicality across Central and Eastern European economies could potentially be explained by differences in banking sector competition, which is proxied by an aggregate Lerner index.

The remainder of the article is organised as follows. Section 2 provides a summary of the literature on the issue. Section 3 shows some stylised facts about credit procyclicality in the CEECs. Section 4 explains the cross-country idiosyncrasies in credit procyclicality in our target countries. In Section 5, we explore whether banking competition matters for this heterogeneity, in Section 6, we run some robustness checks, and then the final section concludes.

2 | RELATED LITERATURE

The idea that financial shocks feed back to the real economy dates back at least to Fisher (1933), but after World War II the notion of financial booms followed by busts feeding into the real economy remained on the side-lines of macroeconomic debate. It was considered either that financial factors delayed the return of the economy to a steady state after the impact of economic shocks (Bernanke, Gertler, & Gilchrist, 1999) or that they could be ignored in efforts to understand business cycle fluctuations (Woodford, 2011). The financial crisis of 2007–2008 has reinvigorated interest in understanding the interplay between financial factors and the business cycle. Macroeconomists have incorporated financial frictions into new Keynesian dynamic stochastic general equilibrium models, and have analysed the pattern of credit-driven boom-bust cycles. In one seminal contribution, Borio (2014) highlights some important points about the financial cycle, noting that it may be explained by taking credit and housing prices into account since it could be less frequent than the traditional business cycle, meaning that peak periods can be followed quickly by financial crises. The frequency and amplitude of the financial cycle depend on policy regimes, most importantly the financial regime, the monetary regime and the real-economy regime.[2]

Procyclicality in the banking sector has been researched with a different focus. Some studies have, for example, analysed the behaviour of demand and supply of loans and their role in economic activity (Bassett, Chosak, Driscoll, & Zakrajšek, 2014; Lown & Morgan, 2006), while others have examined the procyclical behaviour of banking sector profits (Albertazzi & Gambacorta, 2009; Gambacorta, 2016). Most empirical findings indicate that bank credit tends to behave procyclically (Bouvatier, López-Villavicencio, & Mignon, 2014; Panetta et al., 2009). As the variations in lending tend to be more directly linked to the real economy, the dynamics of the loan supply from banks tend to accentuate the business cycle (Berger et al., 2004). Furthermore, credit extensions during business cycle boom periods are often followed by financial crises (Jordà et al., 2013).

Other studies analyse the determinants which may affect the procyclicality of the banking sector. Following Athanasoglou, Daniilidis, and Delis (2014), the potential determinants are, amongst others, the regulatory and supervisory framework, monetary policy, the practices of financial firms such as, for example, their behaviour in acquiring debt and their remuneration policies, and reports from credit rating agencies or the use of automated risk management systems. Various studies suggest that risk management systems such as the Basel I and II framework tend to reinforce banking sector procyclicality instead of smoothing it (Jokipii & Milne, 2008; Kashyap, Rajan, & Stein, 2008). The Basel I and II regulations featured loose capital requirements during periods of economic stability, but enforced tighter capital requirements during economic downturns, which throttled the supply of loans from banks. By contrast, the new Basel III regulations explicitly address the issue of procyclicality by introducing countercyclical capital buffers (Athanasoglou et al., 2014).

There is a lot less literature on the relationship between the structure of the banking sector and credit procyclicality. Dell'Ariccia and Marquez (2006) present a theoretical model in this vein of credit booms driven by increases in competition. Faced with the threat of competition, the incumbent switches from a detailed screening of lenders to lower lending standards, thus increasing the volume of lending but also causing a deterioration in the loan portfolio and so increasing financial fragility. However, the boom increases aggregate output, unlike the inefficient booms modelled by Petriconi (2015). His research shows how more competition between banks can generate inefficient lending booms and pronounced business cycles. This is first because the informed incumbent finds it optimal for a given precision of borrower screening to poison the well for uninformed competitors by lowering credit standards and providing financing for projects that have negative expected net present value. The study also finds that when borrower screening is chosen endogenously, competition during boom periods reduces screening precision to low and inefficient levels that can explain the lending cycles that diminish welfare.

Bouvatier et al. (2012) take the empirical point of view and investigate the relationship between the structure of the banking sector and credit procyclicality. Using hierarchal clustering methods to classify the structures of the banking systems of 17 OECD countries, they estimate a panel VAR model on the resulting sub-groups of countries. Their results highlight that while credit responds significantly to shocks to GDP, the structure of the banking sector is not a determinant of credit procyclicality. In related research Bouvatier et al. (2014) analyse the characteristics of credit that may be procyclical for sample OECD countries using a smooth transition regression model. They show that in some countries, nonlinearities in credit dynamics are driven by the position of the business cycle or by housing prices.

Leroy and Lucotte (2019) investigate how banking competition affects credit procyclicality for a large sample of Western European countries. Estimating an interacted panel VAR (IPVAR) model using macroeconomic data and a single-equation approach provides evidence that rapid credit increases and declines in lending are less important when banks compete fiercely. These results indicate that greater competition in the financial industry decreases the chances of financial distress.

Researchers have not studied the evolution or the heterogeneity of credit in CEECs in these terms. Given the specific characteristics of the banking sector in the CEECs, such as a highly concentrated banking sector in the Baltic States, our research contributes to the existing literature by analysing how credit procyclicality varies over the business cycle and across countries while also providing evidence that concentration in the banking sector can drive credit procyclicality.

3 | THE EVOLUTION OF CREDIT PROCYCLICALITY IN CENTRAL AND EASTERN EUROPE

We start our empirical analysis by investigating the evolution of bank credit procyclicality in the CEECs and whether this procyclicality varies over the phases of the business cycle. To this end, we use a panel VAR framework and consider four macroeconomic variables, which are real GDP, the consumer price index (CPI), the real outstanding amount of credit to the private non-financial sector, and the nominal short-term interest rate. These variables are taken from the International Financial Statistics of the International Monetary Fund (2019).[3] We consider quarterly data over the period 2000Q1–2016Q4 for a sample of 11 CEECs, which are Bulgaria, Croatia, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia.

Since our focus lies on short-term economic fluctuations, we remove trends and work over the cyclical components of the time series. This approach has at least two main advantages. From an economic point of view, it makes it possible to assess whether bank credit reacts to an unexpected change in GDP. From the econometric viewpoint, it ensures a stationary series. We isolate the cyclical components of the series by using the usual Hodrick–Prescott (HP) filter (Hodrick & Prescott, 1981, 1997). The HP filter is applied to the seasonally adjusted series over the period 2000Q1–2016Q4 by setting a smoothing parameter at 1600, as is usual for quarterly data.[4] More precisely, we consider the percentage gap between the observed values and the trend values for the CPI, real GDP and the credit series, while the interest rate variable is the cyclical component deduced from the HP filter.

Our main variables of interest are the business cycle and the credit cycle. Following Bouvatier et al. (2012) and Leroy and Lucotte (2019), we define credit procyclicality as the orthogonalised impulse response function of the credit cycle to a business cycle shock. The reduced form of the panel VAR model that we estimate is:

$$Y_{i,t} = c_i + A(L)Y_{i,t} + \varepsilon_{i,t} \tag{1}$$

where i and t are country and time, respectively, $Y_{i,t}$ is the vector of endogenous variables, $\varepsilon_{i,t}$ is the vector of errors, c_i is the country-specific intercepts matrix and $A(L)$ is the polynomial matrix in the lag operator, L say. The optimal number of lags L is determined by the Schwartz information criterion (BIC) and is equal to two.

The vector $Y_{i,t}$ is given by:

$$Y_{i,t} = (\mathrm{INF}_{i,t}, \mathrm{OG}_{i,t}, \mathrm{CRED}_{i,t}, r_{i,t}) \tag{2}$$

where $\mathrm{INF}_{i,t}$ is the inflation gap, $\mathrm{OG}_{i,t}$ the output gap, $\mathrm{CRED}_{i,t}$ the credit gap and $r_{i,t}$ the cyclical component of the interest rate, and these gaps have been obtained as the cyclical component obtained by the HP filter above. We estimate Equation (1) using a fixed effects (FE) estimator. To obtain the impulse-response functions (IRFs), we first estimate the IPVAR, and apply the following ordering for the variables by means of Cholesky decomposition: INF, OG, CRED and r. The positions of inflation and the output gap are customary in the literature. This implies that financial variables may respond contemporaneously to real shocks but the ordering of the financial variables is subject to some discussion. Following Assenmacher and Gerlach (2008) and Bouvatier et al. (2012), we place bank credit before the short-term interest rate in our recursive identification scheme. Indeed a number of articles that investigate the issue of monetary policy transmission (see, e.g., Leroy and Lucotte (2015)) have shown that the bank interest rate pass-through is sluggish in the short term, explaining why credit does not respond immediately to an interest rate shock.[5]

To assess the evolution of credit procyclicality in the CEECs, we estimate the panel VAR model by considering different sub-periods. We apply the analysis to panel data to gain robustness in the analysis by accounting for cross-section information, capturing both static and dynamic interdependencies, treating the links across countries or units in an unrestricted fashion easily incorporating time variations in the coefficients and in the variance of the shocks, and accounting for cross-sectional dynamic heterogeneities, which we would lose in a time series analysis. In addition in our IPVAR estimations, we need to account for this cross-section information in order to

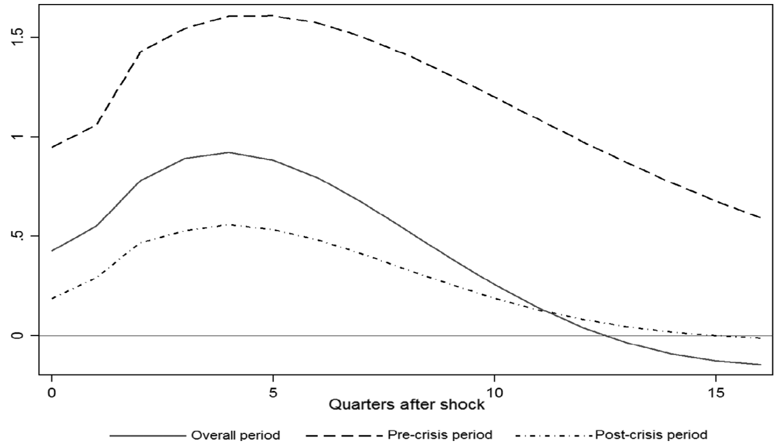


FIGURE 1 Evolution of credit procyclicality in CEECs in the aftermath of the sub-prime crisis. The figure displays the impulse responses of bank credit to a one-unit shock in the output gap by considering three different periods: the overall period (2000Q1–2016Q4), the pre-crisis period (2000Q1–2007Q4) and the post-crisis period (2008Q1–2016Q4). Confidence intervals for each impulse response function are reported in Figure A3 in the Appendix. CEECs, Central and Eastern European countries

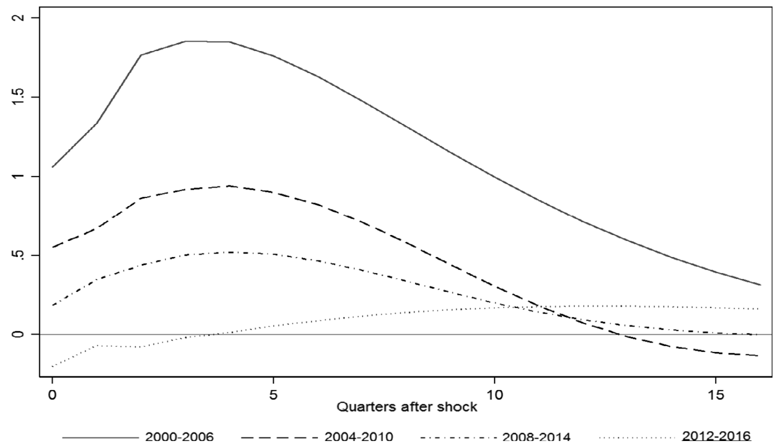


FIGURE 2 Evolution of credit procyclicality in CEECs between 2000 and 2016. The figure displays the impulse responses of bank credit to a one-unit shock in the output gap by considering four different overlapping sub-periods: 2000Q1–2006Q4, 2004Q1–2010Q4, 2008Q1–2014Q4, 2012Q1–2016Q4. Confidence intervals for each impulse response function are reported in Figure A4 in the Appendix. CEECs, Central and Eastern European countries

condition the models. First, we distinguish between the periods before and after the financial crisis. Figure 1 displays the IRFs of bank credit to a one-unit shock in the output gap by considering three different periods: the overall period (2000Q1–2016Q4), the pre-crisis period (2000Q1–2007Q4) and the post-crisis period (2008Q1–2016Q4). For the sake of readability, we do not report the confidence bands, but the full set of results are reported in Figure A3 in the Appendix. The results obtained for the overall period confirm the existence of credit procyclicality in the CEECs and show that a GDP cycle shock has a positive and significant impact on bank credit. The peak impact occurs four quarters after the shock, and the effect of the output gap on the credit gap appears relatively persistent. More importantly, we observe that the degree of credit procyclicality is more or less pronounced depending on the economic conditions. The IRFs suggest that credit procyclicality was higher before the crisis and tended to be weaker in the aftermath of the sub-prime crisis.

We observe comparable patterns in Figure 2, in which we consider four overlapping sub-periods: 2000Q1–2006Q4, 2004Q1–2010Q4, 2008Q1–2014Q4 and 2012Q1–2016Q4. The degree of procyclicality appears relatively high over the period 2000Q1–2006Q4, with the peak impact occurring three quarters after the shock in GDP, and then it tends to decrease during the subsequent periods. As Figure A4 in the Appendix suggests, the effect of the output gap on the credit gap is not statistically significant over the period 2012Q1–2016Q4. Similar results are obtained when we estimate the panel VAR system on 7-year rolling windows. The IRFs reported in Figure 3 clearly show a continued decline in the magnitude of bank credit procyclicality during the period

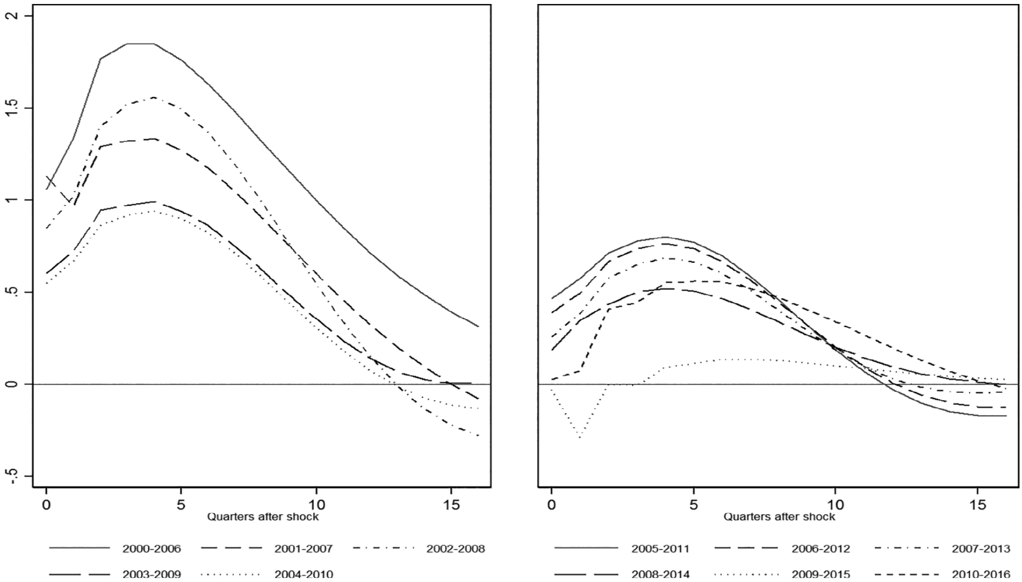


FIGURE 3 Evolution of credit procyclicality in CEECs: Rolling estimates. The figure displays the impulse responses of bank credit to a one-unit shock in the output gap by considering 7-year rolling windows. Confidence intervals for each impulse response function are reported in Figure A5 in the Appendix. CEECs, Central and Eastern European countries

considered, especially in the aftermath of the subprime crisis.

As Bouvatier et al. (2014) argue, the greater procyclicality of bank credit before the crisis could arise because these periods typically have large increases in property and share prices that, in turn, affect the credit gap. This means that the short-run credit behaviour of banks could also be driven by variables other than the business cycle, such as financial assets. Indeed, not only do rising housing prices exert wealth effect on credit demand, but asset and property prices also serve as a collateral, and this makes banks more willing to extend loans during booms and upturns in the business cycle, leading to an increase in the supply of credit to the private sector. Moreover, as Jiménez and Saurina (2006) show, such asymmetries in credit procyclicality could also be explained by the way that the credit policies of banks for collateral requirements depend on the business cycle position. Using bank-level data, Jiménez and Saurina (2006) show clear evidence that banks tend to relax credit standards in boom periods, while the opposite happens in recessions. More precisely, their results indicate that the likelihood of collateral being pledged decreases proportionally more in upturns than it increases in downturns, leading to a rapid growth in credit in good times. One potential explanation for the more lenient credit standards during expansion phases is the misperception of how risk evolves over time (Borio et al., 2001), which leads banks to underestimate risk during the upswing, and through this contributes to excessively rapid credit growth.

4 | CROSS-COUNTRY HETEROGENEITY IN CREDIT PROCYCLICALITY

We extend our previous empirical investigation by assessing the cross-country heterogeneity in credit procyclicality. As before, our main variables of interest are the output gap and the credit gap. Table 1 presents some descriptive statistics of these variables for each economy in our sample. More precisely, we report the first-order autocorrelation for each series and the pairwise correlation between the output gap and the credit gap by considering four different lag structures for the output gap, with 1 lag, 2 lags, 3 lags and 4 lags. These statistics are calculated for the overall period of 2000Q1–2016Q4. It is apparent that credit and business cycles typically have a relatively high degree of persistence, with a first-order autocorrelation of around 0.85, even if the heterogeneity between countries is more important for the credit cycle. More importantly, we can see that the correlation between the two cycles is positive and statistically significant, confirming that credit and

TABLE 1 Descriptive statistics: Output gap and credit gap

	Output gap First-order autocorr.	Credit gap First-order autocorr.	Pairwise correlation—Overall period (2000Q1–2016Q4) 1 lag	2 lags	3 lags	4lags
Bulgaria	0.873	0.936	0.450*	0.550*	0.592*	0.569*
Croatia	0.842	0.776	0.504*	0.462*	0.416*	0.267*
Czech Rep.	0.882	0.895	0.618*	0.600*	0.547*	0.469*
Estonia	0.913	0.930	0.303*	0.389*	0.463*	0.530*
Hungary	0.872	0.625	0.181	0.319*	0.356*	0.331*
Latvia	0.919	0.891	0.347*	0.406*	0.463*	0.499*
Lithuania	0.881	0.971	0.322*	0.408*	0.511*	0.559*
Poland	0.752	0.901	0.373*	0.464*	0.542*	0.567*
Romania	0.840	0.901	0.502*	0.569*	0.602*	0.514*
Slovak Rep.	0.785	0.858	0.620*	0.624*	0.652*	0.553*
Slovenia	0.896	0.886	0.437*	0.483*	0.503*	0.510*
Mean	0.860	0.870	0.423	0.479	0.513	0.488
Median	0.873	0.895	0.437	0.464	0.511	0.514
St. dev.	0.052	0.095	0.135	0.097	0.086	0.099

Note: Authors' calculations, International Financial Statistics, International Monetary Fund. The correlation between the output gap and the credit gap is calculated by considering four different lag structures for the output gap: 1 lag, 2 lags, 3 lags and 4 lags. An asterisk indicates that the correlation is significant at the 5% level.

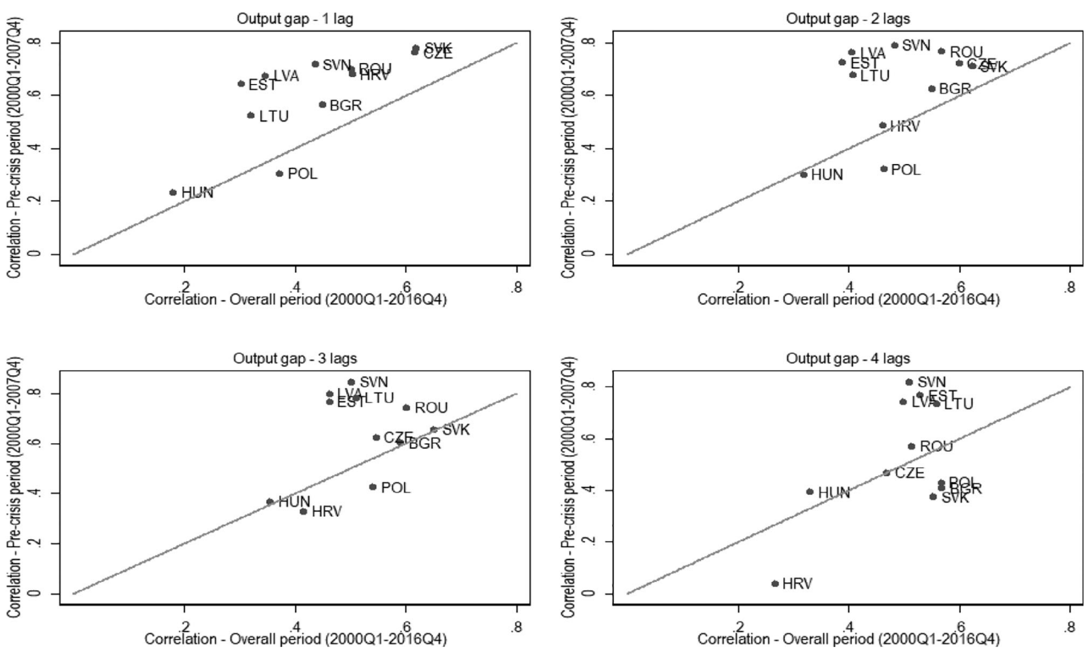


FIGURE 4 Credit and business cycles correlation. Authors' calculations, International Financial Statistics, International Monetary Fund. This figure displays the pairwise correlation between the output gap and the credit gap for the overall period (2000Q1–2016Q4) and the pre-crisis period (2000Q1–2007Q4). The correlation is calculated by considering four different lag structures for the output gap: 1 lag, 2 lags, 3 lags and 4 lags

business cycles are closely linked, even if this correlation appears more pronounced in some countries.[6]

In Figure 4, we compare the correlation between the output gap and the credit gap in the overall period (2000Q1–2016Q4) and in the pre-crisis period (2000Q1–2007Q4). As in Table 1, we consider different lag structures for the output gap. In line with the panel VAR results discussed in the previous section, we can see that most of the countries are located above the 45° line, confirming that the correlation between the two cycles was relatively important during the pre-crisis period, even if the heterogeneity among countries appears more important when the output gap is lagged three or four quarters.

To assess the differences in credit procyclicality across CEECs formally, we estimate a country-specific VAR model for each economy considered in our sample. The VAR model that we consider is the same as those presented above. It comprises the same four endogenous variables (INF, OG, CRED and r) and the identification scheme for computing the individual IRFs is similar. For each country in our sample, we estimate the VAR model using an ordinary least squares (OLS) estimator over the period 2000Q1–2016Q4 (68 observations), and the optimal number of lags is determined by the BIC.

Figure 5 displays the orthogonalised country-specific responses of bank credit to a one-unit shock in the output gap with a simulation horizon of 16 quarters.[7] For the sake of readability, we do not report the confidence bands, but the full set of results is reported in Figure A6 in the Appendix. In most countries, a GDP cycle shock affects the credit cycle contemporaneously and positively. The only exception is Hungary, where the response is initially negative and becomes positive and statistically significant after four quarters. Figure A6 in the Appendix suggests that for the Czech Republic and Slovenia, the confidence intervals are larger than they are for the other countries, rejecting the suggestion that the business cycle has a significant effect on the credit cycle. Overall, Figure 5 clearly shows that the magnitude and the persistence of an output gap shock are widely different across countries, suggesting major asymmetries in credit procyclicality within Central and Eastern European economies.

The comparison of the peak values in Figure 6 confirms the cross-country heterogeneity in credit procyclicality. Indeed, the peak value appears relatively high at more than 1.5 for Bulgaria, Poland, and the Czech Republic, while it is close to 0.5 for Estonia. In most cases, the peak impact occurs three or four quarters after the shock.

As mentioned in the previous paragraphs, we observe a high degree of heterogeneity in the results. We have to bear in mind that we are mixing in the same pool

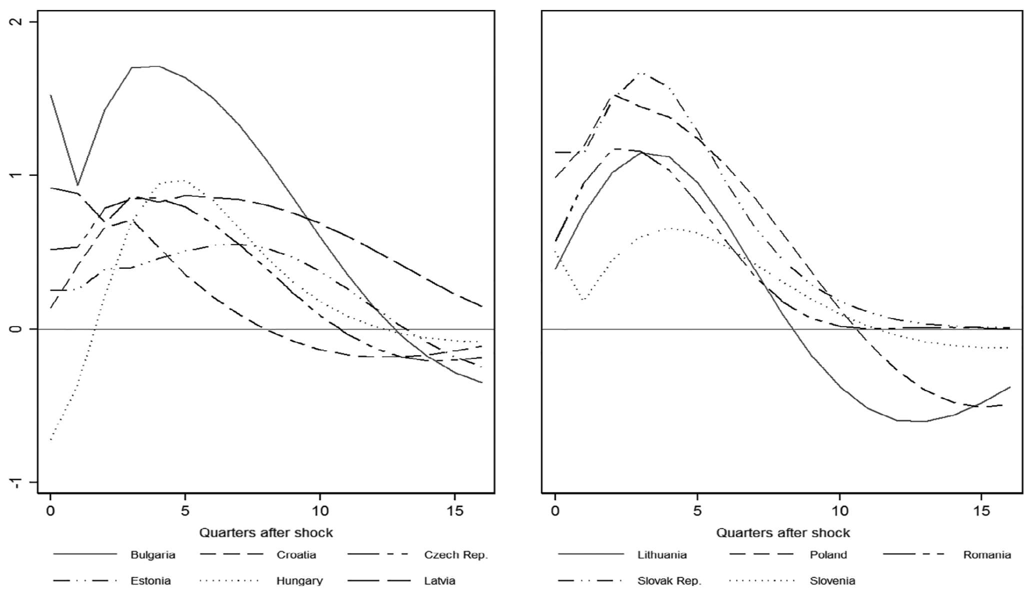


FIGURE 5 Country-specific impulse response functions of bank credit to a GDP shock. The figure displays the country-specific impulse response functions of bank credit to a one-unit shock in the output gap on the overall period (2000Q1–2016Q4). Confidence intervals for each impulse response function are reported in Figure A6 in the Appendix

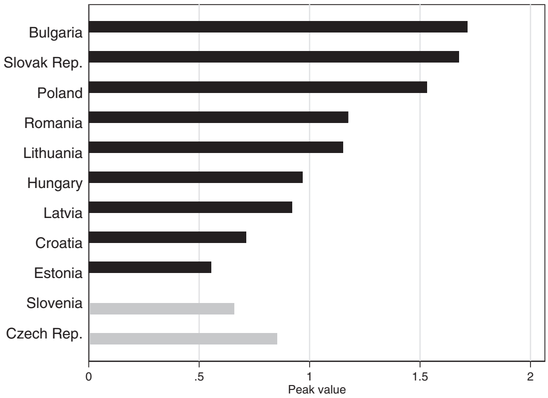


FIGURE 6 Peak value of the response of bank credit to a GDP shock. The figure displays the peak value of the response of bank credit to a one-unit shock in the output gap on the overall period (2000Q1–2016Q4). A grey bar corresponds to a peak which is not statistically significant. See Figure A6 in the Appendix for more details. GDP, gross domestic product

countries with different degrees of financial and economic integration to the rest of the EU and with strong financial links with different EU countries. In addition the degree of economic and institutional development, which also differs between them, plays a role in determining the relationship between GDP shocks and the reaction of bank credit. Different central banks impose different capital buffers, which affected the response of the housing market during the crisis that started in 2008.

5 | DOES BANKING COMPETITION MATTER?

In this section, we investigate empirically if bank competition is an explanatory variable for the credit procyclicality in the CEECs, and then whether it could explain the cross-country heterogeneity in credit procyclicality highlighted above. Leroy and Lucotte (2019) have recently shown for a large sample of Western European countries that a low level of competition in the banking sector could increase the response of loans to the business cycle, increasing the speed of transmission of a real activity shock to the credit market.

Following the recent banking literature (see, e.g., Berger, Klapper, and Turk-Ariss (2009); Beck, Jonghe, and Schepens (2013), and Anginer, Demirguc-Kunt, and Zhu (2014)), we use the Lerner index as an inverse proxy for bank competition. The Lerner index is a non-structural measure of competition that is designed to measure the pricing power of firms. It corresponds to the mark-up of price over marginal cost. The Lerner index is bounded between 0 and 1, with the extreme value of zero corresponding to perfect competition, and the value of one to a pure monopoly. Formally, the Lerner index is calculated as the difference between price and marginal cost as a proportion of price:

$$\text{Lerner}_{it} = \frac{p_{it} - mc_{it}}{p_{it}} \tag{3}$$

with p_{it} as the price and mc_{it} as the marginal cost for bank i in period t. Under the assumption that the flow of services given by a bank is proportional to its total assets, the price p_{it} is obtained as the ratio of total bank revenue to total assets, while the marginal cost is computed using a translog cost function with respect to output (see Beck et al. (2013)).

Given the macroeconomic focus of our study, we consider for each country in our sample an aggregate Lerner index that corresponds to the median of the individual Lerner indexes. The variable is taken from the Global Financial Development Database of the World Bank and is available from 2000 to 2015. The Lerner index is computed annually, and so we match the variable to the quarterly frequency of our study by considering the same value of the Lerner index for each quarter of a given year.[8]

To test whether the differences in credit procyclicality across Central and Eastern European economies could be explained by differences in the level of banking sector competition, we use the IPVAR framework proposed by Towbin and Weber (2013). As previously, we define credit procyclicality as the orthogonalised impulse response function of the credit cycle to a GDP cycle shock. The main advantage of the IPVAR framework is that the autoregressive parameters are functions of the cross-time-varying level of banking sector competition. In this way, we are accounting for the time-varying level of competition in the banking industry as an exogenous determinant affecting the credit response to a GDP shock.

The structural form of the IPVAR model that we estimate is given by:
where i and t are indexes of country and time, respectively, $\text{INF}_{i,t}$ is the inflation gap, $\text{OG}_{i,t}$ the output gap, $\text{CRED}_{i,t}$ the credit gap, $r_{i,t}$ the cyclical component of the interest rate, $\varepsilon_{i,t}$ a vector of uncorrelated iid shocks and L the number of lags. μ_i is a country-specific intercept. The Lerner index ($\text{Lerner}_{i,t-4}$) is lagged four quarters to address the issue of potential endogeneity and is considered as an exogenous control variable. $\alpha_{l,it}^{jk}$ are deterministically varying coefficients as a function of the level of banking competition, which is proxied by the Lerner index.

In order to analyse whether the response of the credit cycle to a GDP shock varies with the level of bank

$$\begin{pmatrix} 1 & 0 & 0 & 0 \\ \alpha_{0,it}^{21} & 1 & 0 & 0 \\ \alpha_{0,it}^{31} & \alpha_{0,it}^{32} & 1 & 0 \\ \alpha_{0,it}^{41} & \alpha_{0,it}^{42} & \alpha_{0,it}^{43} & 1 \end{pmatrix} \begin{pmatrix} \mathrm{INF}_{i,t} \\ \mathrm{OG}_{i,t} \\ \mathrm{CRED}_{i,t} \\ r_{i,t} \end{pmatrix} = \mu_i + \sum_{l=1}^{L} \begin{pmatrix} \alpha_{l,it}^{11} & \alpha_{l,it}^{12} & \alpha_{l,it}^{13} & \alpha_{l,it}^{14} \\ \alpha_{l,it}^{21} & \alpha_{l,it}^{22} & \alpha_{l,it}^{23} & \alpha_{l,it}^{24} \\ \alpha_{l,it}^{31} & \alpha_{l,it}^{32} & \alpha_{l,it}^{33} & \alpha_{l,it}^{34} \\ \alpha_{l,it}^{41} & \alpha_{l,it}^{42} & \alpha_{l,it}^{43} & \alpha_{l,it}^{44} \end{pmatrix} \begin{pmatrix} \mathrm{INF}_{i,t-l} \\ \mathrm{OG}_{i,t-l} \\ \mathrm{CRED}_{i,t-l} \\ r_{i,t-l} \end{pmatrix} + \begin{pmatrix} \chi^{11} \\ \chi^{21} \\ \chi^{31} \\ \chi^{41} \end{pmatrix} \mathrm{Lerner}_{i,t-4} + \varepsilon_{i,t} \tag{4}$$

competition, we allow for interaction terms so that the coefficients in Equation (4) are given by:

$$\alpha_{l,it}^{jk} = \beta_l^{jk} + \eta_l^{jk} \mathrm{Lerner}_{i,t-4} \tag{5}$$

where β_l^{jk} and η_l^{jk} are two vectors of coefficients, and $\mathrm{Lerner}_{i,t-4}$ is the aggregate Lerner index, which is a cross-time-varying inverse proxy for bank competition. Unlike in a traditional panel VAR model, the structural parameters $\alpha_{l,it}^{jk}$ vary over time and across countries with the level of competition in the banking sector. Moreover, we do not impose restrictions on the interaction terms and we assume that all the autoregressive parameters of the VAR system are dependent on competition, which means that all variable dynamics are conditional on the level of competition in the banking sector.

We estimate the IPVAR model using OLS and allow for country FE to control for unobserved unit-specific factors. In this way, we control for structural characteristics other than banking competition that could explain the differences in credit procyclicality across the CEECs. Since the error terms are uncorrelated across equations by construction, we are able to estimate the IPVAR model equation by equation in an efficient way. The lag length and the Cholesky ordering are the same as for the panel VAR estimated in Section 3.

After the IPVAR is estimated, we conduct a structural analysis to assess whether the level of bank competition drives the response of credit to a GDP shock and so could explain differences in credit procyclicality across the CEECs. More precisely, we test in two ways whether the interactions with the degree of bank competition affect the dynamics of the variables. First, we generate the impulse responses of bank credit to a one-unit GDP cycle shock at different percentiles of the sample distribution of the Lerner index. Figure 7 displays the impulse response functions that we obtain.[9] All the impulse responses correspond to the average effects across the countries in our sample. Figure 7 clearly indicates that the response of the credit cycle to an output gap shock tends to decrease when the Lerner index decreases. As the Lerner index is an inverse proxy for competition, this means that the procyclicality of bank credit is greater when the competition within the banking industry is relatively weak, and it is less when the competition between banks is fierce.

Second, we go a step further and assess whether the orthogonalised responses of bank credit to a GDP cycle shock are statistically different for lower and higher levels of bank competition. To this end, we set the Lerner index to be at the 80th percentile and at the 20th percentile of its sample distribution and calculate the difference between the two responses of interest. In this way, we clearly address our initial question of how credit procyclicality could potentially change if the level of competition in the banking sector moved from a lower level to a higher level. Figure 8 presents the IRFs that we obtain. The chart on the left of the figure presents the impulse response function obtained by setting a Lerner index at the 80th percentile of the distribution, and hence it illustrates the mean response of credit in countries where the banking sector is more imperfectly competitive. The chart in the centre shows the impulse response function evaluated at the 20th percentile of the Lerner index sample distribution, where competition between banks is relatively fierce. In both cases, the solid lines are the average responses with a 95% confidence band, obtained by a bootstrap with 1,000 draws. Finally, the chart on the right displays the differences between

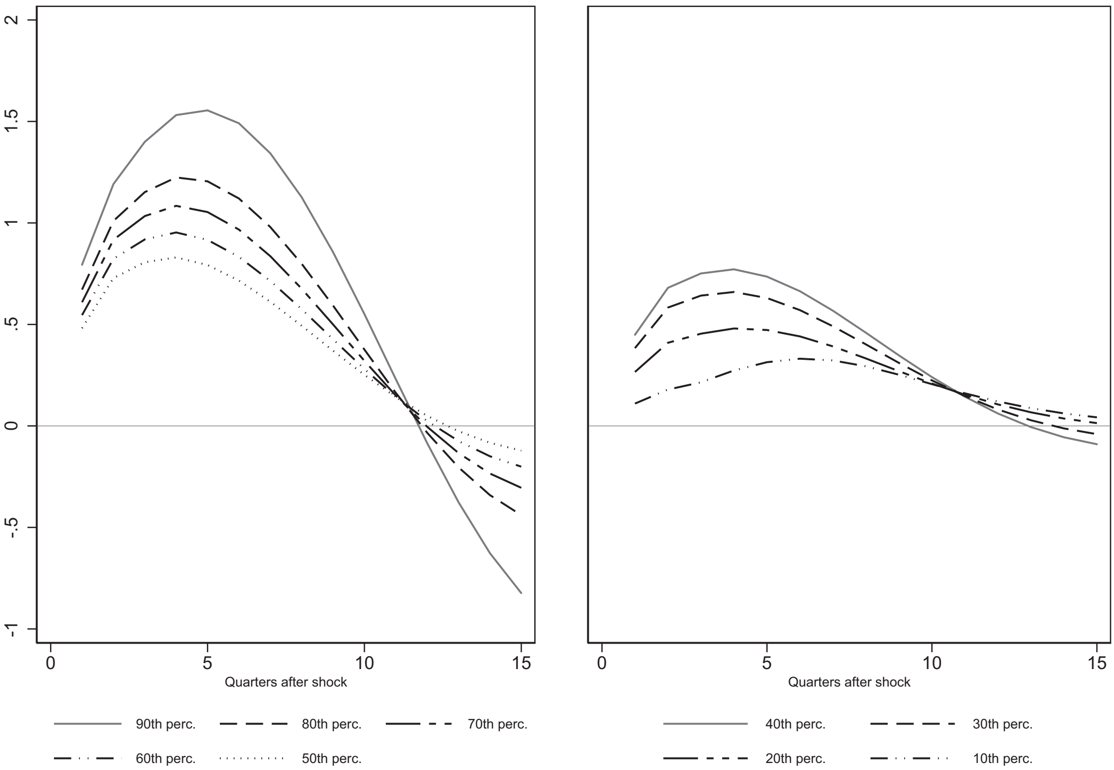


FIGURE 7 Impulse response functions of bank credit to a GDP shock for different levels of bank competition. The figure displays the impulse response functions of bank credit to a one-unit shock in the output gap evaluated at different percentiles of the Lerner index sample distribution. Confidence intervals for each impulse response function are reported in Figure A9 in the Appendix. GDP, gross domestic product

the average response functions for the lower and the higher degrees of competition in the banking industry with a 95% confidence band.

The results that we obtain confirm our previous findings. Bank competition affects credit procyclicality and explains the differences in credit dynamics across the CEECs. Indeed, we find a positive and statistically significant difference between the two IRFs, which means that the reaction of credit to a GDP cycle shock is on average greater in a less competitive banking market. This indicates that credit increases and decreases are less pronounced when bank competition is stronger, and that more competition can absorb shocks more easily. Our results are similar to those obtained by Leroy and Lucotte (2019) for Western Europe.

Three main explanations can be advanced for this negative relationship between bank competition and the intensity of credit procyclicality. The first comes from the asymmetries of information between lenders and borrowers that are a feature of credit markets. Even though there is no consensus in the existing literature, some articles argue that competition could reduce the information gap between lenders and borrowers by affecting both the screening and following-up of the banks. As stated by the quiet life theory of Berger and Hannan (1998), fiercer competition could potentially lead banks to operate more efficiently, and this could then improve the results of the screening and monitoring of potential client borrowers. In this way, the problem of asymmetric information could somehow be relaxed, weakening the effect on financial conditions after a real shock.

A further improvement in the quality of screening can also come about because competition may increase the incentives for banks to generate information, and then may encourage them to invest more in screening technologies. Gehrig (1998) investigates a banking model with imperfect screening by allowing banks to choose the level of their screening effort. The

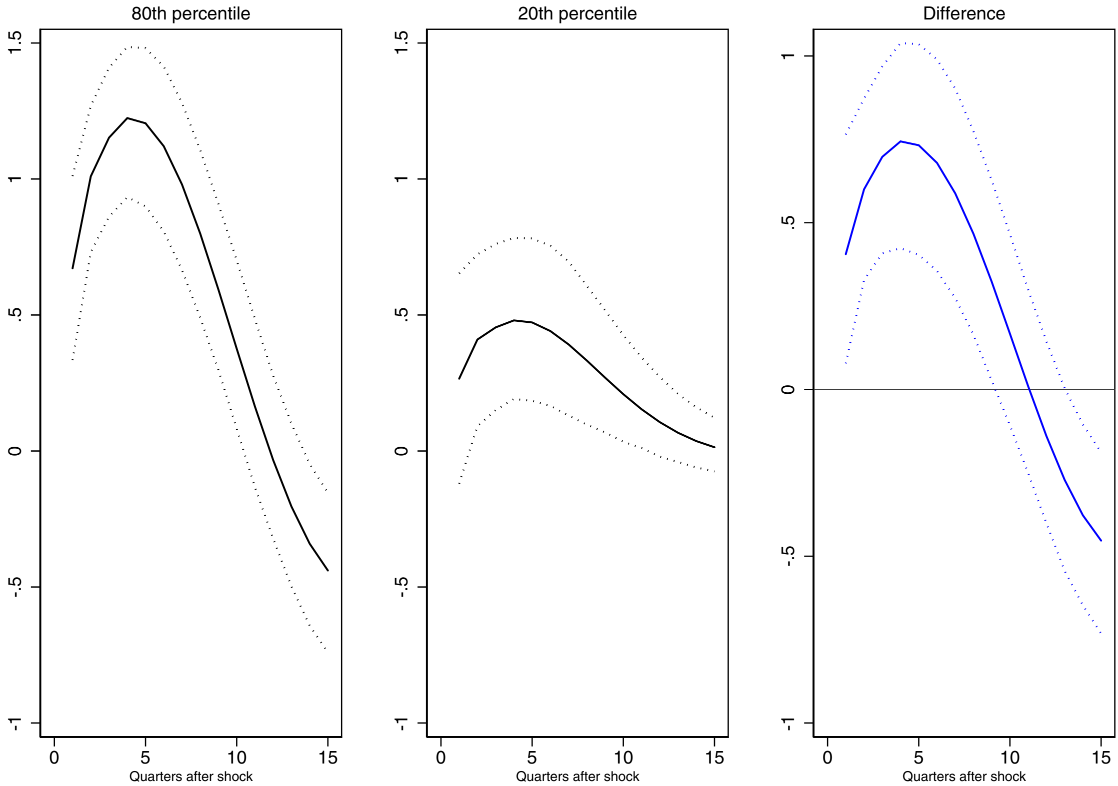


FIGURE 8 Impulse response functions of bank credit to a GDP shock as a function of banking competition. The figure displays the impulse response functions of bank credit to a one-unit shock in the output gap at the 80th and 20th percentiles of the Lerner index sample distribution. The chart on the right represent the difference between the two. The dotted lines represent the 95% confidence bands generated by bootstrapping (1,000 draws). GDP, gross domestic product [Colour figure can be viewed at wileyonlinelibrary.com]

benefits of investing in costly screening activities are twofold. More precise screening reduces the probability of good projects being rejected erroneously, and it also reduces the probability of bad projects being accepted erroneously, and so it reduces credit risk and the cost of lending. As Gehrig (1998) shows, the compression of lending margins induced by fiercer competition between banks negatively impacts screening incentives if, and only if, the value from identifying good projects dominates the value from avoiding risky projects. In other words, in countries where the main benefit from screening is related to avoiding bad projects, intensifying competition in the banking sector may improve the incentives for screening and through this the overall allocation of credit. According to Gehrig (1998), this scenario is particularly relevant for transition economies and developing countries. The relationship between the degree of market competition and the screening incentives of banks is also analysed by Dell'Ariccia (2000), who shows that competition may have two opposite effects. One is that stronger competition is also related to a greater temptation for banks to deviate from a screening equilibrium, and hence it increases the incentive for them not to screen potential borrowers. The other is that fiercer competition between banks corresponds to a stronger adverse selection problem, as the proportion of borrowers known to each bank is reduced, encouraging them to invest more in screening activities. Dell'Ariccia (2000) argues that the sign of the relationship between competition and screening incentives depends on the relative strength of these two forces.[10]

Competition may also reduce asymmetric information problems by encouraging banks to strengthen long-term relations with clients who borrow. Boot and Thakor (2000) argue that a more competitive environment may encourage banks to make more relationship loans, notably by becoming more client-driven and by customising the services that they offer. Yafeh and Yosha (2001) reach a similar conclusion. They show that the level of competition between financial intermediaries may strengthen the intensity of the relationships between banks and their clients, arguing that investment in bank-firm relationships can be used strategically by banks to limit competition in arm's length markets.[11] Since a longer-term relation between the bank and the client is one way to overcome asymmetric information, banks would be more inclined to smooth a real shock, by increasing credit during bad times, for example, Bolton, Freixas, Gambacorta, and Mistrulli (2016) and Gambacorta (2016).

Second, our results are in line with the literature on bank competition and stability. Theoretical works (Allen, Carletti, & Marquez, 2011; Boyd & De Nicoló, 2005) and empirical works (Akins, Li, Ng, & Rusticus, 2016; Anginer et al., 2014; Schaeck & Cihák, 2012; Uhde & Heimeshoff, 2009) show that an increase in the level of competition in the banking sector could imply that banks are more capitalised or are avoiding projects with higher risk. Taking on less risk implies that periods with rapid credit increases are less pronounced during the boom of the cycle, and banks experience lower losses in the decreasing period, which tends to maintain the equity capital of banks and their willingness to engage in newer risky projects and supply new credit in bad times. This would further be strengthened by the positive influence that stronger bank competition might have on policies related to risk management.

Finally, as argued by Leroy and Lucotte (2019), the greater credit procyclicality of banks in a less competitive environment could simply be explained by behaviour intended to maximise profits. Indeed, in general the optimal behaviour of a firm with market power is to adjust quantity rather than price after a variation in demand. Hence, market power would then mean both stronger credit fluctuations and higher bank interest rate hysteresis (Leroy & Lucotte, 2015).

These results imply that less competition in the banking industry is a financial accelerator as it means a shock to the output gap is transmitted faster in the credit market. In this sense the financial accelerator theory establishes that it could make the business cycle bigger, and

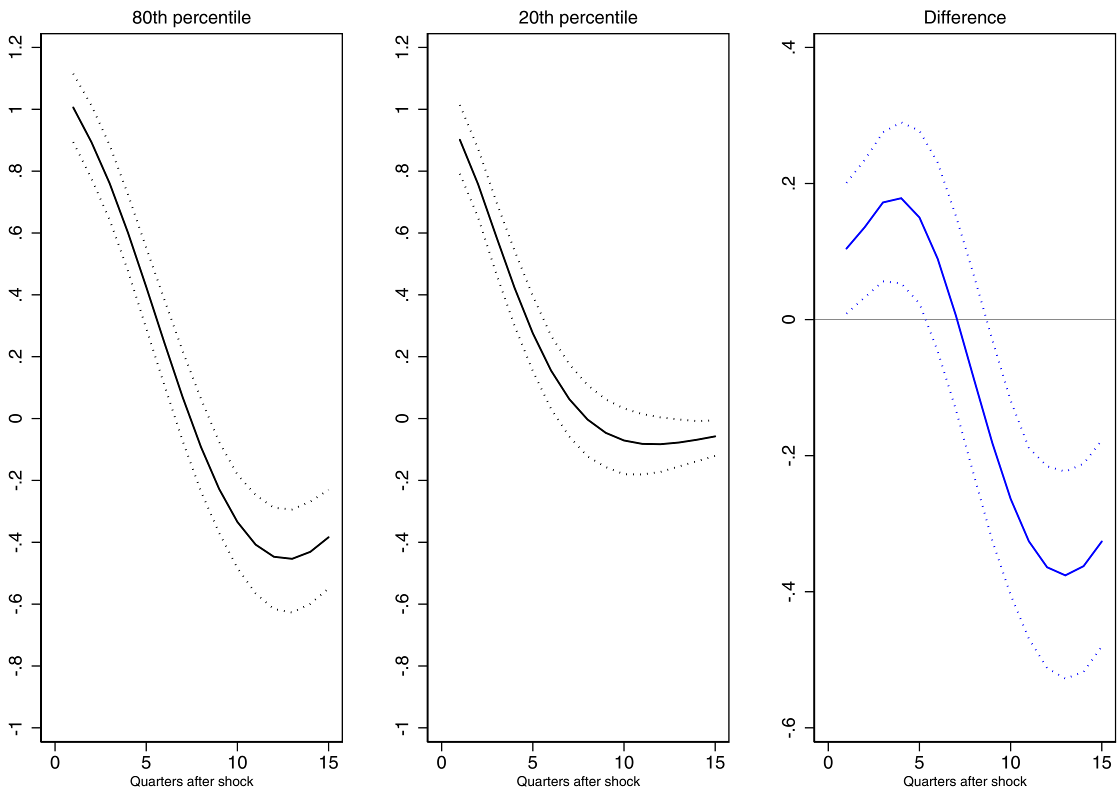


FIGURE 9 Impulse response functions of GDP to a GDP shock as a function of banking competition. The figure displays the impulse response functions of the GDP cycle to a one-unit shock in the output gap at the 80th and 20th percentiles of the Lerner index sample distribution. The chart on the right represents the difference between the two. The dotted lines represent the 95% confidence bands generated by bootstrapping (1,000 draws). GDP, gross domestic product [Colour figure can be viewed at wileyonlinelibrary.com]

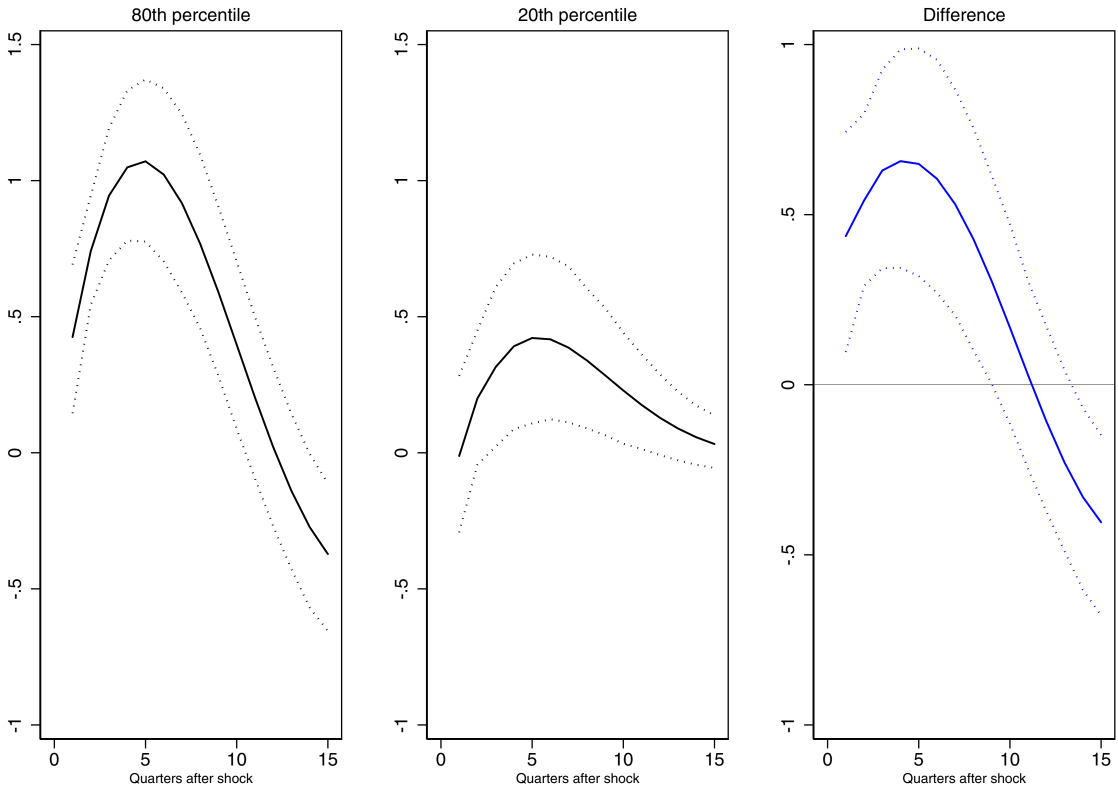


FIGURE 10 Impulse response functions of bank credit to a GDP shock as a function of banking competition: Alternative ordering or variables. The figure displays the impulse response functions of bank credit to a one-unit shock in the output gap at the 80th and 20th percentiles of the Lerner index sample distribution. The chart on the right represent the difference between the two. The dotted lines represent the 95% confidence bands generated by bootstrapping (1,000 draws). GDP, gross domestic product [Colour figure can be viewed at wileyonlinelibrary.com]

the persistence of economic shocks is related to the amplitude of the consequences for financial conditions and for credit dynamics. If that is the case, we could expect that the response of GDP to a shock will be stronger in cases where bank competition is lower since this yields more credit fluctuations.

Figure 9 presents the GDP cycle response to an exogenous output gap shock. The differences between the mean response for low and high levels of bank competition confirm our expectation that a GDP cycle shock has a weaker effect on output when there is a higher level of competition in banking systems.

6 | ROBUSTNESS CHECKS

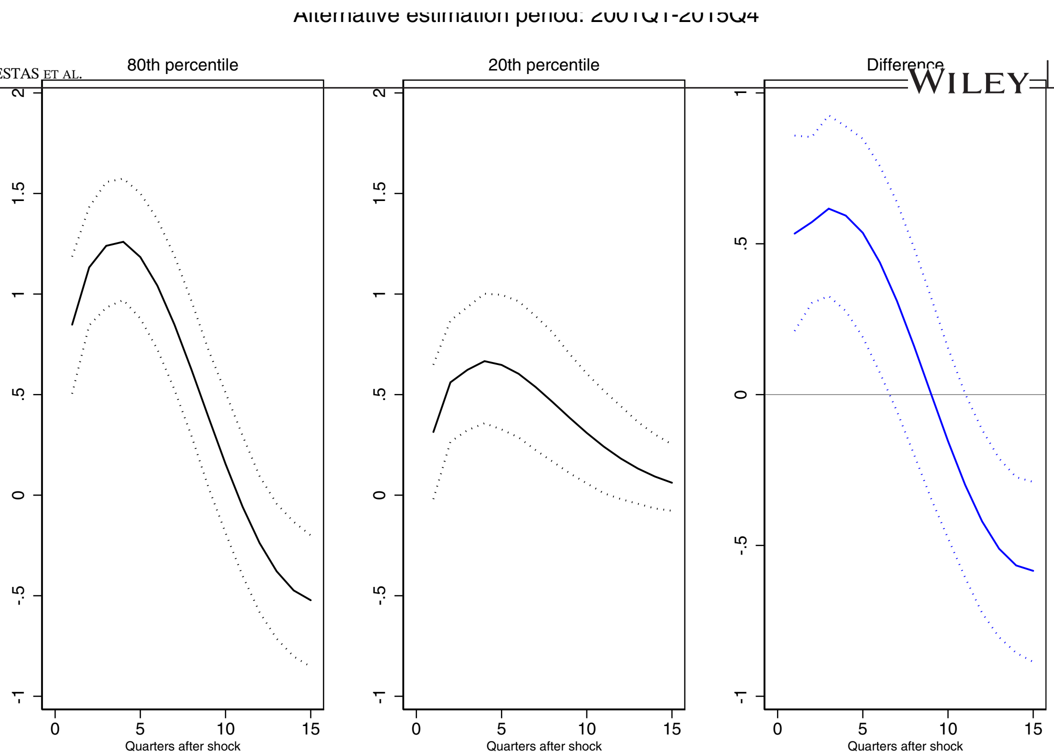
We check the robustness of our previous findings in several ways. To save space, we only report the results of the IPVAR framework. The results of the panel VAR and of the country-specific VAR models are available upon request.

6.1 | Alternative ordering of the variables

In our baseline identification scheme, we place the output gap before the credit gap. We check the robustness of our findings by considering credit as the first variable in the ordering. In this way, credit is considered to be more exogenous than it is in our baseline specification, as it is not contemporaneously affected by a shock to GDP. Figure 10 displays the IRFs obtained with this alternative ordering and confirms our previous results.

6.2 | Hodrick–Prescott filtering

Several criticisms are frequently aimed at the HP filter (see, e.g., Kaiser and Maravall (2001); Mise, Kim, and Newbold (2005)). Most notably the HP filter suffers from a well-known start-point and end-point problem, which affects



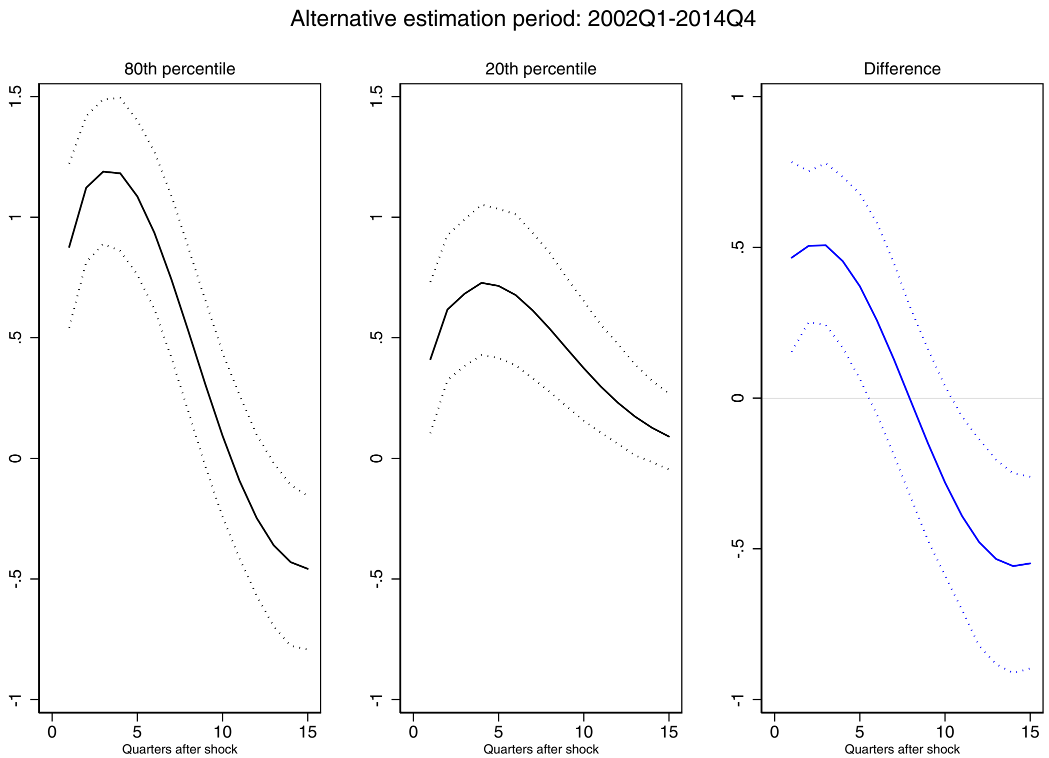


FIGURE 11 Impulse response functions of bank credit to a GDP shock as a function of banking competition: Alternative HP filtering approaches. The figure displays the impulse response functions of the GDP cycle to a one-unit shock in the output gap at the 80th and 20th percentiles of the Lerner index sample distribution. The chart on the right represent the difference between the two. The dotted lines represent the 95% confidence bands generated by bootstrapping (1,000 draws). GDP, gross domestic product; HP, Hodrick–Prescott [Colour figure can be viewed at wileyonlinelibrary.com]

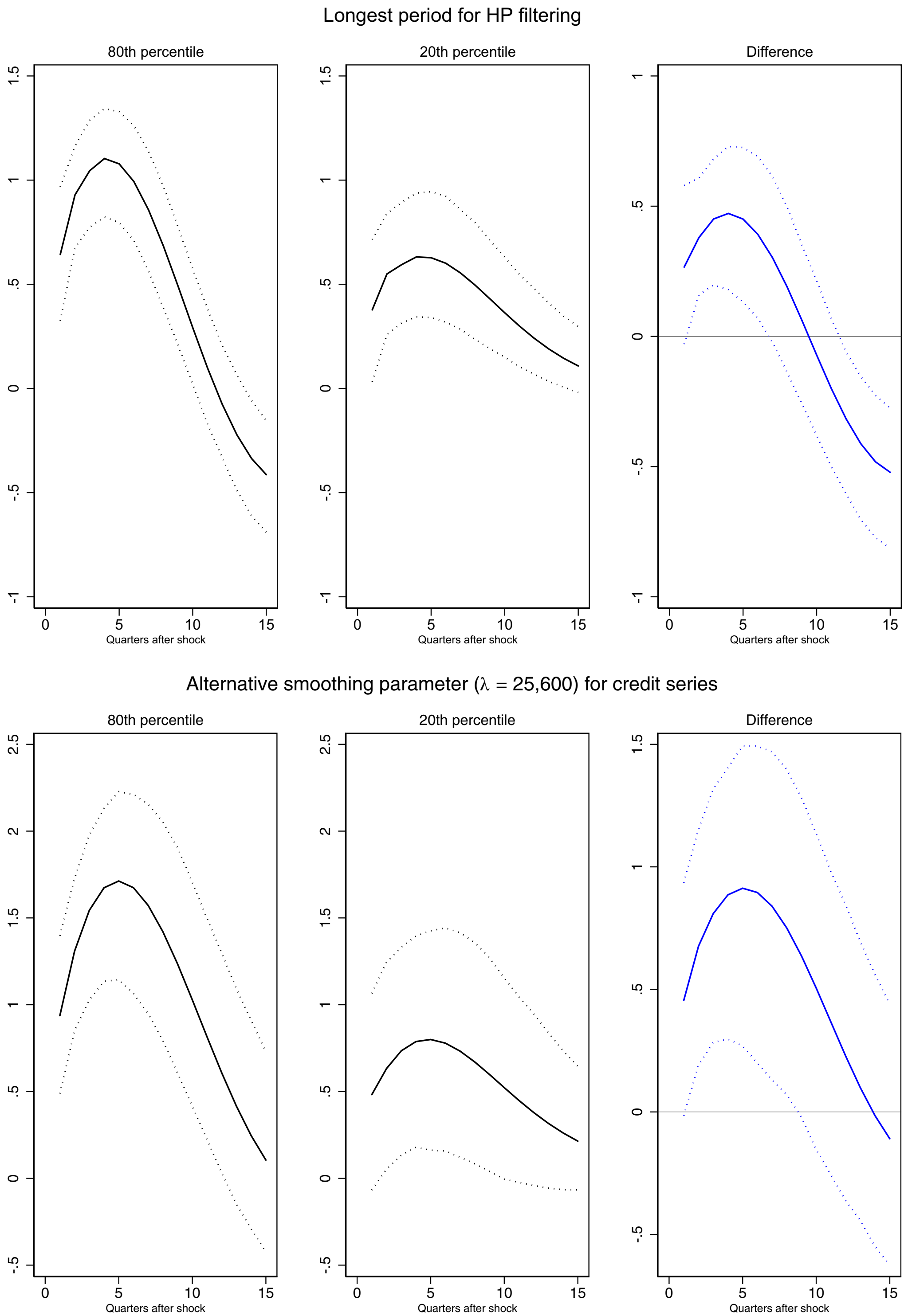


FIGURE 11 (Continued)

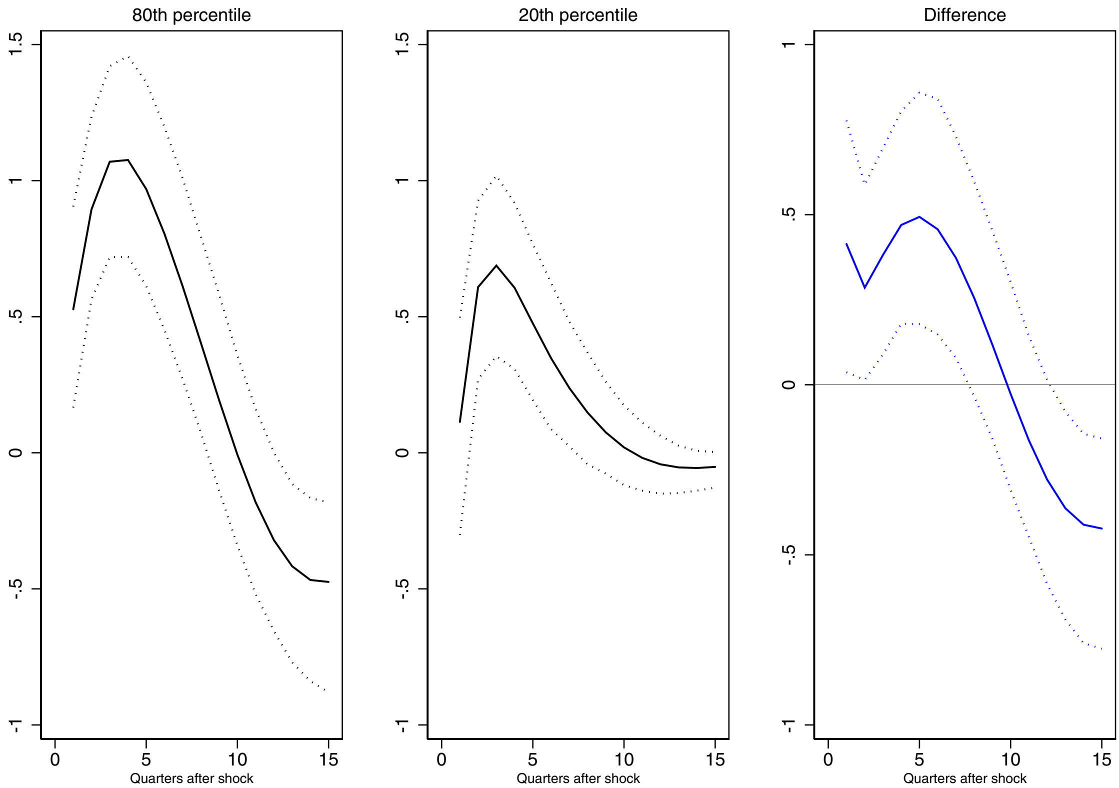


FIGURE 12 Impulse response functions of bank credit to a GDP shock as a function of banking competition: Mean group estimator. The figure displays the impulse response functions of bank credit to a one-unit shock in the output gap at the 80th and 20th percentiles of the Lerner index sample distribution. The chart on the right represent the difference between the two. The dotted lines represent the 95% confidence bands generated by bootstrapping (1,000 draws). GDP, gross domestic product [Colour figure can be viewed at wileyonlinelibrary.com]

HP trend estimates at the start and at the end of the data period (Drehmann & Tsatsaronis, 2014; Gersl & Seidler, 2012). As Figure A1 in the Appendix suggests, the start-point bias is particularly notable for the bank credit series. One usual way of dealing with this problem is to drop the first and last observations of the sample period. We then check the robustness of our previous findings by re-estimating our different VAR frameworks on a shorter period, for which we consider two alternative periods, 2001Q1–2015Q4 and 2002Q1–2014Q4. We also address the start-point problem by estimating a second series of gaps considering a longer period. The HP filter is now applied to the seasonally adjusted series over the 1995Q1–2016Q4 period, which is the longest period for which we can find a comparable data series for our sample countries.[12] A comparison of filtered series is provided in Figures A10–A13 in the Appendix.

Finally, we consider alternative credit gap series by setting a larger smoothing parameter for the HP filter. The smoothing parameter is related to the length of the cycle. In our baseline investigation, we consider the same smoothing parameter of $\lambda = 1,600$ for all four macroeconomic variables. This means that we assume that credit cycles have the same length as business cycles. However, as Drehmann and Tsatsaronis (2014) and Borio (2014) argue, financial cycles tend to be longer than standard business cycles. Given the relatively short length of our panel data, we assume that credit cycles are twice as long as business cycles. Then we follow the rule developed by Ravn and Uhlig (2002), which says that for quarterly data optimal λ of $1,600$ should be chosen and in addition it should be adjusted by taking the fourth power of the observation frequency ratio, and we set a λ of $25,600$. The results that we obtain for the IPVAR framework are reported in Figure 11. They confirm our previous findings. We still find that weaker competition in the banking sector tends to accelerate credit procyclicality.[13]

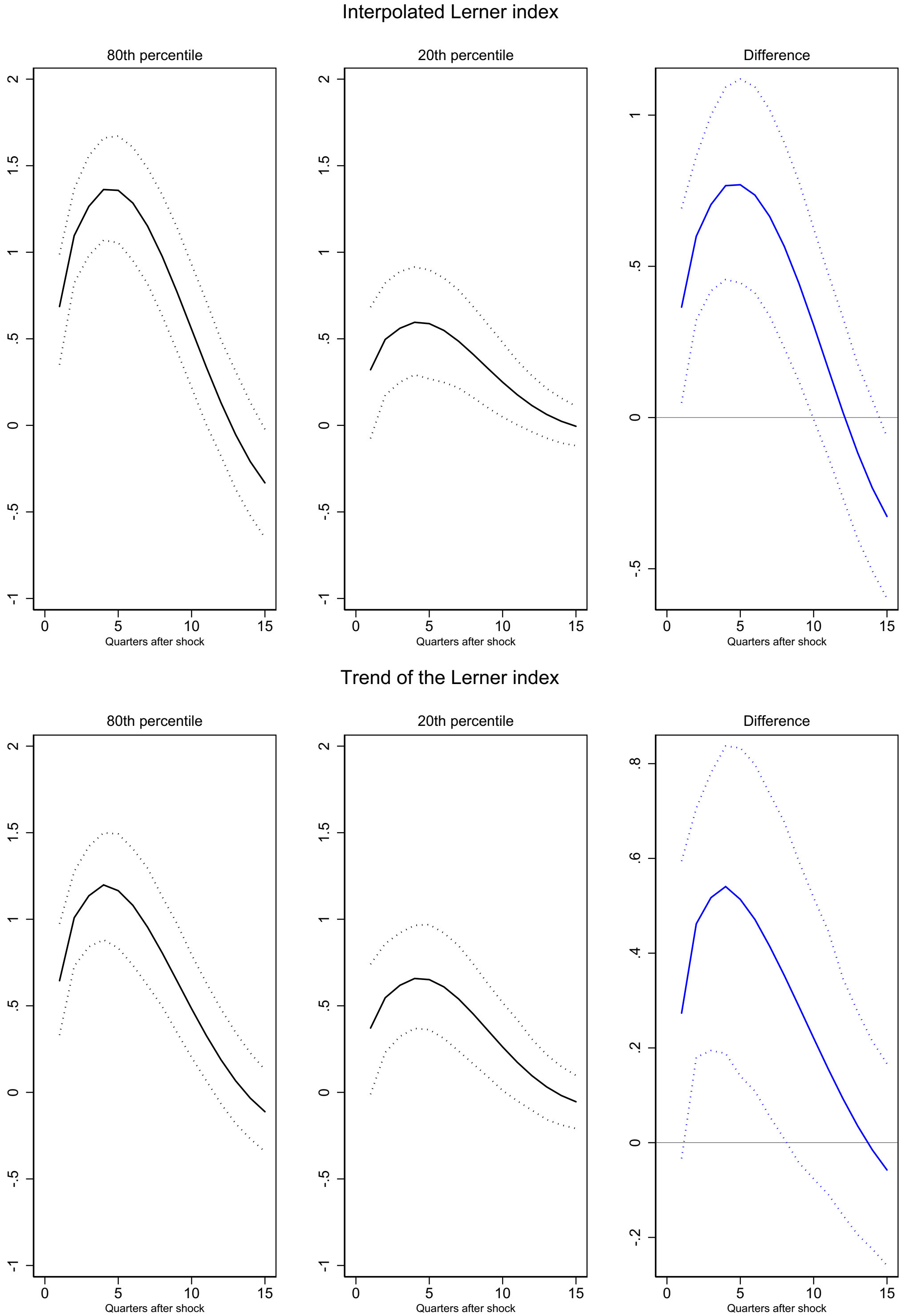


FIGURE 13 Legend on next page.

FIGURE 13 Impulse response functions of bank credit to a GDP shock as a function of banking competition: Alternative Lerner indexes. The figure displays the impulse response functions of bank credit to a one-unit shock in the output gap at the 80th and 20th percentiles of the Lerner index sample distribution. The chart on the right represent the difference between the two. The dotted lines represent the 95% confidence bands generated by bootstrapping (1,000 draws). GDP, gross domestic product [Colour figure can be viewed at wileyonlinelibrary.com]

6.3 | Mean group estimator

We include country FE in our baseline IPVAR framework to control for unobserved unit-specific factors. In this way, we control for structural characteristics other than banking competition that could explain the differences in credit procyclicality across the CEECs. However, by adding country FE we cannot control for factors other than competition which could be correlated with competition. Not controlling for this unobserved dynamic heterogeneity could imply that our estimations become inconsistent (Pesaran & Smith, 1995).

To control for both unobserved country-specific variations and variations that are conditional on specific structural characteristics, Sá, Towbin, and Wieladek (2014) run a mean group-type estimator. We follow their example and expand the initial IPVAR model, which means including the interaction of all the endogenous variables with country dummies. By doing this, we can observe the heterogeneity of the coefficients, which is related to country-specific effects and which is caused by competition in the banking sector. The impulse response functions reported in Figure 12 confirm our previous results.

6.4 | Alternative Lerner indexes

Finally, we check the sensitivity of our baseline results by considering two alternative Lerner indexes. First, rather than considering the same value of the Lerner index for each quarter of a given year, we use a linear interpolation procedure to match the variable to the quarterly frequency of our study. Second, we extract the trend component of the Lerner index using an HP filter.[14] Like our baseline estimates, these two alternative Lerner indexes are lagged four quarters. Figure 13 displays the IRFs obtained when we consider these alternative measures of the Lerner index, and it confirms our previous findings.

7 | CONCLUSION

This article is the first in the literature to investigate empirically credit procyclicality in CEECs. Our findings point to three main results. First, our research indicates that credit procyclicality is more pronounced in boom periods. The comparison of the IRFs for different stages of the business cycle clearly shows that credit reacts to a shock in GDP positively with varying degrees of magnitude. These findings are in line with those of Bouvatier et al. (2014), who finds that the degree of credit procyclicality is more or less pronounced according to the position of the business cycle. This means that procyclicality is higher for the CEECs during boom periods. Boom periods in the CEECs are also characterised by large increases in property and share prices which, in turn, affect credit dynamics.

Second, we show that there are differences in credit procyclicality across the CEECs. Whereas Bulgaria, Slovakia and Poland show a stronger reaction of credit to GDP shocks, procyclicality is more muted in Estonia, Slovenia and the Czech Republic.

Third, we analyse the drivers of credit procyclicality and find evidence in favour of the argument that more highly concentrated banking sectors augment credit procyclicality. This finding is in line with results obtained by Leroy and Lucotte (2017) but in contrast to theoretical predictions put forward by Petriconi (2015).

We have observed an important degree of heterogeneity in the impact of GDP shocks on bank credit, depending on the country analysed. The different degrees of financial and economic integration and differences in the development of institutions, in addition to their dependence on foreign banks, may explain why different countries respond differently. Our results also show that different levels of banking concentration can explain the differences in credit dynamics across the CEE countries.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available from the International Financial Statistics database.

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ENDNOTES

[1] Episodes of credit booms or crunches occur when the level of credit to GDP remains well above or below its long-term trend. For the estimation of boom and crunch thresholds we refer to Gourinchas, Valdes, and Landerretche (2001).

[2] For a detailed discussion of boom-bust cycles see Borio, Furfine, and Lowe (2001); Lowe and Borio (2002); Tornell and Westermann (2002); Eichengreen and Mitchener (2004); Mendoza and Terrones (2008, 2012); Hume and Sentance (2009) and Schularick and Taylor (2012).

[3] The data that support the findings of this study are openly available from the International Financial Statistics database.

[4] See Pedersen (2001) and Ravn and Uhlig (2002) for a discussion on the smoothing parameter.

[5] We check the robustness of our results by considering a different ordering for computing the IRFs. See Section 6 for more details.

[6] For an overview of the evolution of the correlation between the credit and business cycles over the period studied, please see Figure A2 in the Appendix.

[7] Before the IRFs were computed, standard tests were applied to check for residual autocorrelation and to see that the moduli of the eigenvalues of matrix A are less than one. Figure A7 in the Appendix confirms that the VAR process is stable for each country in our sample.

[8] See Figure A8 in the Appendix for more details concerning the evolution of the Lerner index in the CEECs. Please note that the Lerner index is only available until 2010 for Estonia. We also check the robustness of our results by linearly interpolating the values of the Lerner index and by considering the trend of the Lerner index. The results are reported in Section 6.

[9] As previously, for the sake of readability we do not report the confidence bands, but the full set of results is reported in Figure A9 in the Appendix.

[10] See also Caminal and Matutes (2002), who theoretically investigate the existence of a trade-off between monitoring and credit rationing by considering two extreme market structures, which are monopoly and Bertrand competition.

[11] See Presbitero and Zazzaro (2011) for an empirical examination of the link between bank competition and relationship lending.

[12] Please note that data for Bulgaria and Romania are only available from 1996Q1 to 1998Q1, respectively. Please also note that the interest rate series for Slovakia are not available before 2000Q1.

[13] We also checked the robustness of our results by considering the interest rate in levels rather than its cyclical component. The results that we obtain, available upon request, are similar to those reported above.

[14] See Figure A8 in the Appendix for a comparison of the three alternative Lerner indexes considered in our study.

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APPENDIX A.

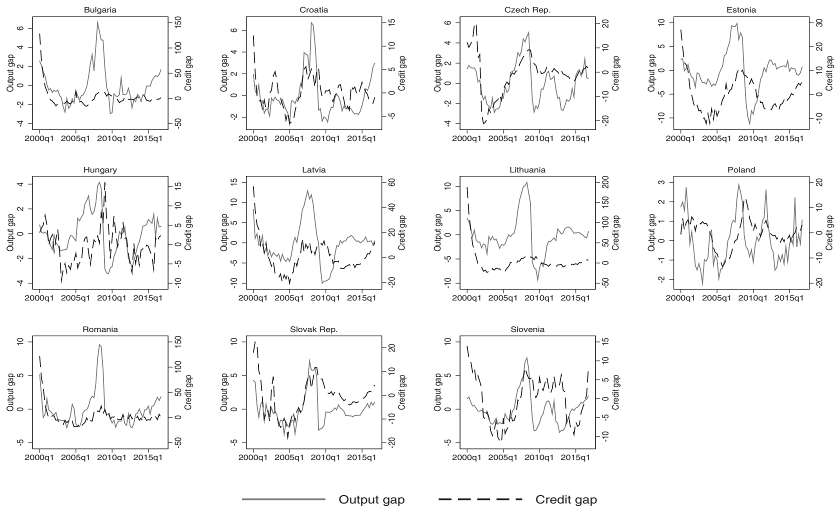

FIGURE A1 Evolution of the business and credit cycles in CEECs. Authors' calculations, International Financial Statistics, International Monetary Fund. The business cycle and the credit cycle are obtained by isolating the cyclical components of real GDP and real credit series using the Hodrick–Prescott (HP) filter. They are defined as the percentage gap between the trend values and the observed values of the series. CEECs, Central and Eastern European countries

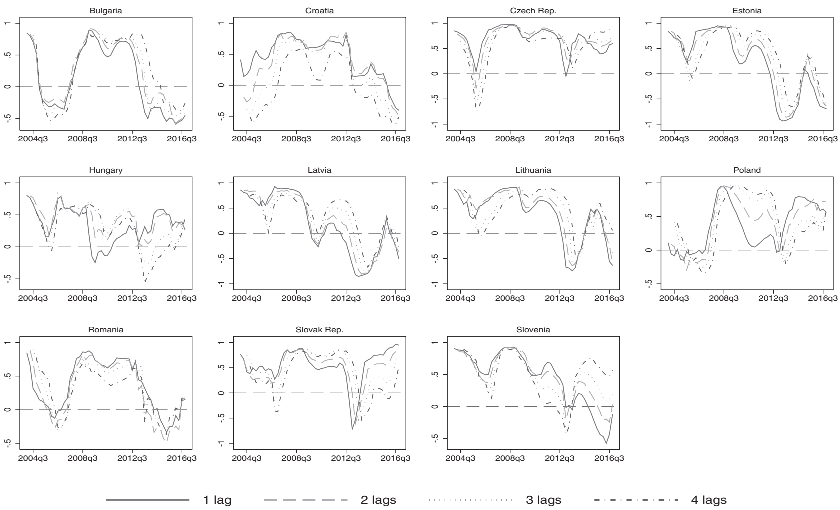

FIGURE A2 Dynamic correlation between the business cycle and the credit cycle in CEECs. Authors' calculations, International Financial Statistics, International Monetary Fund. The dynamic correlation between the business cycle and the credit cycle is calculated by considering a 4-year rolling window. We consider four different lag structures for the business cycle: 1 lag, 2 lags, 3 lags and 4 lags. CEECs, Central and Eastern European countries

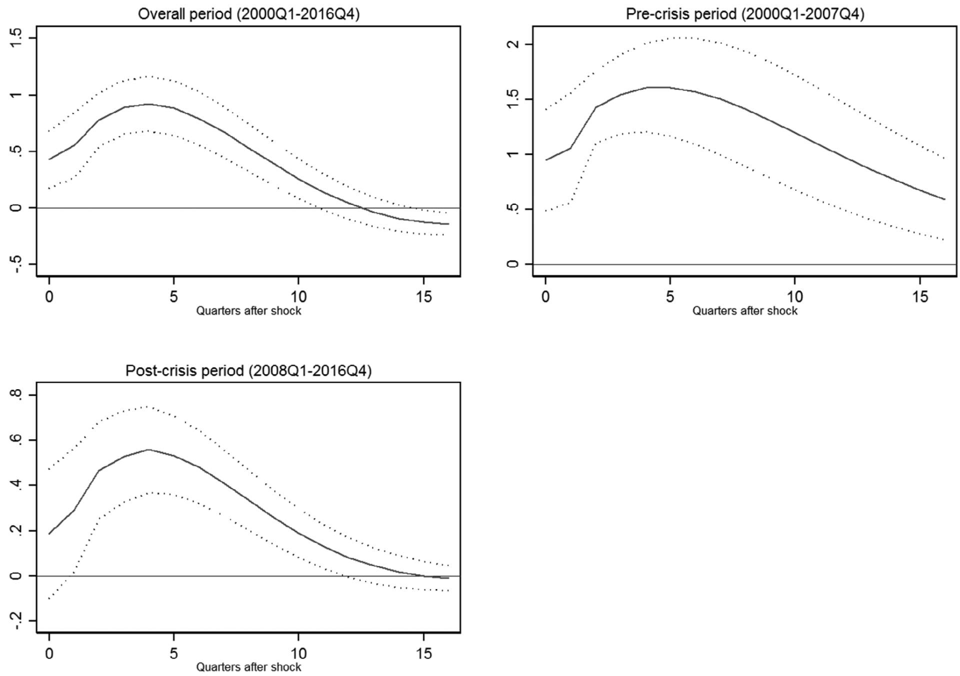

FIGURE A3 Evolution of credit procyclicality in CEECs in the aftermath of the sub-prime crisis. The figures display the impulse responses of bank credit to a one-unit shock in the output gap by considering three different periods: the overall period (2000Q1–2016Q4), the pre-crisis period (2000Q1–2007Q4) and the post-crisis period (2008Q1–2016Q4). The dotted lines represent the 95% confidence bands generated by bootstrapping (1,000 draws). CEECs, Central and Eastern European countries

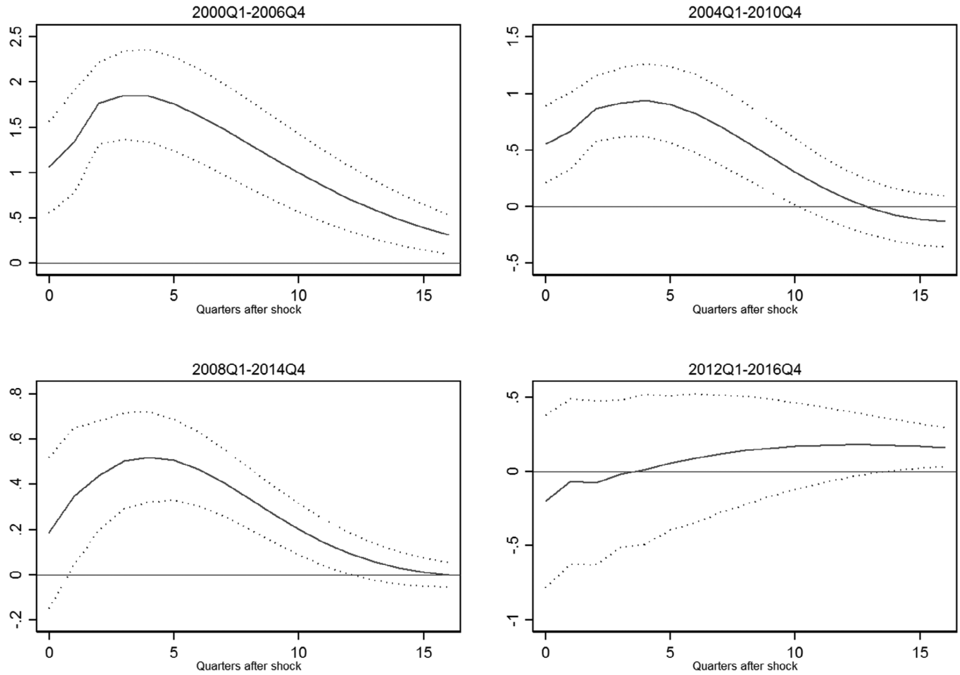

FIGURE A4 Evolution of credit procyclicality in CEECs between 2000 and 2016. The figures display the impulse responses of bank credit to a one-unit shock in the output gap by considering four different overlapping sub-periods: 2000Q1–2006Q4, 2004Q1–2010Q4, 2008Q1–2014Q4, 2012Q1–2016Q4. The dotted lines represent the 95% confidence bands generated by bootstrapping (1,000 draws). CEECs, Central and Eastern European countries

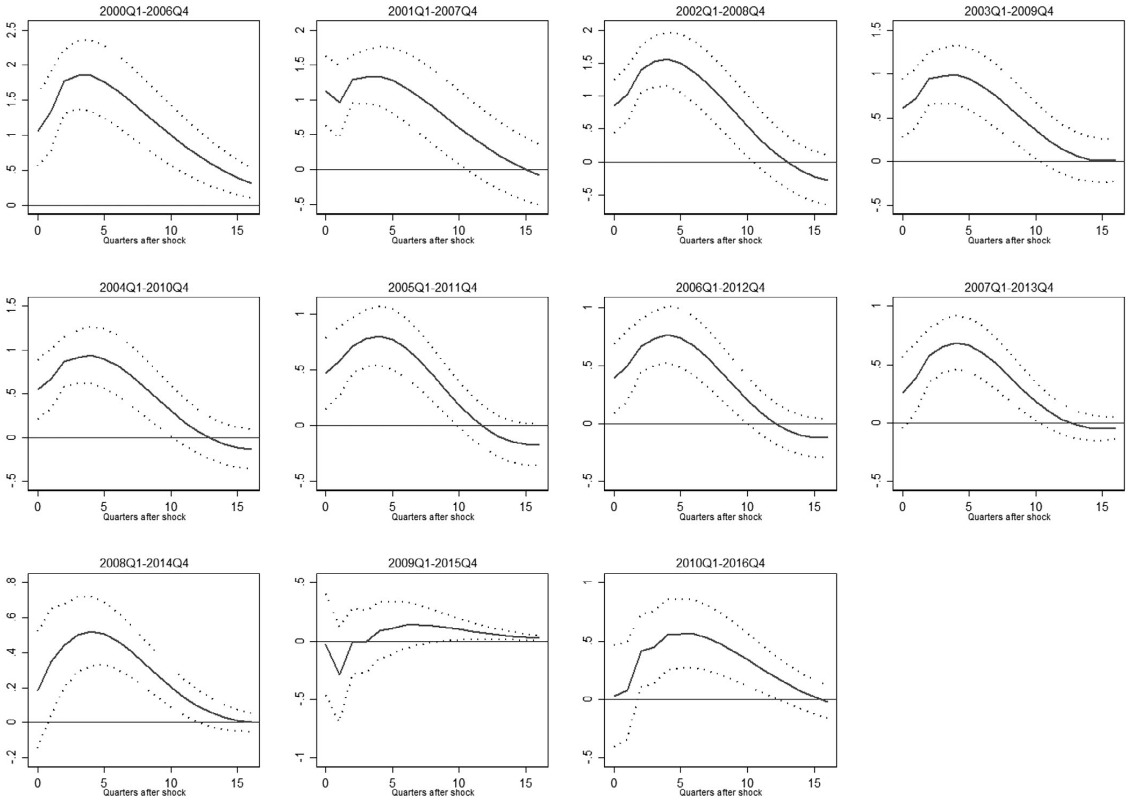

FIGURE A5 Evolution of credit procyclicality in CEECs: Rolling estimates. The figures display the impulse responses of bank credit to a one-unit shock in the output gap by considering 7-year rolling windows. The dotted lines represent the 95% confidence bands generated by bootstrapping (1,000 draws). CEECs, Central and Eastern European countries

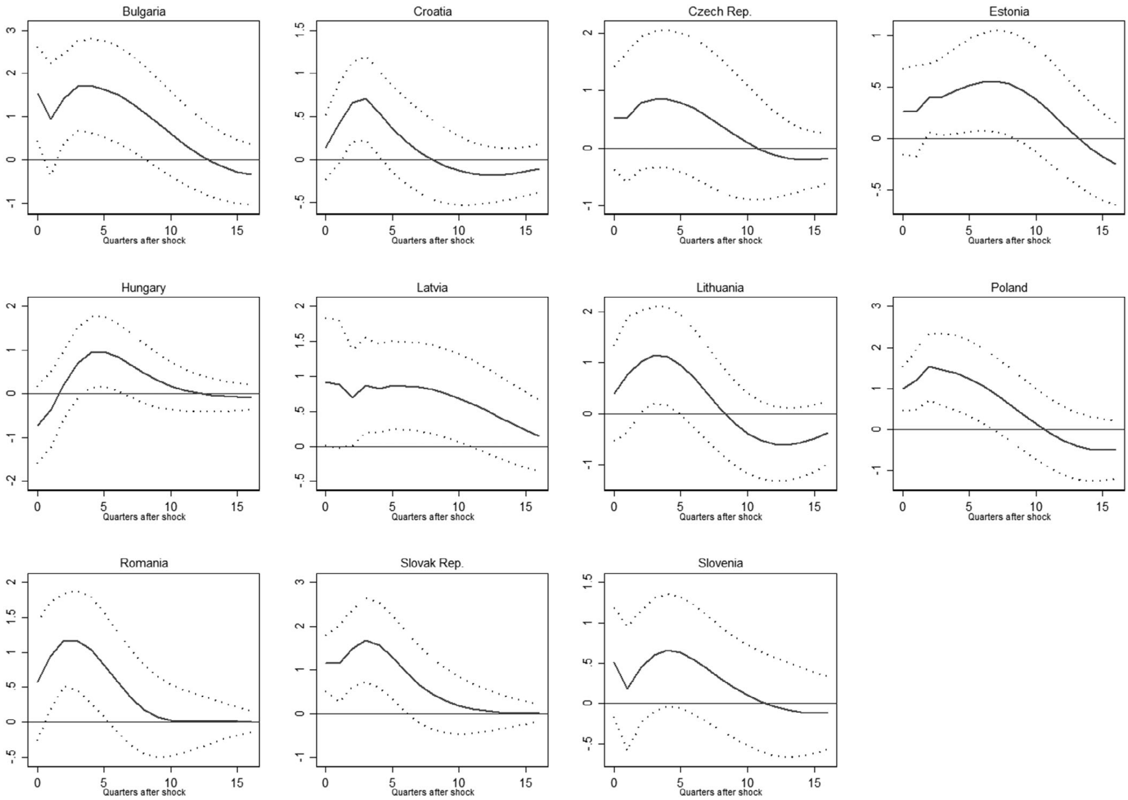

FIGURE A6 Country-specific impulse response functions of bank credit to a GDP shock. The figure displays the country-specific impulse response functions of bank credit to a one-unit shock in the output gap on the overall period (2000Q1–2016Q4). The dotted lines represent the 95% confidence bands generated by bootstrapping (1,000 draws). GDP, gross domestic product

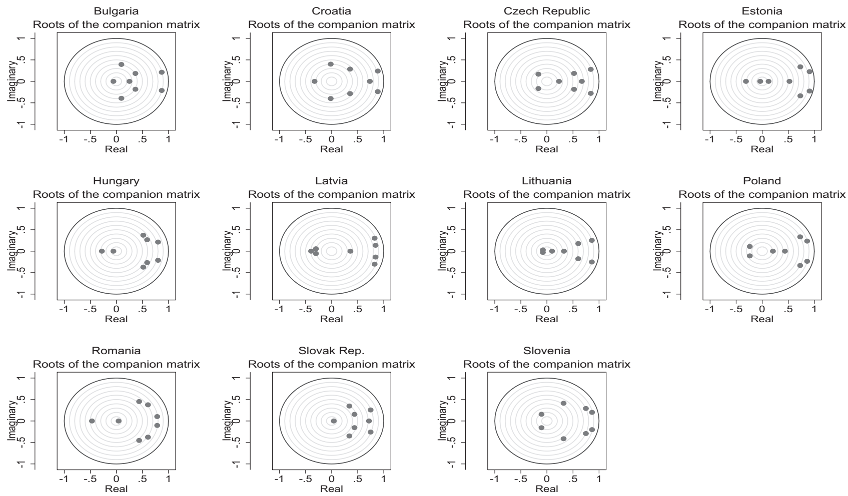

FIGURE A7 Stability of the country-specific VAR models. VAR, vector autoregressive

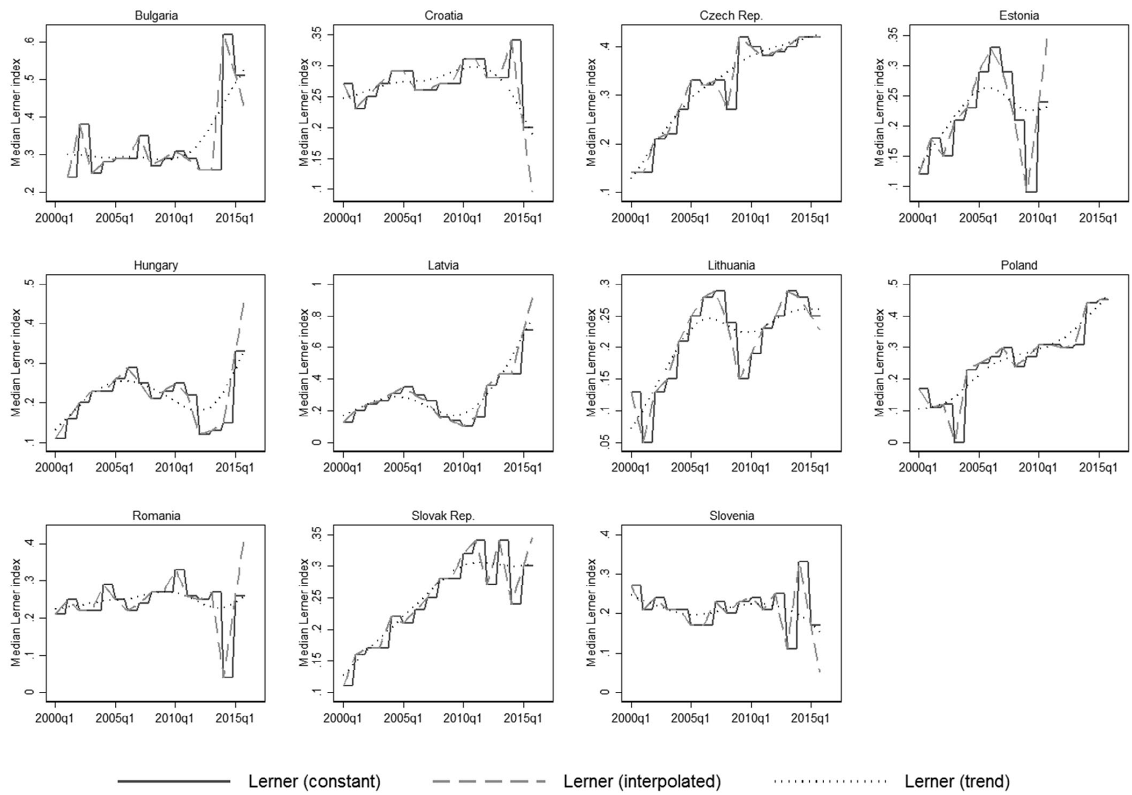

FIGURE A8 Evolution of the Lerner index in CEECs between 2000 and 2015. Authors' calculations, Global Financial Development Database, The World Bank. The Lerner index corresponds to the median of the individual Lerner indexes calculated using bank balance-sheet data from the Bankscope database. Please note that data for Estonia are only available until 2010. CEECs, Central and Eastern European countries

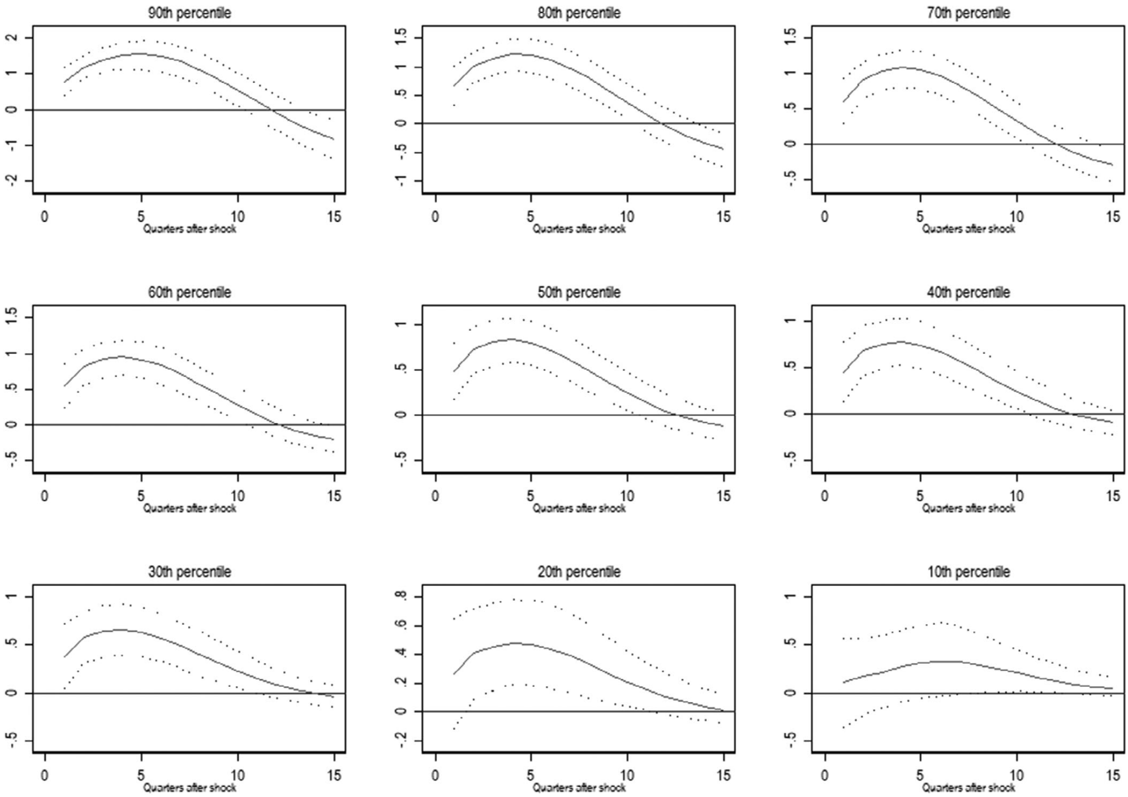

FIGURE A9 Impulse response functions of bank credit to a GDP shock for different levels of bank competition. The figure displays the impulse response functions of bank credit to a one-unit shock in the output gap evaluated at different percentiles of the Lerner index sample distribution. The dotted lines represent the 95% confidence bands generated by bootstrapping (1,000 draws). GDP, gross domestic product

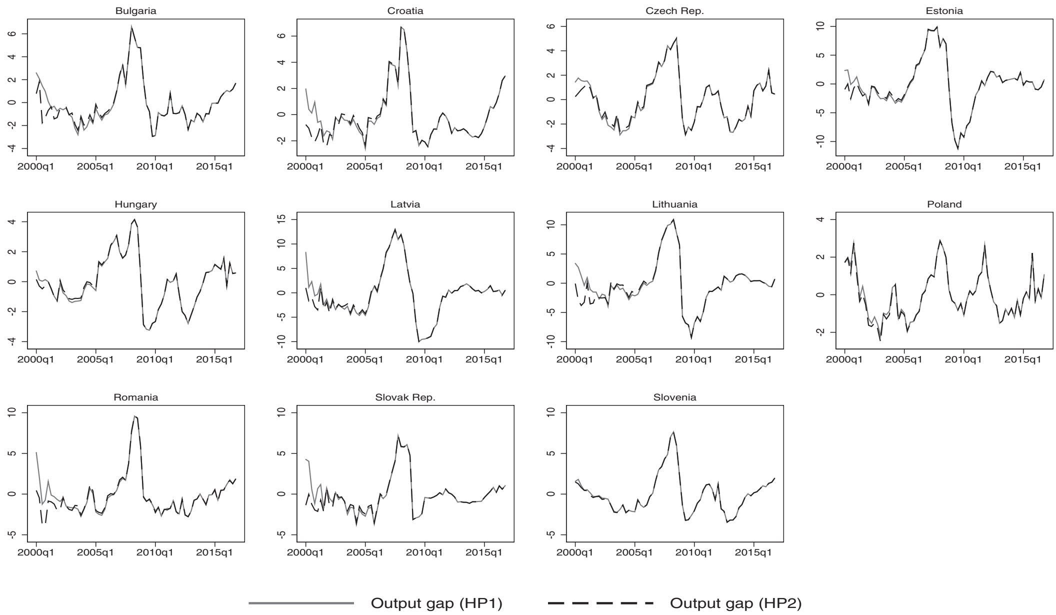

FIGURE A10 Output gap—comparison of HP filtered series. Output gap (HP1) corresponds to the output gap based on a HP filter estimated from 2000Q1 to 2016Q4, and output gap (HP2) to the output gap based on a HP filter estimated from 1995Q1 to 2016Q4. HP, Hodrick–Prescott

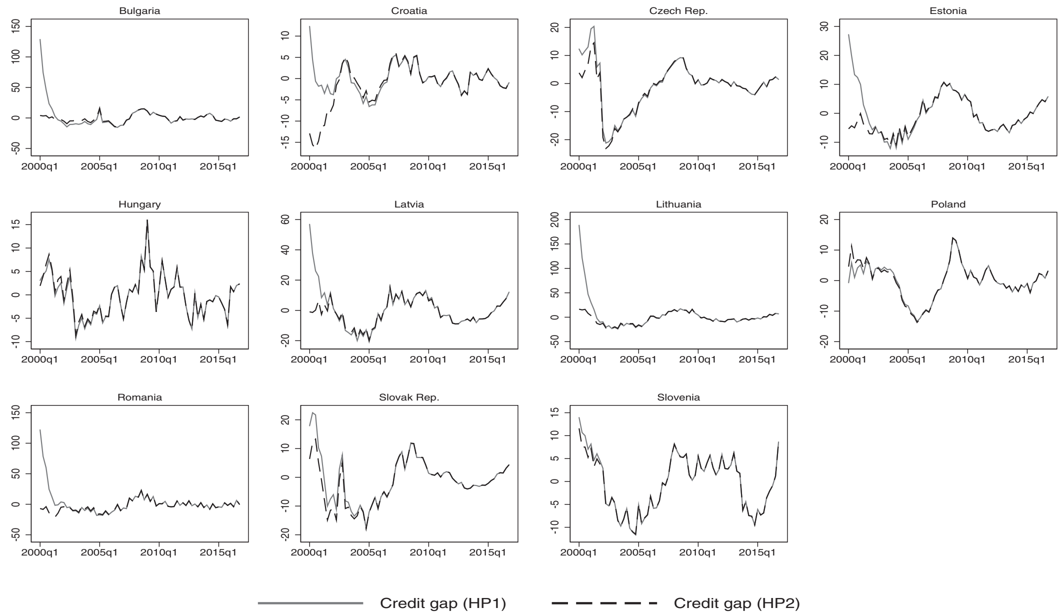

FIGURE A11 Credit gap—comparison of HP filtered series. Credit gap (HP1) corresponds to the credit gap based on a HP filter estimated from 2000Q1 to 2016Q4, and credit gap (HP2) to the credit gap based on a HP filter estimated from 1995Q1 to 2016Q4. HP, Hodrick–Prescott

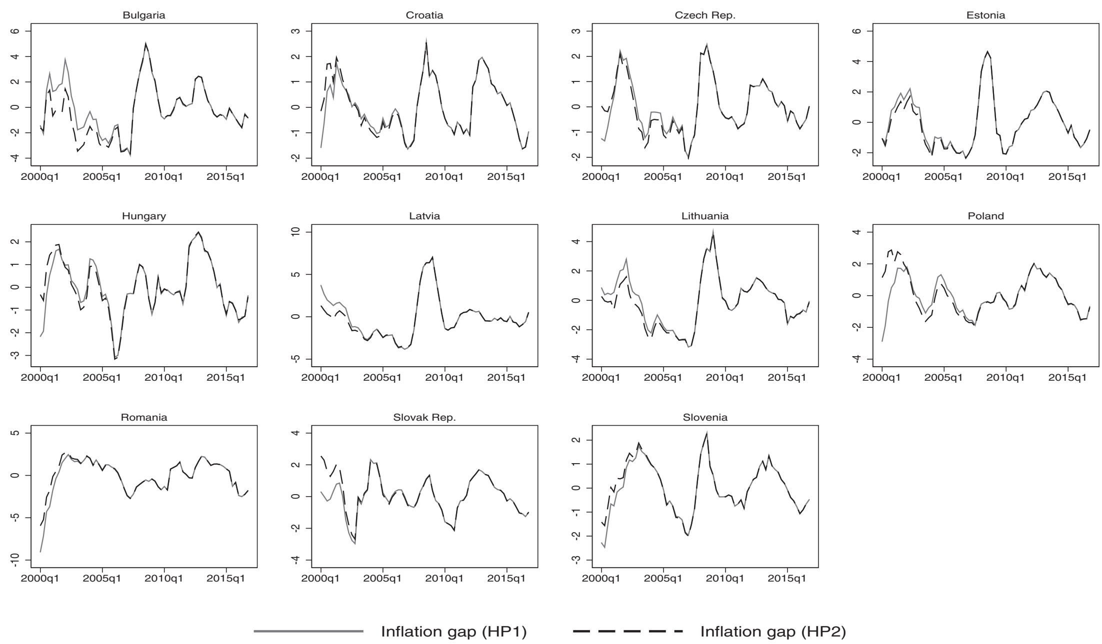

FIGURE A12 Inflation gap—comparison of HP filtered series. Inflation gap (HP1) corresponds to the inflation gap based on a HP filter estimated from 2000Q1 to 2016Q4, and inflation gap (HP2) to the inflation gap based on a HP filter estimated from 1995Q1 to 2016Q4. HP, Hodrick–Prescott

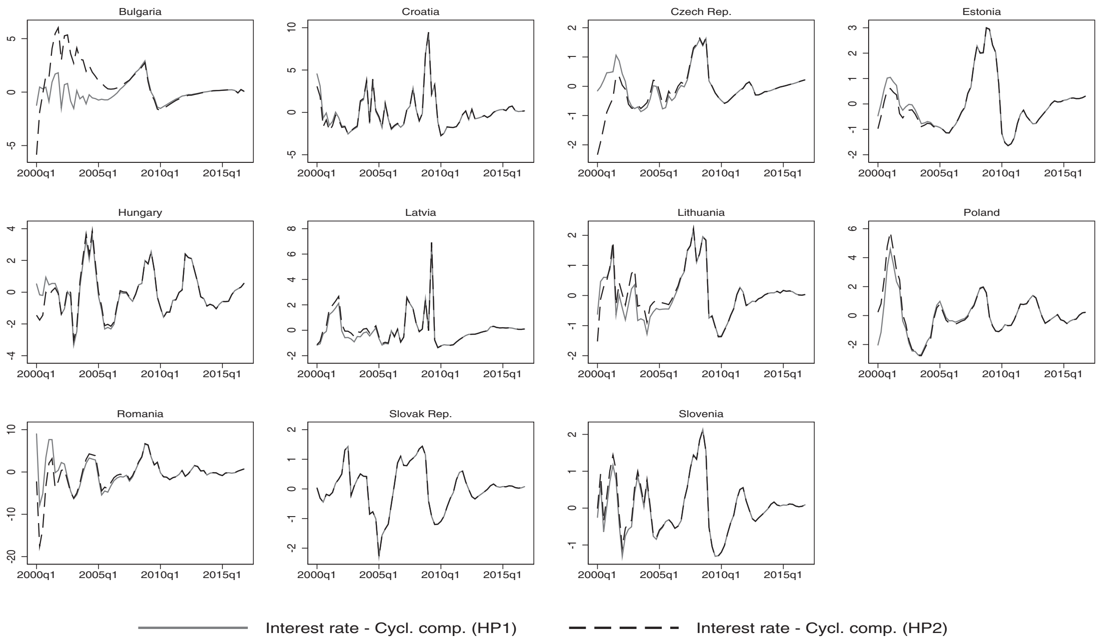

FIGURE A13 Cyclical component of the interest rate—comparison of HP filtered series. Interest rate - Cycl. comp. (HP1) corresponds to the cyclical component of the interest rate based on a HP filter estimated from 2000Q1 to 2016Q4, and Interest rate - Cycl. comp. (HP2) to the cyclical component of the interest rate based on a HP filter estimated from 1995Q1 to 2016Q4. HP, Hodrick–Prescott

Curriculum Vitae

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3. Education

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Estonian	Basic

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6. Computer skills

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- Programming languages: R, Python, Julia
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7. Honours and awards

- 2016, Taltech/TSEBA Master Thesis competition - Best Master's Thesis in Economics
- 2015, Estonian National Student Research Competition - 2nd place best research paper in the area of social scienes on the masters' level

8. Defended theses

- 2015, Forecasting the Estonian inflation rate with diffusion indexes, Lenno Uusküla, Ph.D., Kadri Männasoo, Ph.D., Tallinn University of Technology, School of Business and Governance, Department of Finance and Economics

9. Field of research

- Macroeconomics, Monetary Economics, Financial Stability

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Papers

1. Nicolas Reigl (2022). "Noise Shocks and Business Cycle Fluctuations in Three Major European Economies". *Empirical Economics* (forthcoming)
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3. Nicolas Reigl and Lenno Uusküla (2021). "Alternative Frameworks for Measuring Credit Gaps and Setting Countercyclical Capital Buffers". *Journal of Financial Economic Policy* 13.2, pp. 161–179
4. Nicolas Reigl and Karsten Staehr (2020). "Negative Interest Rates in the Five Eurozone Countries from Central and Eastern Europe". *CESifo Forum* 21.01, pp. 24–30
5. Juan Carlos Cuestas, Yannick Lucotte, and Nicolas Reigl (2020). "Banking Sector Concentration, Competition and Financial Stability: The Case of the Baltic Countries". *Post-Communist Economies* 32.2, pp. 215–249
6. Nicolas Reigl (2017). "Forecasting the Estonian Rate of Inflation Using Factor Models". *Baltic Journal of Economics* 17.2, pp. 152–189

Working papers

1. Gerda Kirpson, Martti Randveer, Nicolas Reigl, Karsten Staehr, and Lenno Uusküla (2022). "Macroeconomic News and Sovereign Interest Rate Spreads before and during Quantitative Easing". *Eesti Pank Working Paper* 6/2022
2. Merike Kukk, Alari Paulus, and Nicolas Reigl (2022). "Credit Market Concentration and Systemic Risk in Europe". *Eesti Pank Working Paper* 4/2022
3. Helen Ljadov, Reet Reedik, Raido Kraavik, Taavi Raudsaar, Lauri Matsulevitš, Dmitry Kulikov, Kaspar Oja, Lenno Uusküla, Nicolas Reigl, and Karsten Staehr (2020). "The Impact of Negative Interest Rates on the Estonian Economy and Financial Sector". *Eesti Pank Occasional Paper* 2/2022
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prantsuse keel	baastase
hispaania keel	baastase
eesti keel	baastase

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- Programmeerimiskeeled: R, Python, Julia
- Teadustarkvara paketid: Stata, Matlab, Stan
- DevOp’id: git, Docker

7. Autasud

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- Makroökonoomika, rahandus, finantsstabiilsus

10. Teadustegevus

Avaldatud artiklid

1. Nicolas Reigl (2022). "Noise Shocks and Business Cycle Fluctuations in Three Major European Economies". *Empirical Economics* (forthcoming)
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