Bank capital constraints, lending supply and economic activity*

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Abstract

We estimate a Bayesian VAR with a rich characterization of the banking sector for Italy since the 1990s. We use conditional forecasting techniques to retrieve bank capital shocks related to regulatory and supervisory initiatives and quantify their impact on lending supply and the economic activity. We study three episodes characterized by increased regulatory/supervisory pressure and large increases in Tier1 capital ratio (the discussion on the Basel III reform; the 2011 EBA Stress test and capital exercise; the ECB's Comprehensive Assessment and start of the SSM). We find evidence of large and persistent shocks to bank capital in all episodes, which had significant negative effects on loan supply and GDP. Our results are robust to allowing for potential instabilities in the estimated relationships. The analysis focuses on the potential short-run costs of the regulatory/supervisory initiatives and disregards the possibly much larger long-run benefits of high bank capitalization.

JEL classification: C32, E32, F34.

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1 Introduction

A large body of theoretical and empirical research has documented how exogenous changes in bank capital may affect lending conditions and, in turn, economic activity. One key channel highlighted in the literature underscores that when bank capital constraints become tighter, intermediaries react by curtailing the availability of loans, increasing lending spreads and changing the composition of assets; the tighter credit supply conditions negatively affect firms' income, investment and employment.

In this paper we focus on the macroeconomic effects of shocks to bank capital arising from regulatory and supervisory initiatives. In the long-run a stronger capital base has several benefits: it improves banks' ability to support economic growth even when adverse shocks occur, reduces the likelihood of financial crises and limits their impact on the economy, and provides further incentives for banks to manage risk effectively. In the short-run the move towards higher levels of capitalization could nevertheless be accompanied by credit supply restrictions. In particular, banks could decide to meet, at least partially, the requirements to increase their capital ratios by reducing their exposures to customers. Banks could also charge higher loan interest rates, reflecting the greater cost of equity compared with other sources of funding. In response to the deterioration in borrowing conditions, households and firms could scale down or defer their spending and investment plans.

In order to assess the short-run impact of regulatory and supervisory shocks on lending conditions and economic activity we estimate a Bayesian VAR model for the Italian economy since 1993. A crucial feature of our model is that it includes a large number of banking-sector variables: the amount and cost of lending, bank loan default rates, banks' income statement variables, banks' regulatory capital and banks' stock prices. The rich and endogenous characterization of the banking sector is a particularly desirable feature of our model and is crucial for isolating the impact of regulatory and supervisory shocks on bank capital from other shocks, as it allows us to consider several potential interactions among developments in the real economy, financial and credit markets. Our main contribution is to provide an alternative method for building a proxy of the impact of bank capital shocks when dealing with scarcity or unobservability of confidential micro data on capital requirements. In this regard, we innovate both relative to the literature on the macroeconomic effects of regulatory/supervisory shocks and on the macroeconomic models that include a banking sector and are typically limited to adding credit volumes and lending rates in small-scale VARs (see Section 2).

Following a strand of the literature on the impact of unconventional monetary policy measures (Lenza et al., 2010; Giannone et al., 2012b; Kapetanios et al., 2012; Altavilla et al., 2016), we exploit conditional forecasting techniques and analyze (three) periods (of two years) during which regulatory and/or supervisory initiatives have raised pressure on banks to increase capitalization and, at the same time, large and persistent increases in the Tier1 ratio were

observed. The first time window starts in the second quarter of 2009, and coincides with the discussion on the reform of prudential regulation (*Basel III* reform), which aimed at improving the quantity and quality of capital and curbing excessive financial leverage in the aftermath of the global financial crisis.[1] The second period starts in the first quarter of 2011 and covers the EBA 2011 Stress Test and Capital exercise; during this period banks raised capital both in anticipation of the stress-test results and as a consequence of the additional buffers requested in the capital exercise.[2] The third forecast period begins in the first quarter of 2014 and overlaps with the implementation of the ECB's Comprehensive Assessment (CA) and the first months of operation of the Single Supervisory Mechanism (SSM).[3]

With the help of the model we try to isolate the component of the capital increases that can be attributed to the various initiatives and thus estimate the impact of regulatory/supervisory intervention on real activity and lending supply. In particular, for each episode we estimate the model up to the quarter preceding the start of the forecast window and we then proceed in two steps. First, based on the estimated relations, we retrieve a counterfactual path for the Tier 1 capital ratio as its out-of-sample forecast conditional on the *realized* values of a large set of macroeconomic, financial and bank-specific variables. The variables in the conditioning set are chosen so as to capture the developments in all the main endogenous drivers of bank capitalization: macroeconomic variables and default rates account for the size and riskiness of bank assets; bank profitability variables account for the direct effect of earnings and losses on capital; financial variables (which include bank stock prices) capture the conditions for new equity issuance, the potential impact of tensions in financial markets on bank capital and the role of "market discipline" forcing banks to strengthen their capital position in times of concerns about their resilience. By construction this counterfactual ratio incorporates the effect of all the structural shocks that affected bank capital "indirectly", i.e., via the effect on the variables included in the (rich) conditioning set; importantly, the counterfactual also incorporates the

[1] The Basel III reform was definitively approved only in September 2010 and scheduled to be introduced since 2013. However, the details of the reform were largely anticipated by the banks, that started increasing their capital buffers as soon as the discussion started. In this regard, two crucial meetings were the April and November 2009 G20 summits, when the Heads of State and Governments committed to completing a global reform of prudential regulation (Banca d'Italia, 2010); subsequently, in December 2009, the Basel Committee on Banking Supervision published a consultation document with concrete proposals for capital and liquidity regulatory reforms (Basel Committee on Banking Supervision, 2009). In the period considered, total capital raised amounted to over 20 billion.

[2] The Stress Test was conducted between January and July 2011. The EBA allowed specific capital actions in the first four months of 2011 to be considered in the final result; the five Italian banks participating to the test raised about 11 billion. The Capital Exercise was announced in October 2011 and banks were prescribed to cover possible shortfalls by the end of June 2012; the total shortfall identified in the exercise for the Italian banks amounted to 15 billion.

[3] The CA was announced at the end of 2013 and completed in October 2014. For Italian banks the results published by the ECB envisaged an aggregated capital requirement of about 3 billion; in addition, between January and September 2014 a number of capital strengthening measures were adopted both by banks that eventually did not pass the CA and banks that did, amounting to about 11 billion. Additional capital increases were recorded in the first part of 2015. Overall, in the period considered equity capital increased by about 20 billion.

systematic reaction (as captured in the data) of regulatory/supervisory pressure to macroeconomic and financial developments as well as bank profitability. The *observed* evolution of bank capital is "by nature" conditional on both the same set of structural shocks and on the shocks that directly hit bank capitalization. Given the richness of the conditioning set we use, and based on the narrative evidence during the event windows considered, we claim that the difference between the actual and the counterfactual series of bank capital is essentially capturing the exogenous increase in regulatory and/or supervisory pressure connected to the initiatives considered.

Second, we estimate the impact on macroeconomic and banking variables of the increase in capital ratio associated to the regulatory/supervisory initiatives by running two simulations of the model: (i) an out-of-sample forecast conditional on the observed path of the Tier 1 ratio (*policy scenario*) and (ii) an out-of-sample forecast conditional on the counterfactual path (*no-policy scenario*). The two simulations differ with respect to the assumptions on the evolution of bank capital but are common in all other respects. As in Giannone et al. (2012b), we can thus (loosely) characterise this difference as a sort of impulse response of each variable to the regulatory/supervisory shocks to bank capital.

The results of the empirical analysis suggest that in all the three episodes considered a large part of the increase in banks' capital ratios can be attributed to the regulatory/supervisory initiatives. In particular, the initiatives determined a (cumulated) increase in the Tier 1 capital ratio – over the two-year windows – of 1.5 pp, on average over the three episodes. In turn, the increases in bank capital were associated to significant and negative effects on credit supply and economic activity: at the end of the two-year window, on average across the three episodes, these effects correspond to a reduction in the stocks of loans to NFCs and HHs by 3.0 and 3.4 per cent, respectively; an increase in loan rates of about 30 and 20 bps (for NFCs and HHs, respectively); and a reduction in GDP and HICP of 1.3 and 0.3 per cent, respectively. Both the size of the shocks and of the estimated effects on the main variables are comparable to those found by, among others, Kanngiesser et al. (2017), Meeks (2017) and **?** (see Section 6).

While the choice of forecast windows no longer than two years allows us to attenuate concerns related to the Lucas critique when carrying out out-of-sample forecasting exercises (Lenza et al., 2010; Giannone et al., 2012b), the financial crisis could have led to quick changes in the estimated relationships Aastveit et al. (2017). In order to address this concern we replicate our analysis with two alternative approaches: we estimate a model with time-varying coefficients and time-varying volatility, using the approach proposed by Koop and Korobilis (2013); and we use "in-sample" conditional forecasts which, by construction, lead to a very conservative definition of bank capital shocks in our framework. Overall, all the results obtained with the baseline model are confirmed and we find evidence of significant shocks – and the associated macroeconomic impact – in all the three episodes. Some of the estimated effects are, however, somewhat larger as the result of changes in the estimated variance-covariance

matrix of the BVAR innovations.

The rest of the paper is organized as follows. Section 2 briefly presents some important contributions related to our work. Section 3 describes the evolution of the Tier1 ratio in Italy. Section 4 describes the empirical framework. Section 5 explains the procedure adopted to recover the shocks to bank capital and discusses their impact on the amount and cost of lending and on the real economy. Section 6 discusses the results. Section 7 shows the evidence found when allowing for time variation in the coefficients and volatility, while Section 8 describes some robustness checks. Finally, Section 9 concludes.

2 Related Literature

This paper relates to several strands of literature. First, the paper relates to the empirical works measuring the effect of regulatory/supervisory shocks based on direct observation of bank-specific capital requirements (Meeks, 2017; Aiyar et al., 2016; De Jonghey et al., 2016) and/or studies using exogenous bank-level losses and exploiting event studies (Jiménez et al., 2017; Mésonnier and Monks, 2015; Gropp et al., 2016). In this regard, our approach provides an alternative method for building a proxy of the impact of bank capital shocks when dealing with scarcity or unobservability of confidential micro data on capital requirements. Compared to this literature, we allow two-way feedback effects between bank capital requirements, macroeconomic and financial conditions, as well as other bank features, which cannot be shaped in single-equation regressions. As for the interpretation of the results, our methodology is somewhat more general, as our shocks are not restricted to exogenous variations in specific capital requirements but also include the effect of a broad range of regulatory measures and supervisory pressures over a longer sample period.

Secondly, our estimation of the counterfactual series of capital ratio is conceptually similar to the notion of "economic capital", i.e. a pre-specified time-varying level of capitalization, consistent with business cycle and financial conditions, that banks target when choosing their actual level of capital Mésonnier and Stevanovic (2017); De Nicolò, Gianni (2015); Berrospide and Edge (2010); Hancock and Wilcox (1994). This literature also needs confidential bank-level data with the obvious advantage of taking into account heterogeneity across banks and to potentially control for all aggregate shocks when recovering the bank capital shocks.[4] An important difference with our study is that in these papers a positive (higher) difference between actual and "economic" capital is interpreted as reflecting banks' ability to maintain (increase)

[4] In these papers the authors follow a "two-step" approach. In the first stage they recover estimates of "economic level of capital" by running panel regressions of bank capital on a number of macroeconomic and bank-level variables, such as measures of profitability and riskiness. Then, they recover bank-level capital shortfall/overhang as the difference between actual and "economic level" of capital, which are summed up to obtain an aggregate measure of bank capital shocks. In the second stage they put the bank capital shock in VAR model and use a Choleski decomposition to recover impulse responses.

a capital buffer beyond their target level. This interpretation crucially relies on the assumption (either implicitly or explicitly acknowledged) that in the period over which those models are estimated the regulatory constraint on bank leverage is slack. With our approach, instead, there is no need to make assumptions on regulatory/supervisory constraints which, by construction (since these they are captured in our shock), may vary over time and affect all the variables in the model.

Third, our work is connected to papers assessing the macroeconomic effects of bank capital shocks with different methodologies, namely DSGE models (Basel Committee on Banking Supervision, 2010, 2015; Angelini et al., 2011) (BCBS, 2010a, 2015; Angelini et al., 2011) and VARs identified with zero and/or sign exclusion restrictions (e.g. Kanngiesser et al., 2017; Noss and Toffano, 2016; Meeks, 2017; Gross et al., 2016) , which have been extended to FAVAR models in order to assess heterogeneity across euro-area banks and countries. Overall, this empirical literature is far from being conclusive about the magnitude of the adverse macroeconomic effects of shocks associated to tighter bank capital constraints. We mainly contribute to this field of research by offering a different identification strategy. In addition, having a significantly larger set of endogenous variables underlying the conditional forecast allows us to improve in the quantitative evaluation of bank capital shocks, while models including a banking sector are typically limited to adding credit volumes and lending rates in small-scale VARs (Prieto et al., 2016; Gambetti and Musso, 2017). Finally, we address the issue of time-variation in the estimated relationships.

The paper also relates to the recently developed medium-scale Bayesian VAR models that are suitable to address the *curse of dimensionality* and whose typical application is counterfactual simulations aimed at detecting misalignments and irregularities in the observable developments of macroeconomic variables (Giannone et al., 2012b,a; DeMol et al., 2008; Aastveit et al., 2017; Jarociński and Bobeica, 2017). Our approach has much in common with the recent class of models studying the monetary transmission mechanism and credit shocks with medium- and large-scale VARs (Giannone et al., 2012b; von Borstel et al., 2016; Boivin et al., 2016). However, as discussed below, differently from these papers, we do not look at impulse responses derived by a structural model but use instead a conditional forecasting approach. Finally, our analysis builds upon single–equation models typically used in central banks for the analysis of credit market developments (Albertazzi et al., 2014; Bofondi and Ropele, 2011); an obvious advantage of a multivariate approach is to model a large number of endogenous variables in a unified framework.

3 Developments in the Tier1 capital ratio and banking regulation and supervision

In this Section we provide some stylized facts on the dynamics of bank capitalization in Italy. Figure 1 plots the evolution of the aggregate Tier 1 capital ratio (left-hand panel) for Italian banks since 1994 and, separately, of its two components: Tier 1 capital and risk-weighted assets (RWAs; right-hand panel). The aggregate ratio is obtained as a weighted average of all the banking groups and individual institutions resident in Italy, on a consolidated basis. The Tier 1 capital ratio is a key regulatory measure of a bank's capital adequacy. The numerator (Tier 1 capital) consists of Common Equity Tier 1 (CET1) – i.e., common shares, stock surpluses resulting from the issue of common shares, retained earnings, common shares issued by subsidiaries and held by third parties, accumulated other comprehensive income (AOCI) – and Additional Tier 1 capital (AT1) – which includes instruments that are not common equity but are eligible to be included in this tier, such as contingent convertible or hybrid securities, which have a perpetual term and can be converted into equity when a trigger event occurs. RWAs are total bank assets (including off-balance-sheet exposures) weighted according to their riskiness.

Three distinct phases can be observed in the evolution of the Tier 1 ratio in our sample: (i) the second half of the 1990s, when the Tier 1 ratio declined from around 10% to below 8%; (ii) the 2000s until the financial crisis, when the ratio hovered in a narrow range (between 7.5 and 9%); (iii) the crisis and post-crisis period, when the ratio showed a sharp and relatively steady increase, reaching almost 13% at the end of the sample (2015:Q4). Looking at the two components of the ratio, the reduction in the second half of the 90s was the result of a rapid expansion in RWAs (with annual growth rates of around 10%) and a modest growth in Tier 1 capital. In the 2000s, up to the onset of the financial crisis, both the numerator and the denominator grew substantially, though at a similar pace. Finally, since 2009 the increase in capitalization reflected both the steady decline in RWAs and the increase in equity capital, which was particularly strong up to 2012.

Our analysis focuses on the most recent period, when the evolution of the Tier 1 ratio was influenced by a number of important regulatory innovations and supervisory initiatives. In particular, we analyze three windows of two years during which regulatory and/or supervisory initiatives have raised pressure on banks to increase capitalization and, at the same time, large and persistent increases in the Tier1 ratio were observed.

1. The first window starts in 2009:Q2 and includes the period following the start of the discussion on the Basel III regulatory reform. In the aftermath of the global financial crisis, international cooperation aimed at strengthening financial regulation and supervision intensified. Since 2008 preparatory work involved the Group of Twenty (G20), the Financial Stability Board (FSB) and the European Union, and led to a number of recommendations that started to put pressures on the capitalization of the banking system.

In November 2008 the Basel Committee on Banking Supervision (BCBS) approved an action plan whose primary objective was to "*strengthen capital buffers and help contain leverage in the banking system [...].*"[5]. At the meetings in April and November 2009, the leaders of the G20 countries committed to completing a global reform of prudential regulation (Banca d'Italia, 2010). In December 2009, the Basel Committee on Banking Supervision published a consultation document with concrete proposals for capital and liquidity regulatory reforms (Basel Committee on Banking Supervision, 2009) (BCBS, 2009). The final text of the Basel III reform was approved at the end of 2010 (BCBS, 2010b).[6] The details of the reform were largely anticipated by the banks, who started increasing their capital buffers as soon as the discussion started. In the period considered, the Tier 1 equity of Italian banks increased by an aggregate amount of 24 billion, about 16% of the initial level of capital.

2. The second window starts in 2011q1 and covers (i) the 2011 Stress Test run by the European Banking Authority (EBA), launched in January 2011, and (ii) the EBA one-off Capital exercise, which was announced in October of the same year following a decision by the European Council. The Stress Test was based on banks' balance-sheets as of December 2010 and the results were published in July 2011. The EBA allowed capital raising measures adopted in the first four months of 2011 to be computed in the final result, in order to incentivise banks to strengthen their capital positions ahead of the stress test (EBA, 2011). As a consequence, between January and April 2011 about 50 billion capital was raised on a net basis by the 90 EU banks participating.[7] About 11 billion was the amount raised by the five largest Italian banking groups participating to the test, which amounts to about 1% of the RWAs at the end of 2010.[8] The Capital Exercise consisted of a one-off package aimed at: (i) building a temporary capital buffer against the depreciation of banks' sovereign portfolios, after having marked exposures to end-September market prices; (ii) establishing a capital buffer such that the Core Tier 1 capital ratio reaches 9%. The EBA reviewed individual banks' capital needs and published the results – and the associated formal reccommendation – in December. For 4 out of the 5 Italian banks participating to the exercise the EBA identified a total capital shortfall of 15.4 billion, which banks were prescribed to cover by the end of June

[5] See `https://www.bis.org/press/p081120.htm`.

[6] Key provisions of the reform included: (i) a minimum of 4.5% for the banks' CET 1, up from the level of 2% dictated in the Basel II framework; (ii) a minimum overall Tier 1 ratio requirement of 6 %, up from 4% in Basel II; (iii) the introduction of a minimum requirement for Tier 1 capital as a ratio to non-risk-weighted assets (the *leverage ratio*, set at 3%); (iv) the introduction of the Capital Conservation Buffer and the Countercyclical Capital Buffer, additional capital requirements with macroprudential purposes; (v) the introduction of minimum liquidity standards (the LCR and the NSFR).

[7] The test included also one bank from Norway.

[8] All the Italian banks passed the test.

2012.[9] Overall, the Tier 1 ratio in the last quarter of 2011 and in 2012 increased by 1.1 percentage points.

3. The third time window starts in 2014q1 and covers the period of the ECB's Comprehensive Assessment (CA) and the first months of operation of the Single Supervisory Mechanism (SSM). The CA was announced in October 2013 and was run in the subsequent 12 months; the SSM started operating at the beginning of November 2014.[10] In anticipation of the CA results Italian banks undertook significant measures that strengthened their capitalization, amounting to about 15 billion; in addition, also taking into account these measures, the results envisaged further aggregated capital needs of about 3 billion euro.[11] In 2015, which coincided with the first year of operation of the SSM, additional capital increases were recorded. Overall, in 2014 and 2015 aggregate equity capital of Italian banks increased by about 20 billion.

4 Empirical framework, data and methodology

4.1 Fixed coefficients Bayesian VAR model

To address our research question we adopt a Bayesian Vector Auto Regression (BVAR) model, which provides us with a flexible tool to deal with the interlinkages between macroeconomic, financial and banking variables without imposing too much structure on the data.[12] Our reference model in the rest of the paper is given by

$$\mathbf{Y}_t = \mathbf{A}_0 + \mathbf{A}_1\mathbf{Y}_{t-1} + \mathbf{A}_2\mathbf{Y}_{t-2} + ... + \mathbf{A}_p\mathbf{Y}_{t-p} + \boldsymbol{\varepsilon}_t, \quad \boldsymbol{\varepsilon}_t \sim \mathcal{N}(0, \boldsymbol{\Sigma}) \tag{1}$$

or, in terms of polynomial matrix form,

$$\mathbf{Y}_t = \mathbf{B}(L)\mathbf{Y}_{t-1} + \boldsymbol{\varepsilon}_t, \tag{2}$$

or, equivalently, in even more compact form,

$$\mathbf{Y}_t = \mathbf{X}_t'\mathbf{B} + \boldsymbol{\varepsilon}_t \tag{3}$$

where $\mathbf{Y}_t$ is a $m \times 1$ vector of endogenous variables, $\mathbf{A}_0$,..,$\mathbf{A}_p$ are $m \times m$ matrix of coefficients

[9] Three banks raised additional own funds (Unicredit, Banco Popolare and UBI Banca); the capital strengthening of Banca Monte dei Paschi di Siena required an intervention by the government, by about 2 billion euro (Banca d'Italia, 2012).

[10] On the CA and its outcome see `https://www.bankingsupervision.europa.eu/ecb/pub/pdf/aggregatereportonthecomprehensiveassessment201410.en.pdf?68911b281b9d831540bb474c334437e7`.

[11] See Banca d'Italia (2014) for a detailed description of the results for Italian banks. The capital increases were undertaken both by banks that passed the CA and by banks for which a shortfall was identified.

[12] The description of the empirical framework largely draws on Aastveit et al. (2017) and Clark and McCracken (2014).

and $\boldsymbol{\varepsilon}_t$ is a vector of residuals, which are assumed to be normally distributed with zero mean and variance-covariance matrix $\boldsymbol{\Sigma}$, and where $\mathbf{X}_t$ contains the constant and the lags of the endogenous variables, whereas $\mathbf{B}$ contains the matrices $\mathbf{A}_0$,..,$\mathbf{A}_p$.

Since our aim is to exploit a large amount of information to correctly underpin the correlations between the main macroeconomic variables and the banking sector, we choose a Bayesian framework, which is particularly useful when dealing with large systems of variables (Banbura et al., 2010; Giannone et al., 2012b; Banbura et al., 2015). This class of models, indeed, allows to attenuate over-fitting problems, performs very well in terms of out-of-sample forecasts and provides reliable impulse responses of main macroeconomic variables in the euro area to strucutural shocks (see Giannone et al., 2014; Banbura et al., 2015).

Let $\boldsymbol{\alpha}$ be the vector that stacks the reduced–form coefficients in $\mathbf{A}(L)$. In setting the prior distribution for our baseline sepcification, we adopt a version of the so–called Minnesota prior, due originally to Litterman (1979), with modifications proposed by Kadiyala and Karlsson (1997) and Sims and Zha (1998). We consider conjugate prior distributions that belong to the Normal-Wishart family, where the prior for the vector of coefficients is Normal while the prior for the variance-covariance matrix is inverse-Wishart. This allows us to take into account possible correlation among the residual of different equations and depart from the Litterman's standard assumption of fixed and diagonal covariance matrix.

The basic idea behind the prior distribution is that each endogenous variable follows an independent random walk process, possibly with drift. Accordingly, in each equation the prior mean of all coefficients is equal to zero except for the first own lag of the dependent variable, which is equal to one. In detail, the prior moments for the VAR coefficients are set as follows:

$$\mathbb{E}\left[(A_l)_{ij}\right] = \begin{cases} 1 & \text{if } i = j \text{ and } l = 1 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

$$\mathbb{V}\left[(A_l)_{ij}\right] = \begin{cases} \frac{\phi_0^2}{\phi_1^2} & \text{if } i = j \\ \left(\frac{\phi_0^2}{l^{\phi_1^2}} \frac{\sigma_i^2}{\sigma_j^2}\right) & \text{otherwise} \\ \phi_2^2 \sigma_i^2 & \text{for intercept} \end{cases} \tag{5}$$

In this framework the hyperparameter ϕ_0 controls the *overall tightness* of the prior distribution around the random walk and governs the relative importance of the prior beliefs with respect to the information contained in the data. As ϕ_0 approaches very large values, the posterior collapses to ordinary least squares (OLS) estimates. On the contrary, small values of ϕ_0 imply a tighter overall prior and more limited information stemming from the data. In large system (like ours) DeMol et al. (2008) suggest that the overall tightness hyperparameter be shrunk significantly in order to avoid over-fitting. The hyperparameter ϕ_1 is known as *decay factor* and allows the variance of the coefficients on higher order lags to shrink as the lag length increases. Uncertainty about the prior for the intercept is governed by a specific

hyperparameter ϕ_2. The terms σ_j/σ_i account for the relative scale of the variables, which are obtained from m univariate AR(1) OLS regressions of each variable on its own lagged values. This is the only use of the sample data in the specification of the prior, which allows the scale of the prior covariance of the parameters to be approximately the same as the scale of the sample data.

Following Doan et al. (1986) and Sims (1993) we complement the prior beliefs above with additional priors which favour unit roots, trends and cointegration among endogenous variables. These priors allow us to avoid having an unreasonably large share of the sample period variation in the data accounted for by the deterministic component. Moreover, the priors reflect the belief that macroeconomic and banking variables typically exhibit unit roots and cointegration. Accordingly, we add the so–called *sum of coefficients* and *dummy initial observation* priors, which can be implemented by augmenting the system with dummy observations, as detailed in Sims and Zha (1998) and Waggoner and Zha (1999) and widely used in the recent literature (Giannone et al., 2015; Clark and McCracken, 2014, see, e.g.). The sum of coefficients prior is consistent with the belief that when the average of lagged values of a variable is at some level $\bar{y_{0i}}$, this value is likely to be a good forecast of future observations. It is implemented by augmenting the system with the dummy observations Y_{d_1} and X_{d_1} with generic elements:

$$y_d(i,j) = \begin{cases} \bar{y}_{0i}/\phi_3 & \text{if } i = j \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

$$x_d(i,s) = \begin{cases} \bar{y}_{0i}/\phi_3 & \text{if } i = j, \text{ s<M} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

where $M = m \times p + 1$ and $s = 1..M$. When the shrinkage hyperparameter ϕ_3 approaches zero the model tends to a specification with differenced data, with as many unit roots as variables and with no cointegration.

The dummy observation prior introduces a single dummy observation such that all values of all variables are set equal to the corresponding averages of initial conditions up to a scaling factor. It is implemented by adding to the system the dummy variables Y_{d_2} and X_{d_2} with generic elements:

$$y_d(j) = \bar{y}_{0i}/\phi_4 \tag{8}$$

$$x_d(s) = \begin{cases} \bar{y}_{0i}/\phi_4 & s < M \\ 1/\phi_4 & s = M \end{cases} \tag{9}$$

When the shrinkage hyperparameter ϕ_4 is set at zero the model tends to a form in which all variables are stationary with means equal to the sample averages of the initial conditions, or in which there are unit roots components without drift terms, which is consistent with

cointegration.

Based on the above considerations, we here discuss our calibration of the hyperparameters, with the shrinkage parameters choses so as to ensure that the unconditional forecasts of changes in the main variables do not exhibit exploding paths in the long run. More specifically, we set the overall tightness (ϕ_0) equal to 0.05, the decay factor (ϕ_1) at 1.0, and both the sum of coefficients (ϕ_3) and the dummy observation (ϕ_4) hyperparameters at 1.0, following the parametrization suggested by Sims and Zha (1998). The hyperparameter for the intercept (ϕ_2) is also equal to 1.0.

An alternative approach is suggested by Banbura et al. (2015), who also estimate the shrinkage parameters instead of calibrating them, by maximizing the marginal likelihood. Aastveit et al. (2017) perform a grid search over the space of shrinkage parameters, ending up with similar choices to the one we implemented. We check the robustness of our main results to the use of this alternative approach in Section 8. We set the number of lags in the VAR to five, based on the serial correlation of the residuals.[13]

The posterior distribution of the reduced–form parameters of the VAR, which is obtained by combining the (normal) likelihood of the VAR with the prior distribution, is normal conditional on the covariance matrix of the residuals, which has an inverse Wishart distribution.

4.2 Time–varying coefficients Bayesian VAR model

When we switch to the time–varying coefficients case we are constrained by the relatively large dimension of our system of variables which prevents us from using the seminal approach by Cogley and Sargent (2005) and Primiceri (2005). Instead, we closely follow the steps by Aastveit et al. (2017), who deal with a 13 variables model of the US economy by sticking to the methodology proposed by Koop and Korobilis (2013). Model (1) is now allowed to have both time varying coefficients and volatility and it is estimated by Kalman filter techniques, as it can be casted in state space form:

$$\mathbf{Y}_t = \mathbf{A}_{0,t} + \mathbf{A}_{1,t}\mathbf{Y}_{t-1} + \mathbf{A}_{2,t}\mathbf{Y}_{t-2} + ... + \mathbf{A}_{p,t}\mathbf{Y}_{t-p} + \boldsymbol{\varepsilon}_t, \quad \boldsymbol{\varepsilon}_t \sim \mathcal{N}(0, \boldsymbol{\Sigma}_t) \tag{10}$$

or

$$\mathbf{Y}_t = \mathbf{B}_t(L)\mathbf{Y}_{t-1} + \boldsymbol{\varepsilon}_t, \tag{11}$$

or, equivalently, in even more compact form,

[13]Standard information criteria tend to select a smaller or equal lag length in our setting. However, our choice is more conservative, as we select the longest lag length and then control the prior variance of longer lags by means of the decay factor ϕ_1. In any case, the results are robust to using a smaller lag length and/or different values of such hyperparameter.

$$\mathbf{Y}_t = \mathbf{X}_t^{'}\mathbf{B}_t + \boldsymbol{\varepsilon}_t \tag{12}$$

$$\mathbf{B}_t = \mathbf{B}_{t-1} + \boldsymbol{\eta}_t, \quad var(\boldsymbol{\eta}_t) = \mathbf{Q}_t \tag{13}$$

Koop and Korobilis (2013) propose to approximate the Kalman filtering formula for the state variance $\mathbf{V}_{t|t-1} = \mathbf{V}_{t-1|t-1} + \mathbf{Q}_t$ with $\mathbf{V}_{t|t-1} = \frac{1}{\lambda}\mathbf{V}_{t-1|t-1}$, i.e. by introducing a forgetting factor $0 < \lambda \leq 1$ in order to eliminate the need for estimating or simulating the matrix $\mathbf{Q}_t$, which is particularly cumbersome and intensive from a computational point of view. A similar approximation is then used to bypass the need for a posterior simulation algorithm for multivariate stochastic volatility in the measurement equation. Indeed, Koop and Korobilis (2013) use an Exponentially Weighted Moving Average (EWMA) to model volatility estimator for the measurement error covariance matrix: $\hat{\mathbf{\Sigma}}_t = \kappa\hat{\mathbf{\Sigma}}_{t-1} + (1-\kappa)\hat{\boldsymbol{\varepsilon}}_t\hat{\boldsymbol{\varepsilon}}_t^{'}$, where $\hat{\boldsymbol{\varepsilon}}_t = \mathbf{Y}_t - \mathbf{X}_t\mathbf{B}_{t|t}$ is obtained with the Kalman filter. Following the baseline settings of Koop and Korobilis (2013), we set the forgetting factor λ at 0.99 and the volatility weighting coefficient κ at 0.96.

As for the other prior settings, the approach relies on the standard Minnesota prior with a normal distribution for the vector of coefficients and a fixed and diagonal covariance matrix. Accordingly, we do not introduce the sum of coefficients and the dummy observation prior, while allowing for cross-variable shrinkage in each equation, as follows:

$$\mathbb{V}\left[(A_l)_{ij}\right] = \begin{cases} \frac{\phi_0^2}{\phi_1^2} & \text{if } i = j \\ \phi_5 \left(\frac{\phi_0^2}{l^{\phi_1^2}}\right) \frac{\sigma_i^2}{\sigma_j^2} & \text{otherwise} \end{cases} \tag{14}$$

In equation 14 the hyperparameter ϕ_5 is known as *relative tightness* and reflects the belief that own lags of the dependent variable provide more reliable information than lags of the other endogenous variables. When it is set to zero, the system collapses to a set of univariate regressions, while a value of one implies that all variables are assumed to provide the same information content. The hyperparameters governing overall and cross-variable shrinkage (ϕ_0 and ϕ_5) are both set at 0.05, consistently with a relatively tight prior for large models.[14] In the following sections, for sake of comparison, we also report the results using a standard Minnesota prior in a fixed-coefficient framework in order to evaluate whether differences with respect to the baseline model described in 4-9 stem from the use of a different prior or really from time-variation.

4.3 The data

The specification of the VAR model is designed to capture the most relevant interrelations between the banking system and the macroeconomy. Our dataset includes quarterly information

[14] The other hyperparameters are calibrated as in the fixed-coefficient model.

on the Italian banking sector as far in the past as possible, and is rich enough to capture four recessions: the one in the early 1990s; the one in the early 2000s; the one following the Global Financial Crisis of 2008–09; and the one following the Sovereign Debt Crisis of 2011–12.

The choice of the endogenous variables takes as a starting point the growing literature on the impact of credit shocks on the business cycle (Prieto et al., 2016; Gambetti and Musso, 2017). These works typically limit themselves to adding credit volumes and rates to the usual macroeconomic variables. In addition to these variables, our paper includes information on loan default rates, the main items of banks' profitability, bank stock prices, Tier 1 capital and RWAs. Including a large number of banking variables allows for a rich account of the interactions between financial intermediation and the business cycle.

The benchmark model includes 16 variables: (i) four core macroeconomic and financial variables: Italian real GDP; consumer-price inflation; a measure of the short-term interest rate (the 3–month Euribor rate until 1998 and a "shadow rate" measure afterwards),[15] which captures both conventional and unconventional monetary policy and the financial strains originated in the interbank market during the global crisis; a measure of the long-term interest rate (the 10-year Italian government bond yield), which reflects developments in both long-term risk-free rates as well as changes in term and risk premia during the most acute phases of the financial crisis and the implementation of unconventional measures; (iii) six variables related to the credit markets: the cost and the quantity of loans to non-financial firms (NFCs);[16] the cost and quantity of loans to households (HHs) for house purchase;[17] default rates of both NFCs and HHs;[18] (iv) four variables related to the main items of bank income statement: net interest income; non-interest income; operational expenses; loan loss and other provisions;[19] (v) the Italian bank stock market index;[20] (vi) the Tier1 capital ratio.[21]

Besides the four macroeconomic variables and the bank stock price index, the other variables are taken from the Bank of Italy supervisory reports. In the baseline model all the variables enter in log–levels, with the exception of interest rates, default rates and the Tier 1 ratio, which

[15] The shadow rate captures the effects of unconventional monetary policy when the economy is stuck at the Zero Lower Bound (ZLB) and it is successfully used as a simple alternative way to identify central banks' balance sheet shocks. See Krippner (2013) and Wu and Xia (2016) for a description of the shadow rates estimation; von Borstel et al. (2016), Conti (2017) and Albertazzi et al. (2016b) for empirical applications in monetary analysis.

[16] Bank lending is outstanding amount of loans extended by Italian Monetary and Financial Institutions (MFIs) to non financial corporations (NFCs) resident in Italy, adjusted for including the impact of securitizations and reclassifications; the NFC lending rate is the average rate on the stock of loans with maturity up to one year.

[17] Bank lending is the outstanding amount of loans for house purchase extended by Italian Monetary and Financial Institutions (MFIs) to HHs resident in Italy, adjusted for including the impact of securitizations and reclassifications; the HH lending rate is the average rate on the flow of new loans for house purchase in a given quarter.

[18] Default rates are the seasonally-adjusted quarterly flow of new bad loans of Italian banks, expressed as a ratio to the stock of outstanding loans at the beginning of the period.

[19] Each variable is the 4-quarter moving sum of the item reported by Italian banks in aggregate.

[20] The index is the sectoral Index FTSE Italia All-Share Banks, from Borsa Italiana.

[21] The Tier 1 ratio is the total amount of Tier 1 equity of Italian banks divided by RWAs.

are expressed in levels. Figure A-1 in the Appendix provides a graphical representation of all the series used in the model.

The estimation sample runs from 1993:Q1 to 2015:Q4. The choice of the period is constrained by the availability of high–quality information for some banking variables, namely the capital ratio, default rates and measures of bank profitability. To check the robustness of our results we replicate the exercises in the paper by considering the first–differences of variables expressed in stocks. Accordingly, in the model we specify a prior mean lower than one on the own lag of the dependent variable, which is consistent with the evolution of stationary variables.[22]. All the results are broadly confirmed.

4.4 Conditional forecasting

As noted by, among others, Waggoner and Zha (1999) and Antolin-Diaz et al. (2018), the conditional forecasting methodology provides answers to crucial applied and policy questions of the following form: "what happens to the forecasts of some k variables of interest Y_1 ,..., Y_k under the assumption of a certain predetermined dynamic path of a variable X for the subsequent periods of time?". For example, in this paper we are going to use this methodology to answer an important question such as "what is the likely path of banking variables, and in particular of the Tier 1 capital ratio, given that business cycle and financial variables follow a specific dynamics?". This exercise is called "conditional-on-observables forecast". In contrast, it is also possible to build forecasts of some k variables of interest Y_1 ,..., Y_k on a particular path of some structural shocks of interest over the forecast horizon. This framework can be labeled "conditional-on-shocks forecast" (see, for example, Baumeister and Kilian, 2014; Antolin-Diaz et al., 2018). There is a key difference between these two methodologies: while the latter requires the estimated parameters of the structural form of the VAR model, and thus identifying assumptions for the shocks of interest, the former relies on the reduced–form parameters of the VAR only. This implies that the conditional-on observables forecasts are independent from the chosen identification procedure, i.e. identification is irrelevant and the structural shocks are not needed (Waggoner and Zha, 1999; Antolin-Diaz et al., 2018).

Our empirical exercise belongs to the "conditional-on-observables forecast", i.e. we condition on the actual path of variables of interest, as we are going to explain in Section 5. The interested reader may see Antolin-Diaz et al. (2018) for a more complete description and mathematical details.

To produce conditional forecasts, we use the standard algorithm in the VAR literature developed by Doan et al. (1986), which consists of solving a least squares problem to pick the shocks needed to satisfy the conditions. For example, conditioning the forecasts on the path of actual real GDP can be seen as determining the set of shocks to the VAR that, by a least

[22]In particular, for each variable, we estimate an AR(1) model via Box-Jenkins techniques over the entire sample period and set the prior at the value of the estimated coefficient.

square maetric, best meets the conditions on real GDP. Under this minimum-MSE approach, the conditional forecasts are not dependent on the identification of strucutural shocks in the VAR.[23]

For each model, we use Monte Carlo simulations to obtain draws of the BVAR coefficients and the error variance matrix from the standard posterior. In the case of models with time-varying coefficients and time-varying volatility, to simplify calculations of conditional forecasts we hold the various parameters and volatilities constant at their end-of-sample estimation values over the two-year forecast horizon.

5 The effects of bank capital shocks

In this Section we describe the procedure used to recover the size of bank capital shocks and provide a quantification of their impact on the banking variables and the real economic activity. In dealing with the methodological aspects.

5.1 Step 1: estimating the "size" of the bank capital shock

First, we borrow from the literature on the estimation of non-standard monetary policy measures (i.e. central bank balance sheet shocks, see Lenza et al., 2010 and Giannone et al., 2012b and retrieve the regulatory/supervisory shocks to bank capital as the difference between the actual value of Tier 1 capital ratio k and its forecast conditional on a large set of macroeconomic and banking variables. The *conditional forecast* captures the value of bank capital consistent with the developments in all its main drivers and can be thus interepreted as the desired or equilibrium level target of the banking sector k^*, which is of course unobserved.[24]

. Macroeconomic variables included in the conditioning set are: real GDP, inflation, the short- and long-term rates. Banking variables - which are included to control for factors affecting developments in bank capital not fully captured by macroeconomic dynamics- include: (i) the four variables related to bank profitability: net interest income; non-interest income; operational expenses; loan loss and other provisions; (ii) households' and firms' default rates; (iii) the bank stock market index. Including these variables is important for the following reasons. All these variables affect the estimation of the unobserved target for banks' capital. The observed evolution of bank capital is - by nature - conditional on the same set of variables

[23] In the implementation we form the posterior distribution of VAR paramters without taking into account the conditions to be imposed. Waggoner and Zha (1999) developed a Gibbs sampling algorithm that provides the exact finite-sample distribution of the conditional forecasts, by taking the conditions into account when sampling the VAR coefficients. We abstract from this method because it is computationally very intensive in medium-scale models. Moreover, Clark and McCracken (2014) and Aastveit et al. (2017) found that, in smaller models, the various methods provide extremely similar results.

[24] One can think about k^* as the aggregation of the desired Tier 1 ratio for the i-th generic bank (see Mésonnier and Stevanovic, 2017).

and on the exogenous shocks that compelled banks to increase their capital level beyond the amount consistent with the evolution of its main determinants. We claim that these shocks are related to regulatory and supervisory pressure and we interpret positive values of the shock as being associated to a tightening of capital constraints.

Banks set their "optimal economic capital ratios" in reaction to changes in macroeconomic conditions mostly by modifying their RWAs. In periods of strains in financial markets, indeed, raising funds in the capital market becomes much more difficult and banks could prefer to achieve the new level of desired capital by means of a deleveraging process. An important consideration is that, over these periods, financial shocks hit the banking system and the ECB reacted by implementing unconventional measures. These represent shocks that affected banks' capital position. In principle, our measure of the short-term interest rate (i.e. the 3-month Euribor) captures the financial tensions hitting the interbank market in 2007-2008 and the effects of the extraordinary liquidity injections of the ECB in the following years aiming at restoring more ordinate conditions in the interbank market. In the same vein, the long-term rate used to produce forecasts is the Italian 10year Government bond yield, which controls for the large upswings of the sovereign spread until 2012:Q2 and the subsequent decrease following Draghi's "whatever it takes" speech in 2012:Q3, which contributed to bring the spread back to a value of around 200 bps at the end of 2013.

We now discuss in detail why enlarging the conditioning set to including banking variables is important to recover regulatory shocks. Inclusion of (i) and (ii) captures the fact that banks could have raised their capital ratio in advance to counteract factors lowering their current profitability that are different from macroeconomic conditions, which, in turn, could have put pressures on banks' evaluation about their future capital position. The strong increase in default rates implied larger amounts of loan-loss-provisions in banks' income statements, thus consistently eroding their net operating profits.

In addition, throughout the financial crisis, banks increased their overall provisions not only because of the net value adjustments for loan impairments but also to report goodwill impairments. For example, in 2011 the profitability of the Italian banking system was strongly affected by the huge one-off write-downs of goodwill made by the leading groups to bring their book values in line with market developments and to increase the transparency of their balance sheets. Goodwill impairments exerted relevant downward pressures on bank profitability in 2013-2014 as well. Notice that changes in bank profitability also depend on changes in banks' business model and reconfiguration of locally branches to reduce operational expenses. Based on these considerations, we add default rates and the various components of bank profitability in the conditioning set of variables.

Finally, we condition on share prices because an important concern in the interpretation of our bank capital shocks is that, during the financial crisis, banks faced relevant market pressure to rebuild capital as market participants were afraid about the resilience of the banking

system. In this regard, we cannot exclude that the shocks reflected "market discipline" instead of pressures from regulation and supervision.

Including some of these bank-specific variables in the conditioning set of variables, in our view, leads to a very conservative approach in the estimation of the size of bank capital shocks. In particular, our definition of the shock excludes the effect of regulatory- (or supervisory-) induced actions which have an effect on capital only indirectly. One example is the significant increase in loan-loss provisions induced by the ECB Comprehensive Assesment in 2014: in our exercises this effect is excluded, as the counterfactual path for bank capital is conditional on provisions.[25]

More generally, all actions inducing banks to increase loan-loss-provisions (like, for example, in the AQR episode) have affected bank capital. On the other hand, our measure rightly captures changes in dividend policies which increase the share of earnings that transform into "new capital" and were often induced by supervision.

5.2 Step 2: estimating the impact of the shock on the main macro and banking variables

After having explained how the regulatory/supervisory shocks are recovered, we move on to describe how we compute their effects on the cost and availability of loans, on GDP and inflation. For each variable of interest we compute the difference between two scenarios (in line with the papers by Lenza et al., 2010, Giannone et al., 2012b and Kapetanios et al., 2012, who focus on the evaluation of central banks' balance sheet expansion): (i) a scenario obtained as a conditional forecast on the actual path of the Tier 1 ratio (the *policy scenario* because it includes the effect of regulation/supervision), and (ii) a scenario obtained as a forecast conditional on the (counterfactual) path for bank capital that would have occurred absent regulatory/supervisory shocks, i.e. the conditional forecast described above in Step 1 (the *no-policy scenario*). This procedure is (loosely) equivalent to computing impulse responses to a shock of interest (Waggoner and Zha, 1999; Jardet et al., 2013; Banbura et al., 2015). [26]

[25] Accornero et al. (2017) use a bank-firm level dataset from Credit Registers and find that the exogenous increase in NPLs related to the AQR had a negative effect on bank lending, similarly to a negative shock to the capital buffers. Other papers using macro information, such as Albertazzi et al. (2016a) and Notarpietro and Rodano (2016), instead find that the contraction of Italian economic activity is the main driver of the large increase in defaults on loans to firms, meaning that default rates should not have marginal predictive content for other banking variables wit respect to business cycle indicators. In particular, Notarpietro and Rodano (2016) quantified the contribution to the evolution of bad debts made by the two recessions, or, to be precise, by the double-dip recession (see Banca d'Italia, 2018, Annual Report) that have hit the Italian economy for the period 2008-2015 using the Bank of Italy's Quarterly Model (BIQM). The counterfactual simulations suggest that, in the absence of the two crises - and of the economic policy decisions that were taken to combat their effects, the ratio of bad debts to the total amount of loans to non-financial corporations would have reached 5%, a value in line with the pre-crisis period

[26] In particular, this is obtained by imposing a dynamic pattern of residuals ε_t compatible with the required *conditions on observables* for a given desired horizon H. The distribution of such conditional forecasts is invariant to an orthonormal transformation of the underlying factorization of the covariance matrix of the residuals, which

More in detail, as shown by Lenza et al. (2010), for each endogenous variable Y_i, the policy scenario is the conditional expectation based on the estimated parameters $A(L)$, the past and current values $Y_{i0}, Y_{i1}, ..., Y_{it}$ and the actual value of the Tier1 capital

$$E_{(A(L))}\left(Y_{it}|Y_{i0}, Y_{i1}, ..., Y_{it}, k_{P,t+1}, ..., k_{P,t+H}\right) \tag{15}$$

where H is the forecast horizon. The no-policy scenario is obtained as above replacing the actual value of the Tier1 with its counterfactual path $k_{NP,t+H}$, obtained in Step 1:

$$E_{(A(L))}\left(Y_{it}|Y_{i0}, Y_{i1}, ..., Y_{it}, k_{NP,t+1}, ..., k_{NP,t+H}\right) \tag{16}$$

The implicit underlying assumption is that changes in regulation and/or supervision have affected bank capital in the period under analysis. The impact of the shocks for the generic variable Yi is thus the difference between (2) and (3).

6 Results

Figures 2–4 report, for each episode, the actual values of the banks' Tier 1 capital ratio (the black lines) against its forecast conditional on the full set of macro, financial and banking variables (i.e. the magenta solid lines). We derive the empirical distribution of the conditional out-of-sample forecasts by Montecarlo simulations based on 1,000 draws. For illustrative purposes, we plot the median forecast together with the 0.68 and 0.90 probability intervals of the posterior distribution of conditional forecasts, along with the unconditional forecasts. In order to show how changing the conditioning set is important for a proper quantitative assessment of the shock, we also report forecasts conditional only on four macroeconomic variables (real GDP, inflation, the short- and long-term rates; i.e. the blue dashed lines). While the forecast of bank capital conditional on the smaller set is relatively accurate, precision improves somewhat when the full set is considered. This is largely due to the inclusion of bank provisions. In what follows, the discussion will only consider the shocks retrieved using the full conditioning set.

The same set of figures also report the estimated impact on real GDP, inflation, loans and loan rates to NFCs and HHs. The graphs display the percentage difference between the level of each variable in the policy scenario with respect to the no-policy scenario. As discussed in Section 4, these graphs can be loosely interpreted as impulse response functions.

In all three episodes our approach leads to large (and statistically significant) positive bank capital shocks. The estimated size of the shock – measured as the increase in the Tier 1 ratio at the end of the two-year window is similar across the three episodes and corresponding to about 1.5 pp.

is assumed to be triangular.

As expected, these shocks acted as credit supply restrictions: at the end of the two-year window, on average, the stocks of loans to NFCs and HHs were lower by 3.0 and 3.4 per cent, respectively (results are also reported in Table 1); loan rates increased only moderately (by 27 and 21 basis points, respectively for NFCs and HHs), in line with the idea that capital constraints mainly affect the volume of loans rather than their cost.[27] The credit supply shocks had significant repercussions on the level of GDP, which declines, on average, by 1.3 per cent at the end of the period; the impact on the HICP was less severe in all three episodes, equal to -0.3 per cent on average.

The size of the shocks lies in the low range of estimates in the most recent reference papers: the aggregate bank capital buffer estimated by Mésonnier and Stevanovic (2017) and Kanngiesser et al. (2017) fluctuates between -3% and -4% after the bankruptcy of Lehman Brothers as well as during the sovereign debt crisis. They are instead broadly in line with the difference between target capital and actual capital in Berrospide and Edge (2010), which ranges between -0.5 and 1%, as well as the trigger ratio reported by Meeks (2017), which fluctuates between 8 and 9%. The estimated effects are quantitatively very similar to those reported by Kanngiesser et al. (2017) for the euro area and, for loans supply to both households and non–financial corporations, to those found by Meeks (2017). [28]

7 Bank capital shocks or structural breaks?

The results obtained with a conditional forecasting approach could be subject to concerns related to potential instability issues in a BVAR model. In an application for the US economy, Aastveit et al. (2017) showed that discrepancies between the main macroeconomic variables and their conditional out-of-sample forecasts could reflect instability in the estimated relationships in the aftermath of the Great Recession.

In our framework the methodology we use to recover the shocks is valid to the extent that the difference between actual values of the Tier1 ratio and its out-of-sample conditional forecasts is entirely driven by unprecedented large shocks hitting the variables. An additional explanation, however, could be that the lack of fit depends on the fact that some historical relations between the Tier1 ratio and the macroeconomic variables broke down exactly when the bank capital shocks occurred. Yet another explanation could relate to a change in the transmission mechanism over time, as the result of structural breaks in the estimated relationships among endogenous variables. As an example, up until the breakout of the financial crisis, the sovereign spread was virtually flat since the second part of the 1990s, after convergence in the euro area was achieved. Therefore, we could not deal with a shock with unprecedented nature but with a dramatic time-variation in the relationships between sovereign yields, lending con-

[27] A similar result for Italian banks is found by DelGiovane et al. (2017).
[28] Meeks (2017) finds somewhat smaller effects on GDP.

ditions and bank capital.[29] Finally, an additional possible concern is that in an out-of-sample forecasting exercise the estimated coefficients and the variance-covariance matrix of the BVAR model are kept constant over the forecast window.

As already mentioned, the choice of a forecast window no longer than two years should help limiting these drawbacks. However, the financial crisis may have induced quick changes in the relations between the business cycle, the financial markets and the banking variables. Thus, in what follows, we test the robustness of the main results by using two alternative econometric approach. First, we rely on BVAR models allowing for time-varying coefficients and time-varying volatility, which allow for "smooth" changes in the estimated coefficients and/or variance-covariance matrix. Secondly, we look at "in-sample" conditional forecasts: while this approach deals with potential sudden breaks in the estimated relationships, it may lead to a "too conservative" definition of the shocks and more muted responses of the variables of interest.

7.1 Allowing for time-varying coefficients and volatility

We explore the instability issue in our framework by considering a BVAR model with time-varying (TV) parameters and volatilities. As already mentioned in Section 4.2, in light of computational constraints in large models we use the approach proposed by Koop and Korobilis (2013), which introduces shortcuts to make computation tractable.

The estimated bank capital shocks and the effects on the variables of interest over the three episodes are presented in Figures 5–7. In each figure the blue solid line refers to estimates based on the baseline BVAR model with the Normal-Wishart prior; these are compared with the estimates obtained with the time-varying coefficient model (the red solid lines). As explained in Section 4.2, for the sake of comparability, we also report the estimates based on a fixed-coefficient model with a standard Minnesota prior (the solid green line).

Qualitatively, we confirm all the results obtained with the fixed-coefficient model and find evidence of significant shocks – and the associated macroeconomic impact in all the three episodes. Quantitatively, some differences emerge. First, the shock in the Basel III episode is less severe in the TV model. This model, however, leads to significantly larger effects on GDP and loans to NFC, than the baseline. These differences arise only partly from the use of the Minnesota prior, while they tend to reflect time variation in the volatility of innovations in some of the estimated equations. Figure 8, indeed, shows large innovations in the Tier1 equation following the announcement of the Banking Union and large shocks in the real GDP equation with the breakout of the global crisis. Significant innovations in the consumer price equation also appear to be relevant in the recent "low-inflation" period.

[29] Albertazzi et al. (2014) indeed use reduced-form single-equation models for the case of Italy in which a break dummy since 2011Q3 is able to capture changes in the estimated relationships between the sovereign spread and a number of banking variables, including lending conditions and profitability.

Overall, we find evidence that the recovery of bank capital shocks is robust to the use of a time-varying coefficient framework but the estimated effects could be somewhat larger as the result of changes in the estimated variance-covariance matrix of the BVAR innovations.

7.2 "In-sample" conditional forecasts

Our second approach to address the implications of potential structural breaks in the estimated relationships for our estimates consists in performing an "in-sample" evaluation exercise, in which we estimate the model up the end of each forecast horizon and use the estimated coefficients to produce the conditional forecasts. This allows the estimated coefficients to embody the "new relationships" between the banking and the macroeconomic variables beyond what one could do by means of econometric models allowing for time-variation.

Accordingly, we estimating the BVARs with data up to the end of the sample period (2015:Q4) and then perform a forecasting exercise on the same conditioning set of variables. Extending the estimation sample, by construction, produces a much more conservative estimation of the bank capital shocks, as "in-sample" forecasts are usually closer to actual values than "out-of-sample" forecasts. In this regard, the corresponding estimated effects are likely to be a lower bound of the true effects of regulatory- and supervisory-induced capital constraints. For sake of completeness, in Figures 9–11 we report the estimation results for both fixed-coefficient and time-varying coefficient models (see also Table 2 for a cross-models comparison, both out-of-sample and in-sample, on the effects of bank capital shocks on real GDP and loans to NFCs).

Also the results with the in-sample conditional forecasts are qualitatively fully in line with those of the baseline model. Like in the TV model, the procedure retrieves a significantly smaller shock in the Basel III episode, though the effects on loans and GDP are also less pronounced in this case. In the EBA and CA/SSM episodes, instead, the shocks are quantitatively similar to the baseline but the effects on loan volumes and on the real variables are somewhat more pronounced.

Overall, these results in this Section corroborate the view that, even if some breaks occurred in the estimated relationships, significant and negative effects for the real economy stemming from changes in regulation and supervisory activity may arise in the short-run.

8 Robustness checks

8.1 Bank capital shocks or other credit supply shocks?

A potential concern in our analysis is that our measure of the bank capital shock could be observationally equivalent to other type of adverse shocks to credit supply. For example, the Bank Lending Survey suggests that banks' credit standards also reflected banks' funding and

liquidity shocks as well as an increase in banks' risk perception (DelGiovane et al., 2017). The inclusion of market interest rates and stock prices in our conditioning set is able to capture the effects of such shocks. For robustness, we add bank lending volumes and rates to the conditioning set: by doing so, we control for any other shock implying a negative co-movement between the cost and quantity of credit (i.e. affecting credit supply).[30] Results suggest that the estimate of the bank capital shocks remains virtually unchanged and so are the effects on all the variables of interest.

8.2 Including other controls for credit demand conditions

We also consider a larger model comprising three additional macroeconomic variables which may relate to sectoral loan developments: households' real disposable income, residential house prices and firms' financial needs (as captured by the ratio of private investment and net operating profits). These variables may capture demand shocks that are specific to individual segments of the credit market. House prices are important drivers of housing demand in Italy and, in turn, of mortgage loans to households Nobili and Zollino (2017) and their developments are comprised in scenarios used for stress testing exercises. Firms' financing needs capture the dynamics of internal cash-flow as alternative source of financing, which, in turn, affects the demand for loans of NFCs (Albertazzi et al., 2014). We re-estimate the bank capital shocks adding these variables to the conditioning set and evaluating the macroeconomic effects. The results, however, are unchanged.[31]

8.3 Changing the prior distribution

The choice of the prior mean may strongly affect the estimation results, especially when the information in the data is scant. In all our forecasting exercises we have kept fix the hyperparameters to the standard values suggested by Sims and Zha (1998). Alternatively, one can choose the values that maximize the log-marginal likelihood, following the suggestion in Giannone et al. (2015). We apply this optimization procedure to the hyperparameters governing the overall shrinkage, the tightness on the sum of coefficients prior and the tightness on the cointegration prior in the various sample periods. In general, the procedure suggests a different value only for the overall tightness. In particular the value of 0.3 which is consistent with a relatively "loose" Sims-Zha prior, which, however, does not significantly affect or main results.

[30] One way to further check robustness along this dimension would be to include additional variables in the VAR more directly capturing banks' funding and liquidity conditions and risk tolerance, such as banks' CDS, funding costs, earnings forecast.

[31] Figures are not shown but available upon request.

9 Conclusions

In this paper we estimate a Bayesian VAR with a large number of macroeconomic, financial and banking variables, on quarterly data for the Italian economy over the period 1993:Q1-2015:Q4. The framework allows for a richer characterization of the banking sector than existing studies in the literature. A clear advantage of such a data-rich environment is that it is able to take into account the feed-back loops between economic activity, financial developments and banks' balance sheet conditions.

Borrowing from the methodology proposed in the literature to assess the macroeconomic impact of unconventional monetary policy measures (Lenza et al., 2010; Giannone et al., 2012b; Kapetanios et al., 2012), we use conditional projections to retrieve shocks to bank capital related to three specific regulatory and/or supervisory initiatives in the last decade and to assess their impact on loan supply and real activity. The analysis shows that these shocks were sizeable and had significant effects on loan volumes, loan rates and GDP . The estimated short-run negative impact of bank capital shocks on lending conditions and the real economic activity differ across model specification: nonetheless they are large also when considering the most conservative definition of the shocks.

We replicate our analysis allowing for time-varying coefficients and via in-sample model simulations. All in all, these checks confirm that the effects of the bank capital shocks on lending conditions and real economic activity are large also when considering the most conservative definition of the shocks. Moreover, the estimated impact differs across periods and forecasting models as the result of sudden increases in the stochastic volatility in some estimated equations. This suggests that the evaluation of the effects of bank capital shocks remains challenging and call for statistical models allowing time-varying coefficients and volatility.

Our results yield a number of important policy implications. First, when increasing bank capital requirements, supervisory authorities should carefully take into account the possible feedback effects between changes in regulatory capital and the macroeconomy: in a low-growth environment, regulatory pressures induce banks to tighten credit supply and reduce real GDP, which, in turn, exert pressure on banks to strengthen their capital position, thus reinforcing the initial negative effects on credit supply and economic activity. Moreover, this negative feedback may affect the transmission of monetary policy, possibly crowding out the effectiveness of expansionary measures, and should be thus taken into account also by central banks. A deeper analysis of the multifaceted interactions between microprudential policy and monetary policy will require further research.

An important aspect to bear in mind is that our focus is on the short-run costs of the reforms in the banking system and our methodology disregards the large long-run benefits of banking regulation and supervision, which improve banks' resilience to shocks and foster financial stability.

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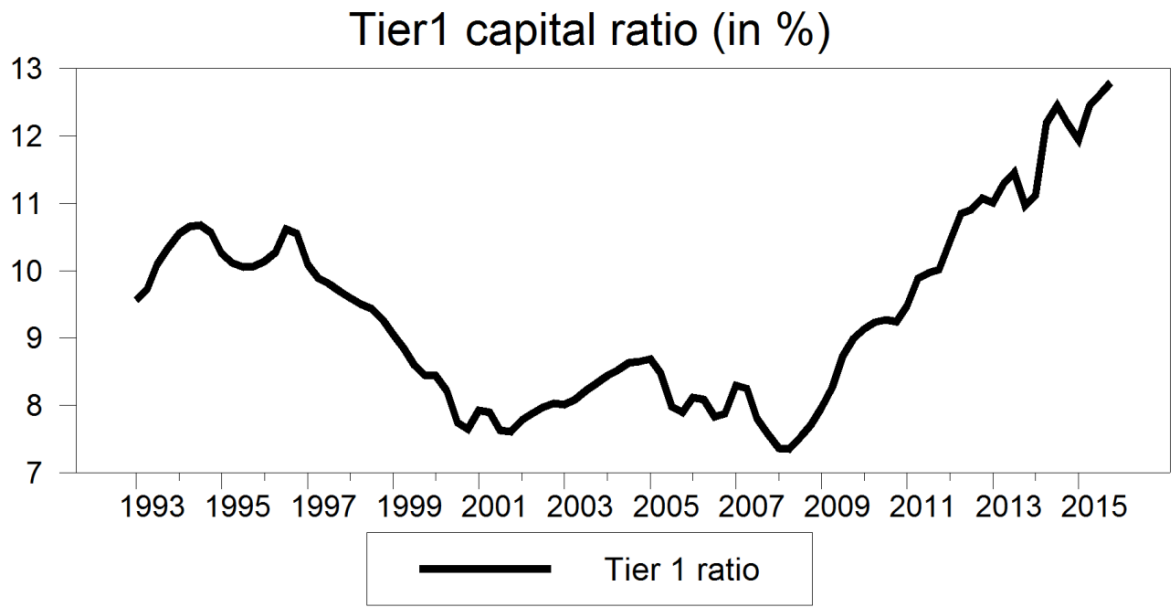
Figures and Tables

Figure 1: The dynamics of bank capital requirements

(*quarterly data for the period 1993-2015*)



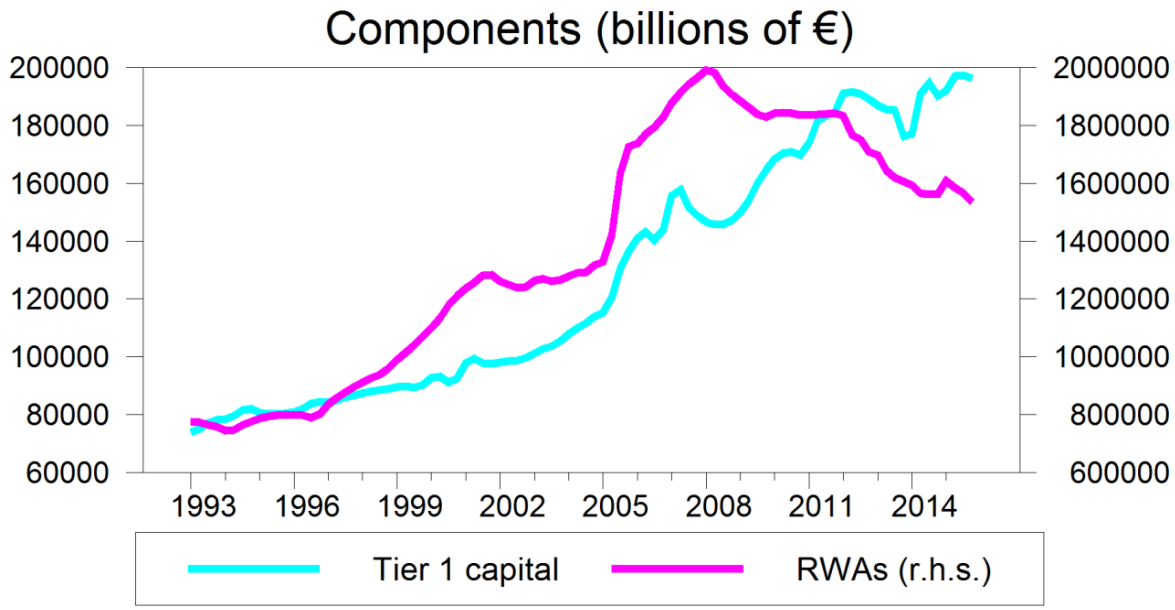
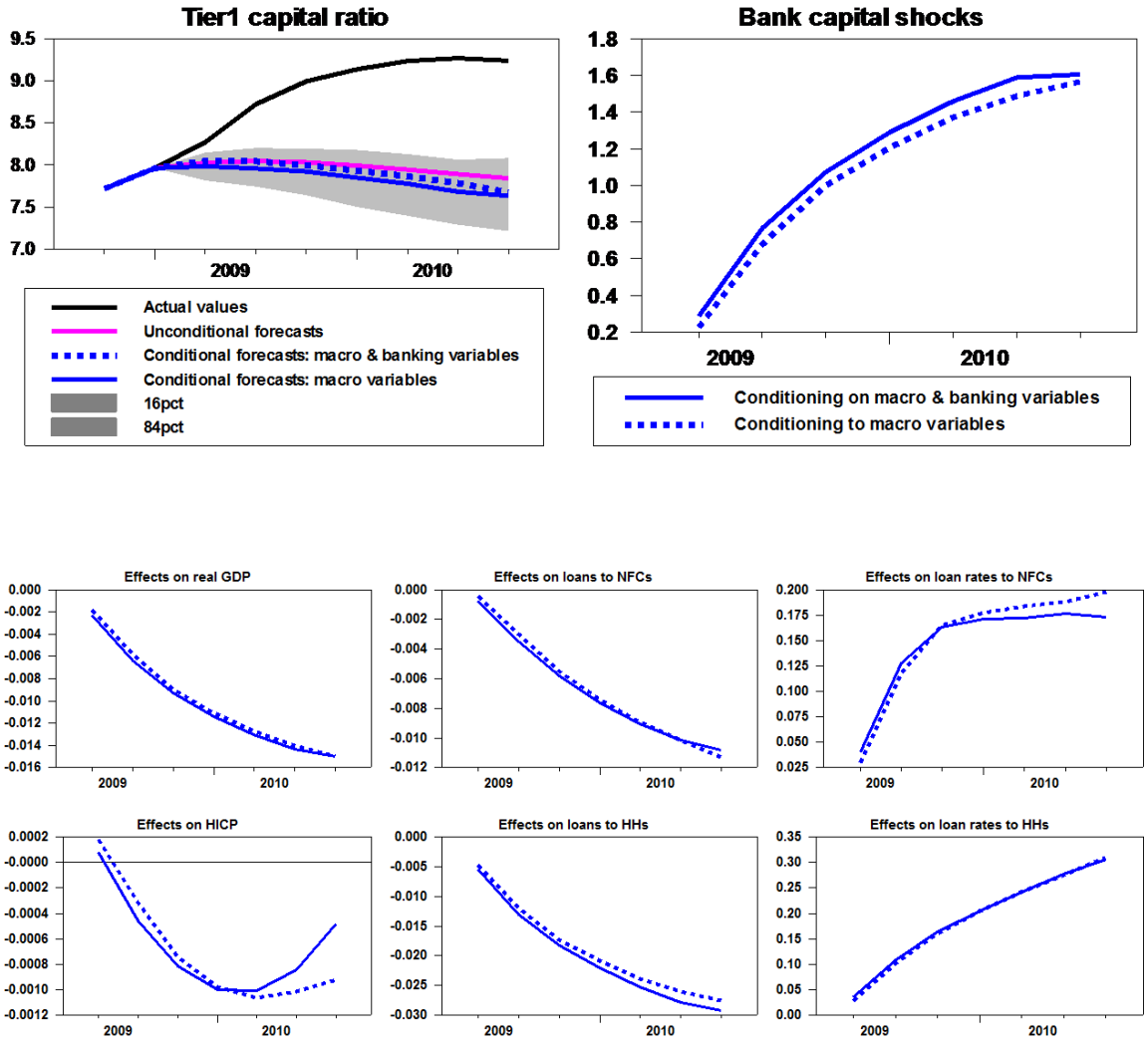


Figure 2: THE EFFECTS OF BANK CAPITAL SHOCKS: BASEL III EPISODE

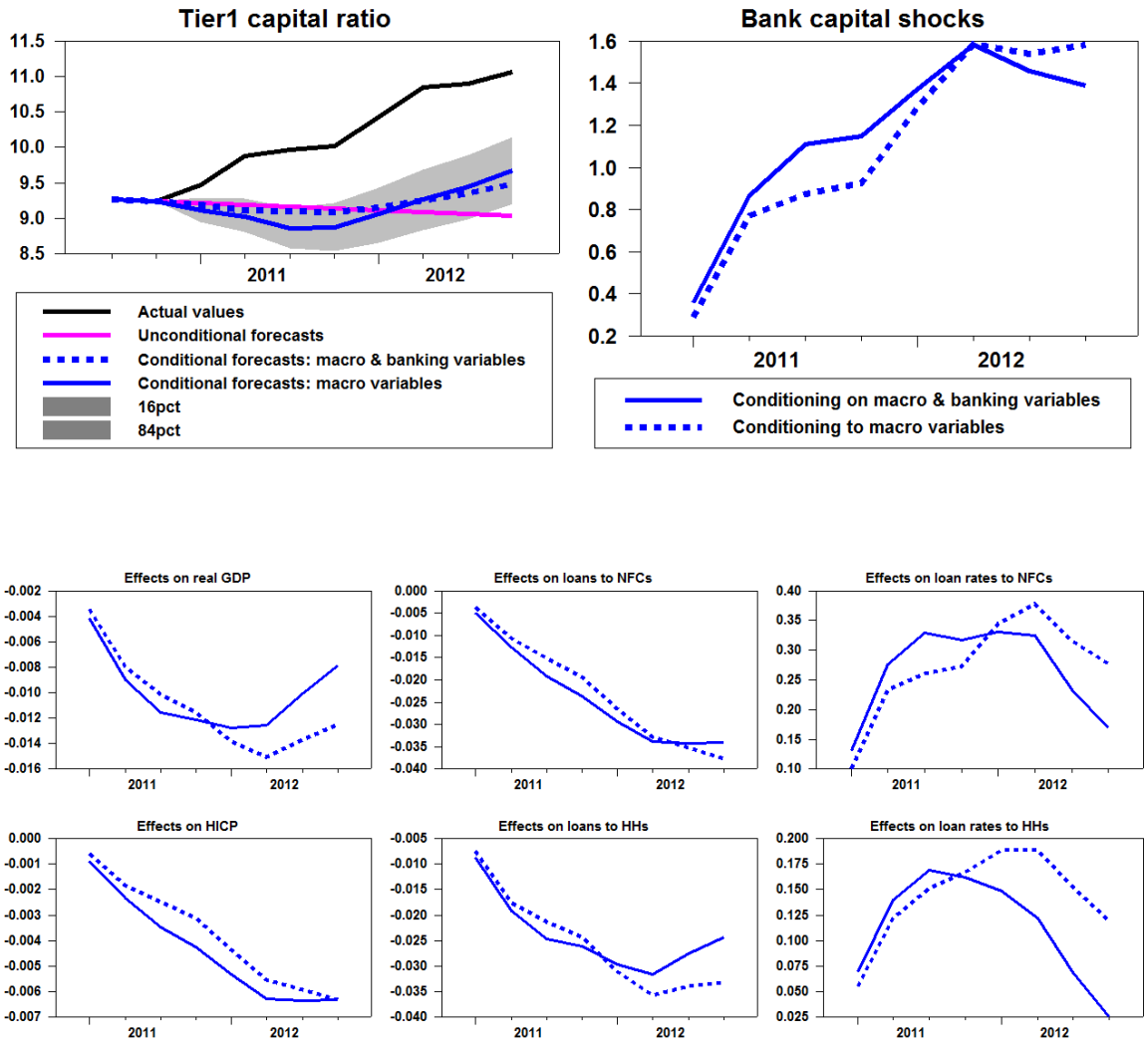
(*difference between the policy and non–policy scenarios, percentage points*)



Notes: For each variable, the "policy scenario" is given by the forecast conditional on the actual path of the Tier 1 capital. The "no policy scenario" is the forecast conditional on the counterfactual path of Tier 1 capital based on the full conditioning set, either of macro variables only, either of macro and banking variables, as described in Section 5. Percentage differences in the level of the indicated variable between the two scenarios. Left top panel: the black line represents the actual data, while the magenta line is the out–of–sample VAR unconditional forecast and the straight blue one is the out–of–sample VAR conditional forecast obtained on the main macroeconomic variables, respectively Italian real GDP, HICP, the short–term interest rate (3-month Euribor) and the long–term interest rate (Italian 10–year government bond). The dashed blue line is the out–of–sample VAR conditional forecast obtained on the main macroeconomic variables and banking variables, respectively Italian the bank stock market index, households' and firms' default rates, loan–loss provisions. The dark grey shaded area and the light grey shaded area represent $16-84\%$ and $5-95\%$ bands of the empirical distribution of conditional forecasts, obtained by a simulation of 1,000 draws. Estimation sample is 1993:Q1 – 2009:Q1. Right–top panel and bottom panels: the blue straight line is the difference between the policy and no policy scenario when conditioning on macro variables only, the blue dashed line is the difference between the policy and no policy scenario when conditioning on macro and banking variables.

Figure 3: THE EFFECTS OF BANK CAPITAL SHOCKS: EBA EPISODE

(*difference between the policy and non–policy scenarios, percentage points*)



Notes: For each variable, the "policy scenario" is given by the forecast conditional on the actual path of the Tier 1 capital. The "no policy scenario" is the forecast conditional on the counterfactual path of Tier 1 capital based on the full conditioning set, either of macro variables only, either of macro and banking variables, as described in Section 5. Percentage differences in the level of the indicated variable between the two scenarios. Left top panel: the black line represents the actual data, while the magenta line is the out–of–sample VAR unconditional forecast and the straight blue one is the out–of–sample VAR conditional forecast obtained on the main macroeconomic variables, respectively Italian real GDP, HICP, the short–term interest rate (3-month Euribor) and the long–term interest rate (Italian 10–year government bond). The dashed blue line is the out–of–sample VAR conditional forecast obtained on the main macroeconomic variables and banking variables, respectively Italian the bank stock market index, households' and firms' default rates, loan–loss provisions. The dark grey shaded area and the light grey shaded area represent $16-84\%$ and $5-95\%$ bands of the empirical distribution of conditional forecasts, obtained by a simulation of 1,000 draws. Estimation sample is 1993:Q1 – 2010:Q4. Right–top panel and bottom panels: the blue straight line is the difference between the policy and no policy scenario when conditioning on macro variables only, the blue dashed line is the difference between the policy and no policy scenario when conditioning on macro and banking variables.

Figure 4: THE EFFECTS OF BANK CAPITAL SHOCKS: SSM/CA EPISODE

(*difference between the policy and non–policy scenarios, percentage points*)

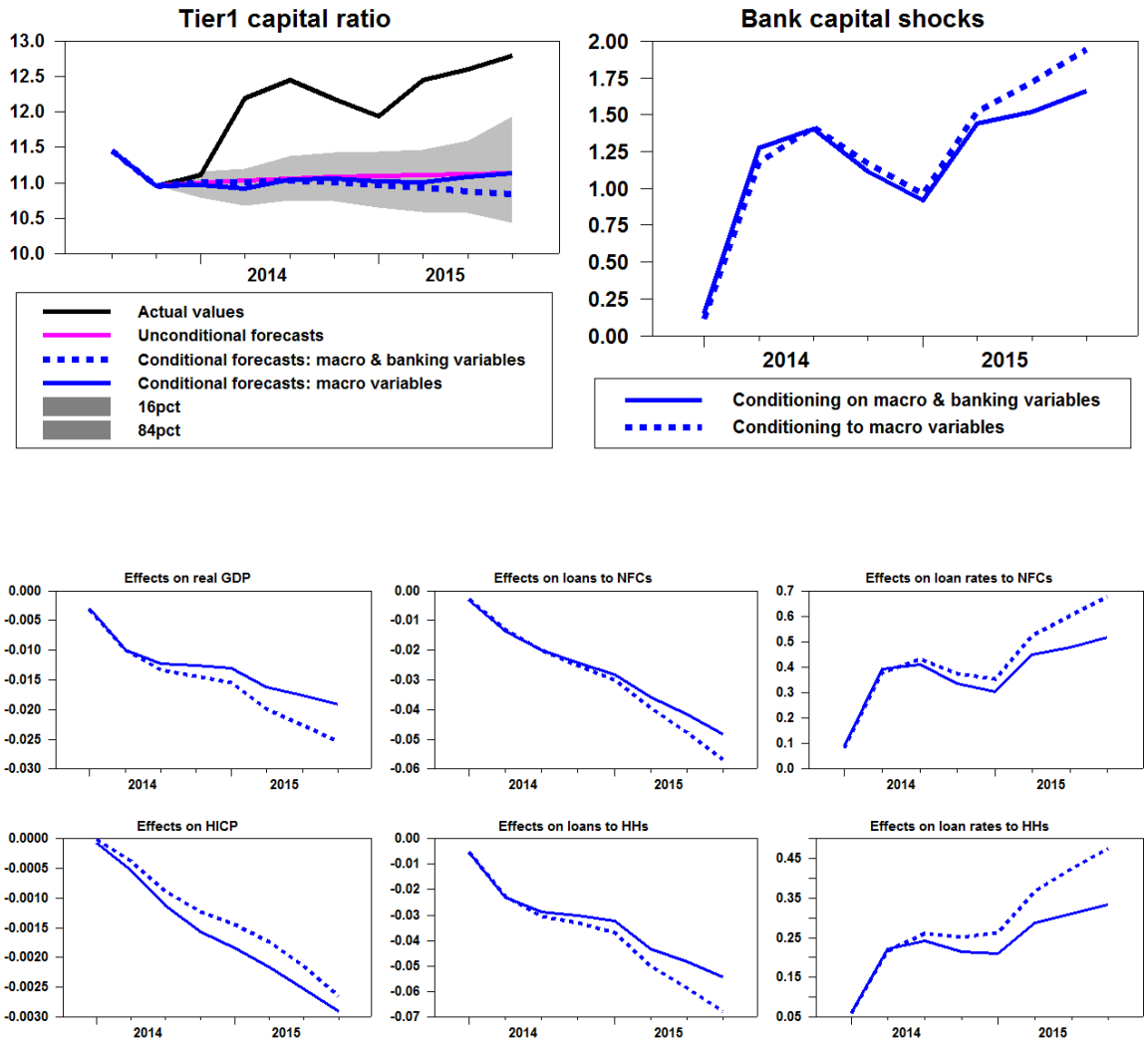


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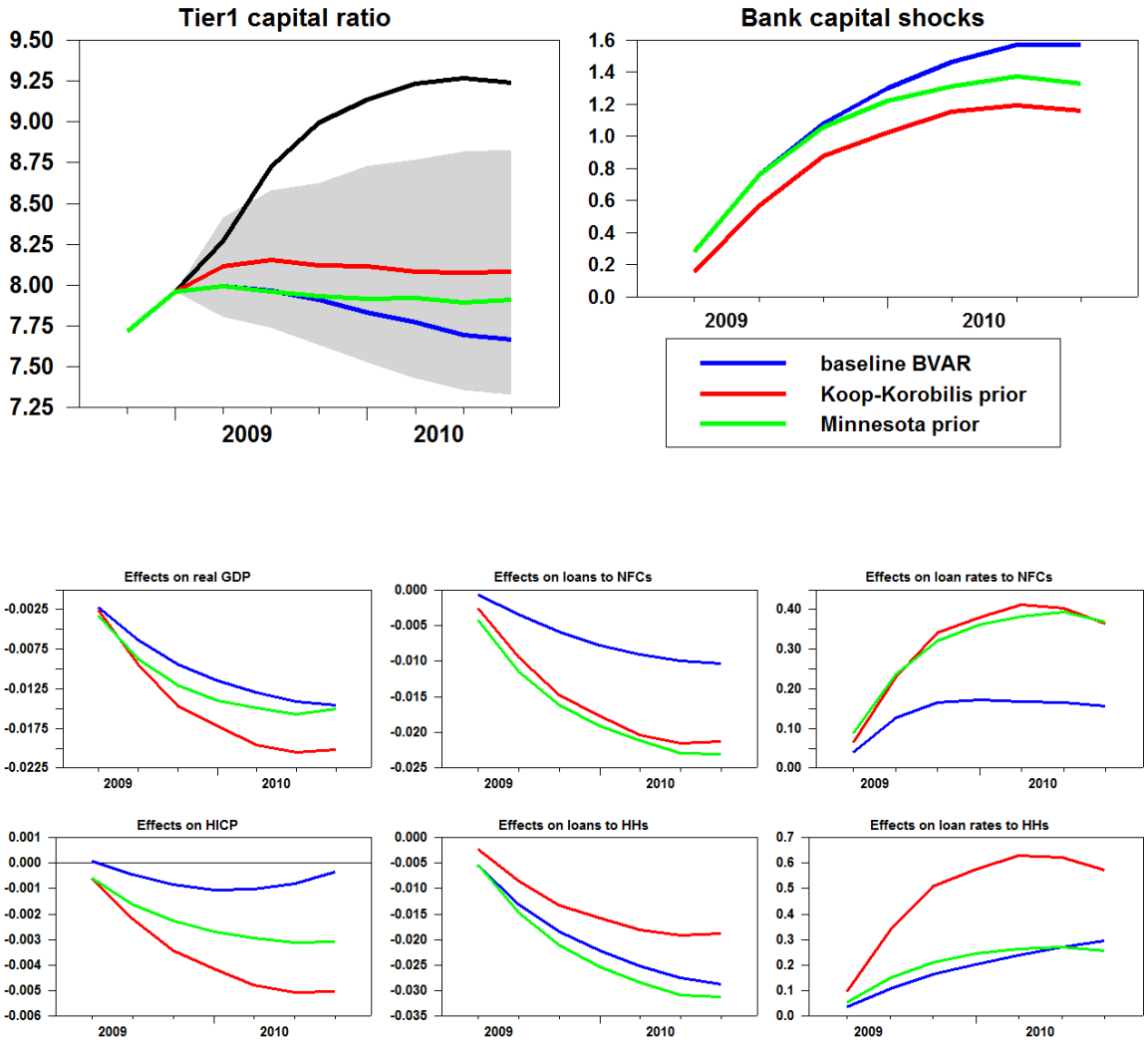
Figure 5: Fixed- vs. time–varying coefficient models: The effects of bank capital, Basel III episode

(*difference between the policy and non–policy scenarios, percentage points*)



Notes: The "policy scenario" is the forecast of each variable conditional on the actual path of the Tier 1 capital. The "no policy scenario" is the forecast conditional on the counterfactual path of Tier 1 capital based on the full conditioning set, macro and banking variables, as described in Section 5. Right–top panel: the black line is the actual Tier1 capital ratio series. The dark grey shaded area and the light grey shaded area represent $16-84\%$ and $5-95\%$ bands of the empirical distribution of conditional forecasts, obtained by a simulation of 1,000 draws. "Out-of-sample" forecasts: blue line, conditional forecasts using a fixed-coefficient model with Sims-Zha prior; red line, conditional forecasts using a time-varying coefficient model with the prior proposed by Koop and Korobilis (2013); green line conditional forecasts using a fixed- coefficient model with standard Minnesota prior. Estimation sample is 1993:Q1 – 2009:Q1. Bottom panels: Percentage differences in the level of the indicated variable between the two scenarios, with blue line corresponding to fixed-coefficient model with Sims-Zha prior, red line corresponding to time-varying coefficients model (Koop and Korobilis, 2013) and green line representing fixed-coefficients model with Minnesota prior.

Figure 6: Fixed- vs. time–varying coefficient models: The effects of bank capital shocks, EBA episode

(*difference between the policy and non–policy scenarios, percentage points*)

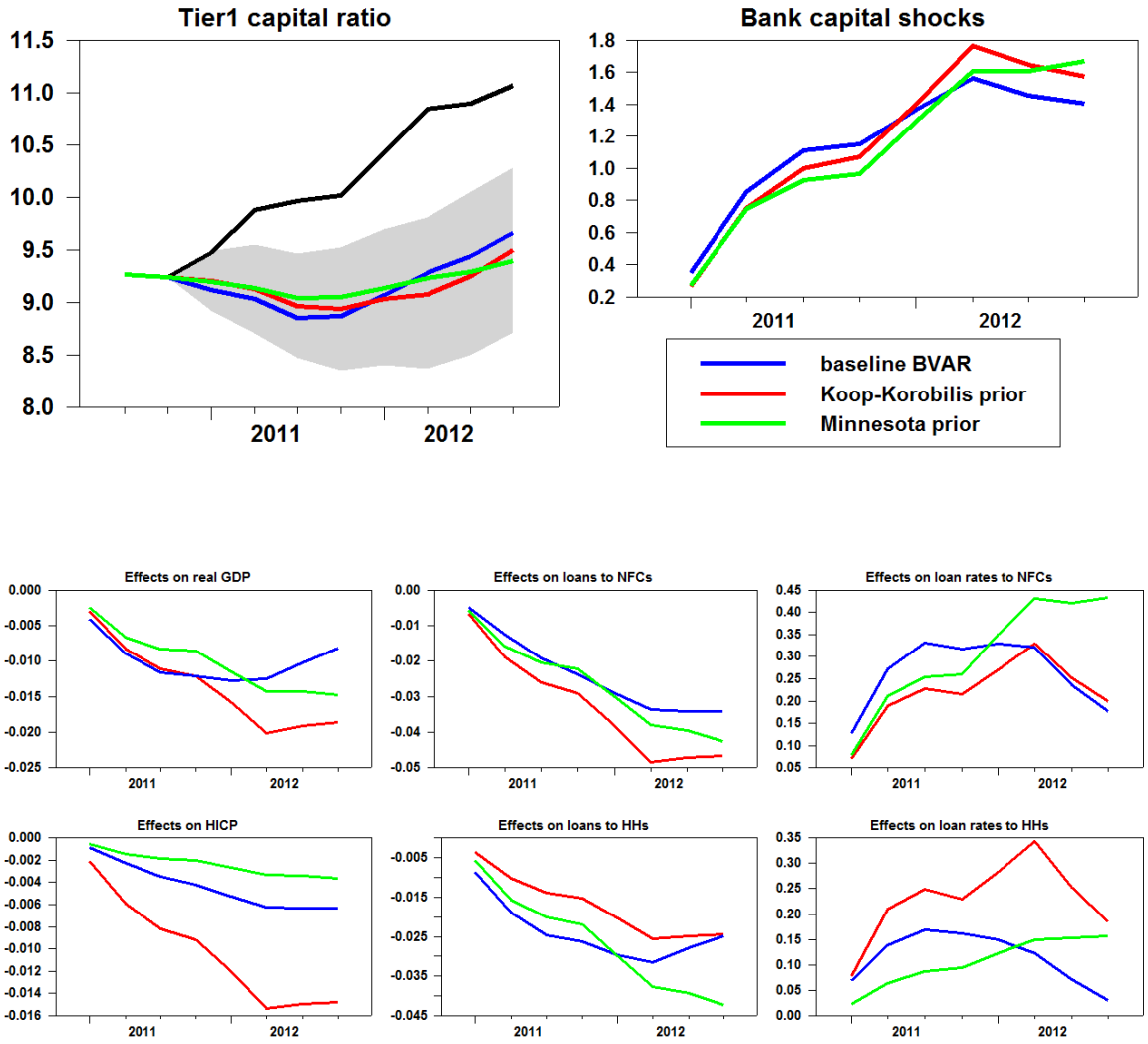


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Figure 7: Fixed- vs. time–varying coefficient models: The effects of bank capital shocks, SSM/CA episode

(*difference between the policy and non–policy scenarios, percentage points*)

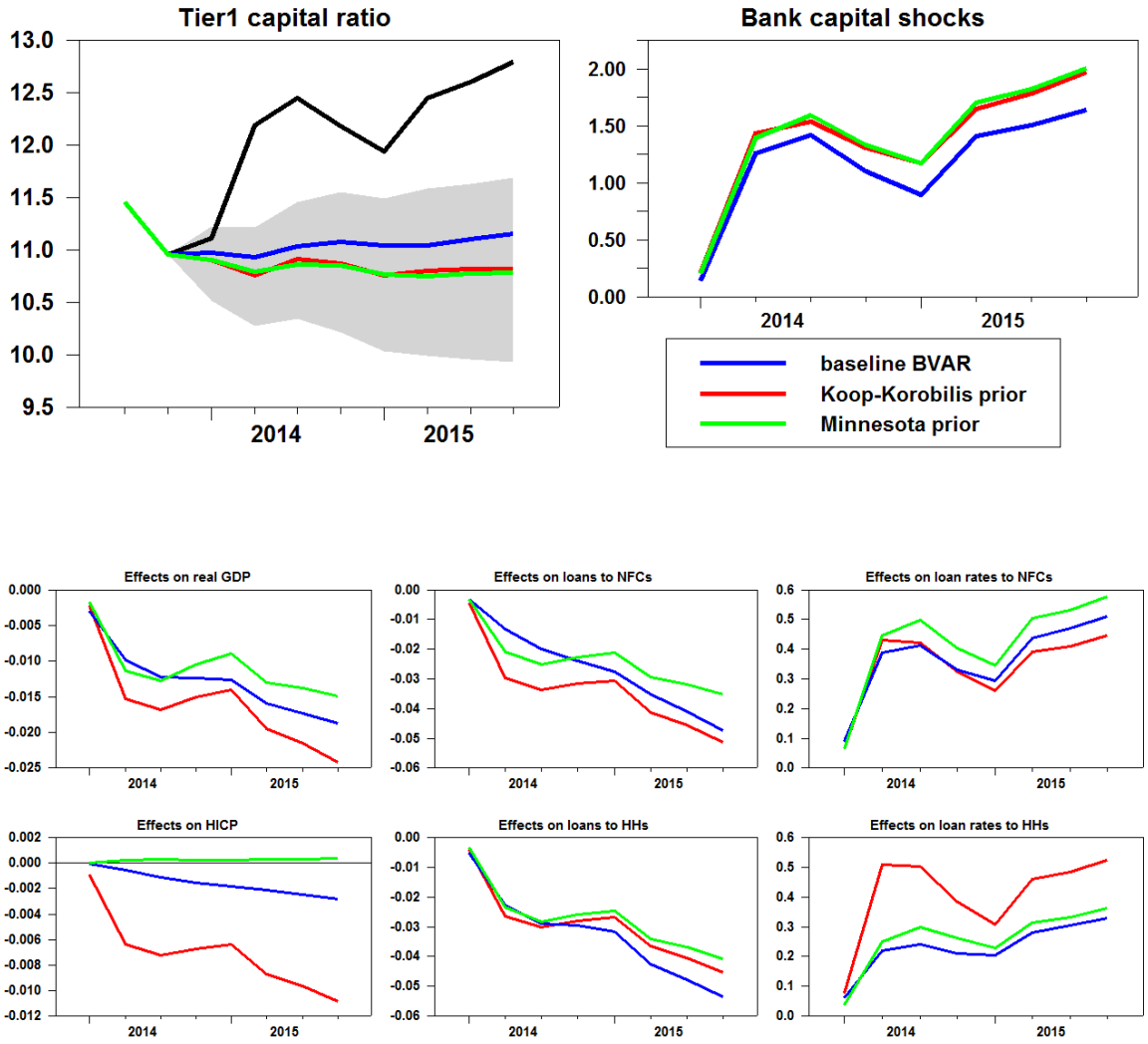

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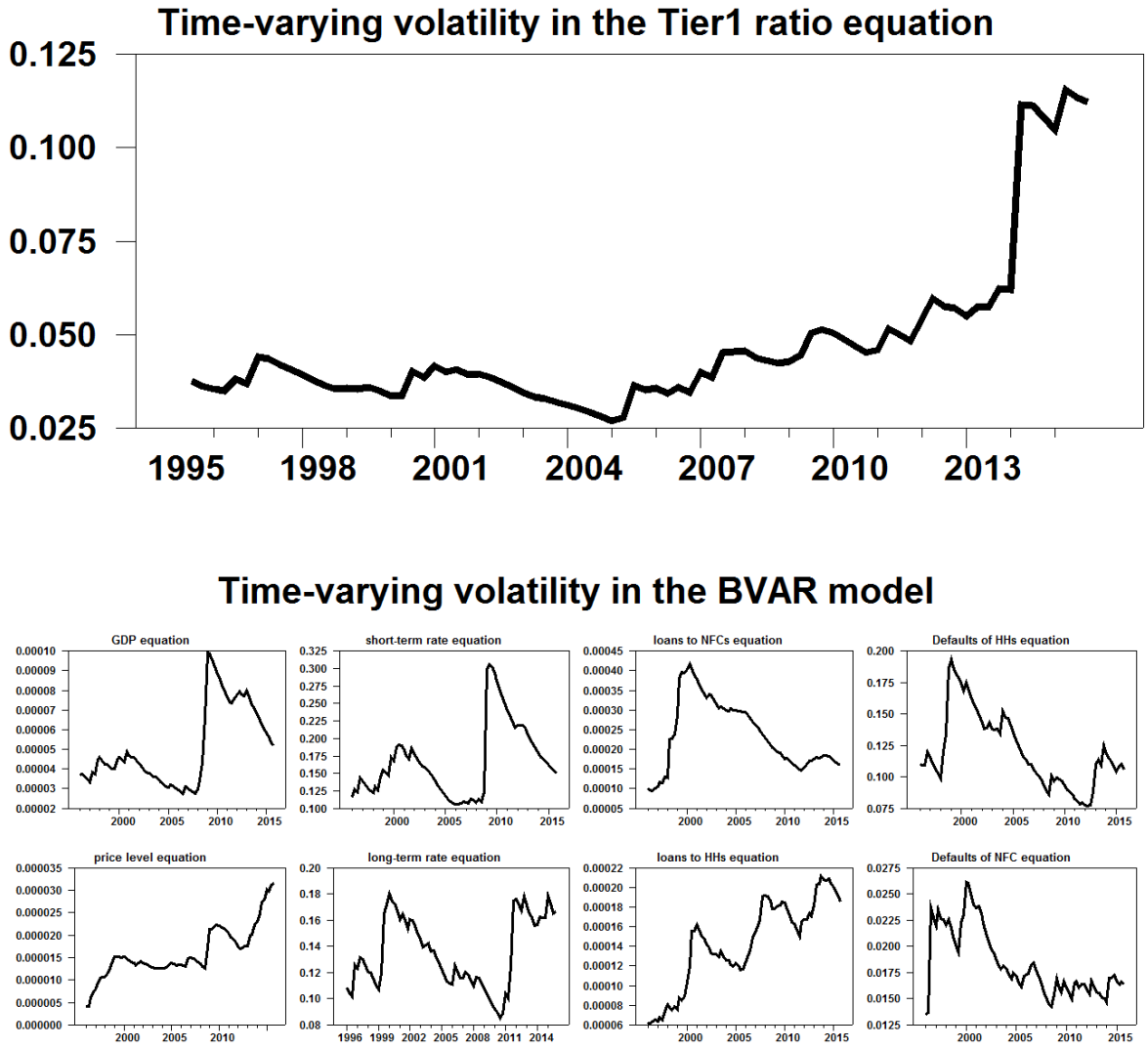
Figure 8: Estimated time–varying volatility



Notes: The upper panel plots the estimated time–varying volatility of the Tier1 ratio equation in the BVAR model (posterior median). The lower panel presents the same statistics for real GDP, the short-term interest rate, loans to non-financial corporations, the HICP, the long-term interest rate and loans to households.

Figure 9: "In-sample" forecasts from BVAR models: the effects of bank capital shocks, Basel III episode

(*difference between the policy and non–policy scenario: percentage points*)

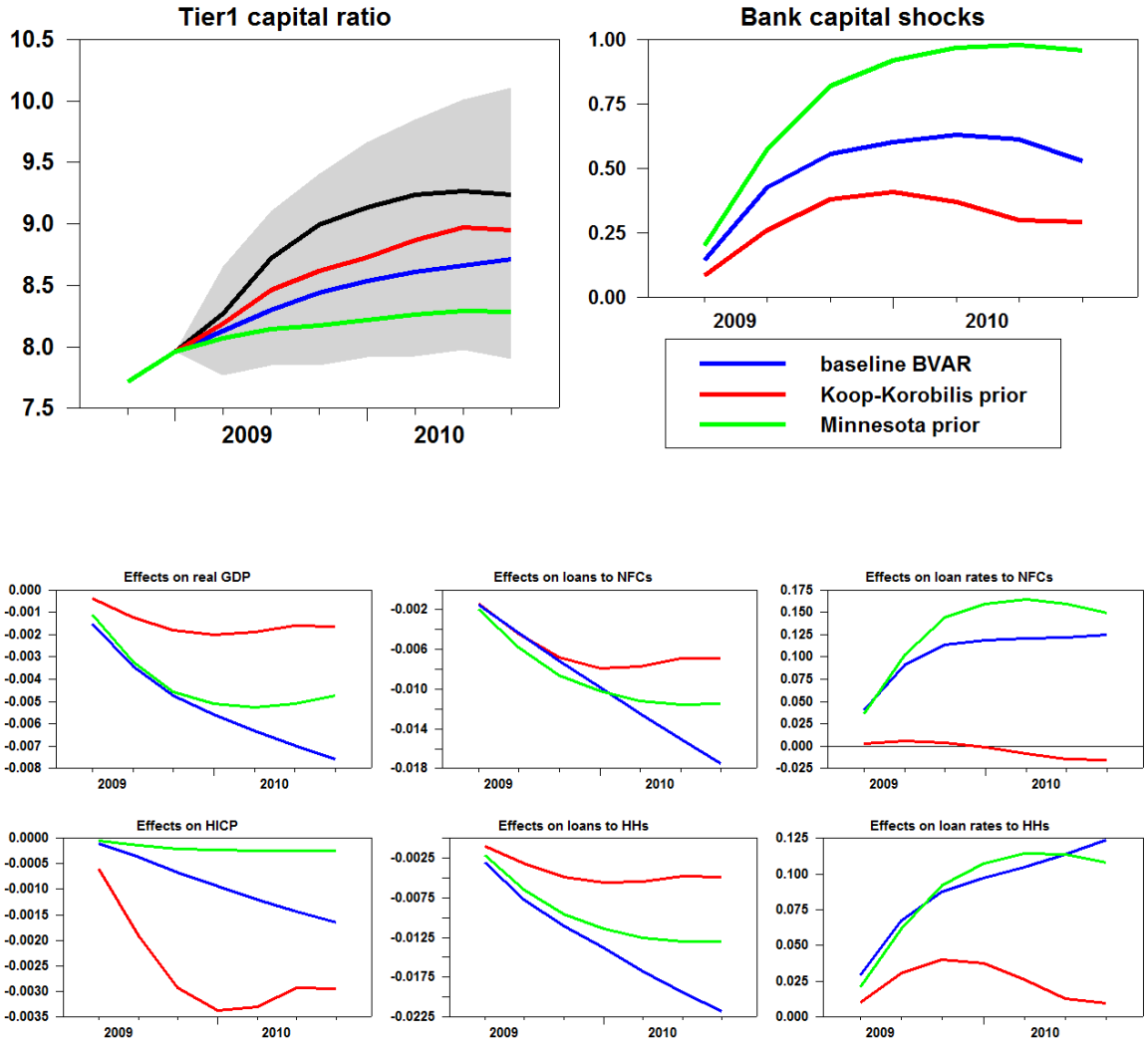


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Figure 10: "In-sample" forecasts from BVAR models: the effects of bank capital shocks, EBA episode

(*difference between the policy and non–policy scenario: percentage points*)

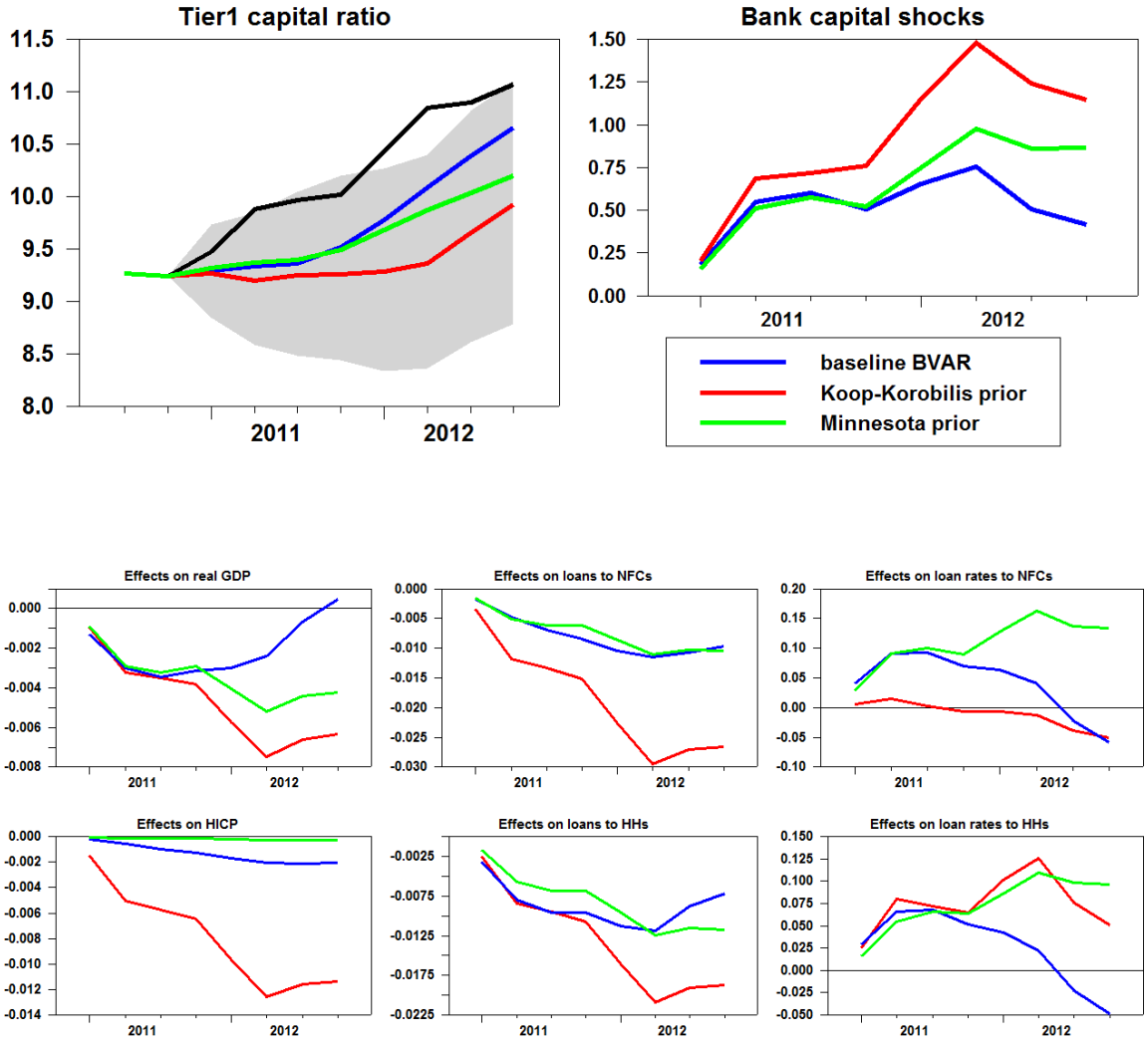

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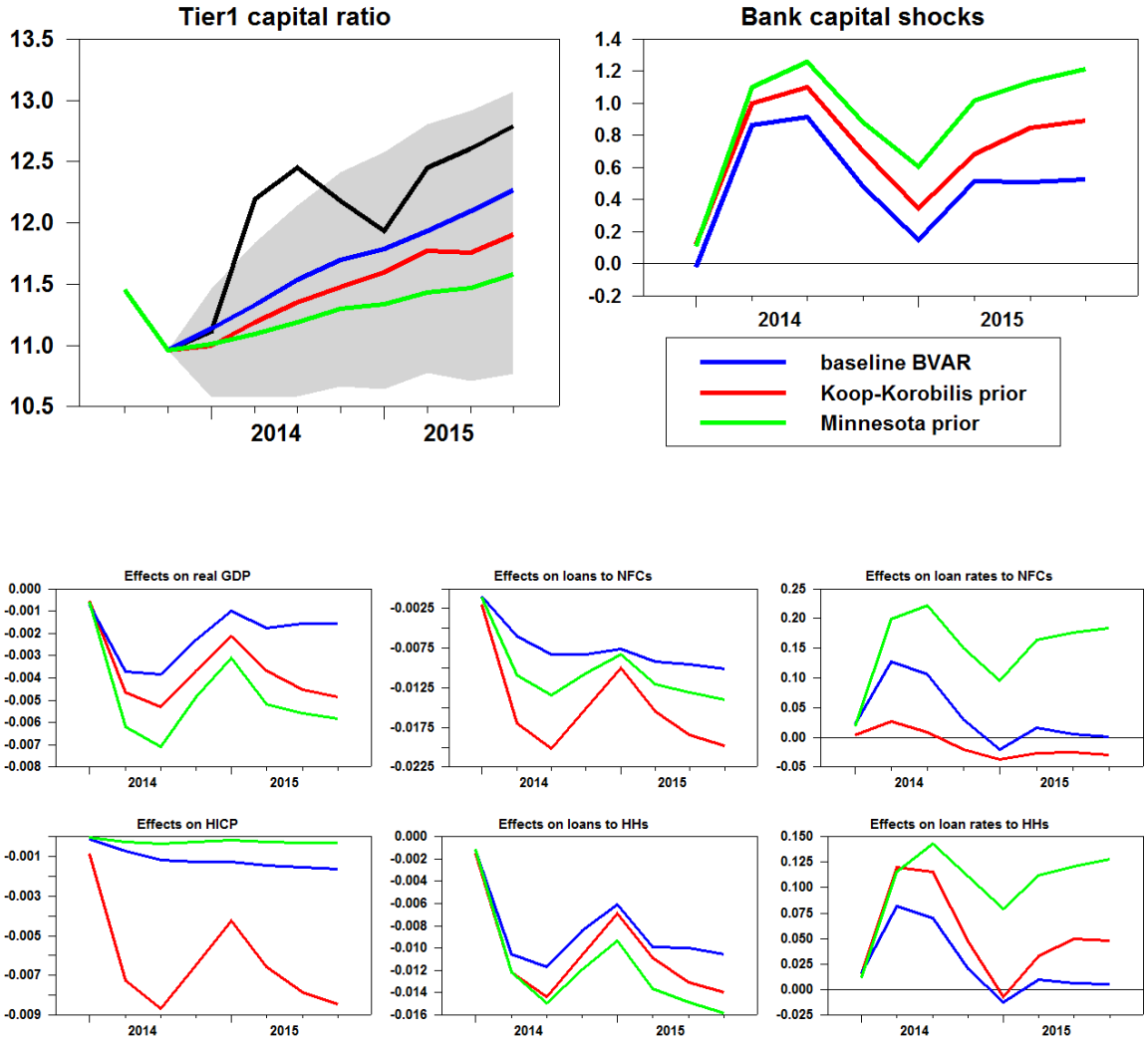
Figure 11: "In-sample" forecasts from BVAR models: the effects of bank capital shocks, SSM/CA episode

(*difference between the policy and non–policy scenario: percentage points*)



Notes: The policy scenario is the forecast of each variable conditional on the actual path of the Tier 1 capital. The no policy scenario is the forecast conditional on the counterfactual path of Tier 1 capital based on the full conditioning set, macro and banking variables, as described in Section 5. Right–top panel: the black line is the actual Tier1 capital ratio series. The dark grey shaded area and the light grey shaded area represent $16-84\%$ and $5-95\%$ bands of the empirical distribution of conditional forecasts, obtained by a simulation of 1,000 draws. "Out-of-sample" forecasts: blue line, conditional forecasts using a fixed-coefficient model with Sims-Zha prior; red line, conditional forecasts using a time-varying coefficient model with the prior proposed by Koop and Korobilis (2013); green line conditional forecasts using a fixed- coefficient model with standard Minnesota prior. Estimation sample is 1993:Q1 – 2015:Q4; forecast sample is 2014:Q1–2015:Q4. Bottom panels: Percentage differences in the level of the indicated variable between the two scenarios, with blue line corresponding to fixed-coefficient model with Sims-Zha prior, red line corresponding to time-varying coefficients model (Koop and Korobilis, 2013) and green line representing fixed-coefficients model with Minnesota prior.

Table 1: Estimated bank capital shocks and impact on variables

	Estimated bank capital shock (pp)	**Estimated impact after two years**					
		Loans %		Loan rates (bps)		Macroeconomic variables %	
Two-year window	Tier 1 ratio	NFCs	HHs	NFCs	HHs	GDP	HICP
Basel III episode	1.6	-1.0	-2.8	17	30	-1.4	-0.1
EBA episode	1.4	-3.4	-2.5	16	3	-0.8	-0.6
SMM/CA episode	1.6	-4.7	-5.0	48	30	-1.8	-0.3
Average	**1.5**	**-3.0**	**-3.4**	**27**	**21**	**-1.3**	**-0.3**

Notes: Cumulated effects over the forecast horizon; GDP is expressed in real terms. HICP is the Harmonised Index of Consumer Prices. NFCs and HHs stand for non-financial firms and households, respectively. Differences between forecasts conditional on the actual path of the Tier 1 ratio (policy scenario) and the counterfactual path (no-policy scenario).

Table 2: The effects of bank capital shocks: comparison across models

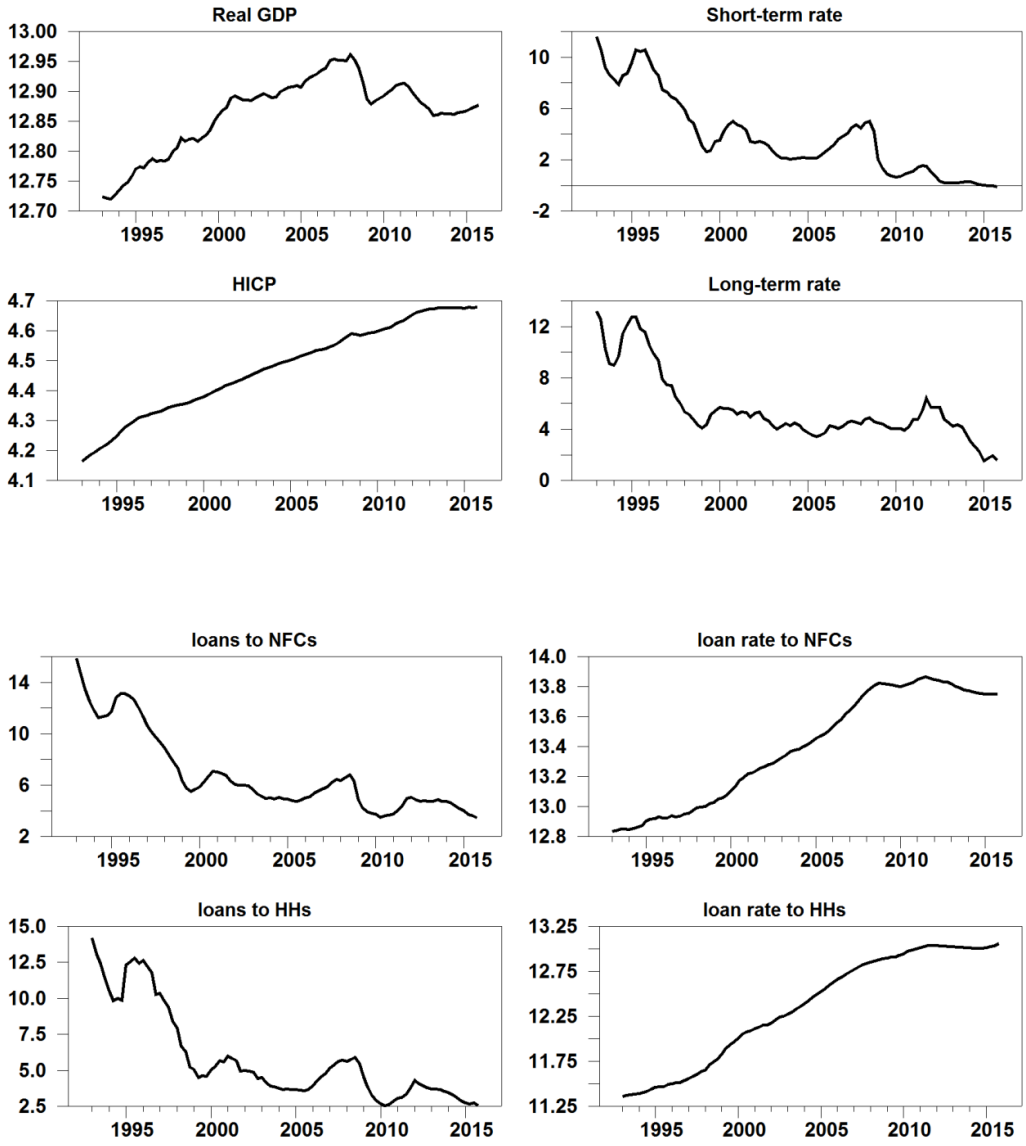
	Out-of-sample exercise				In-sample exercise			
	Baseline BVAR	Minnesota prior	Koop-Korobilis prior	Average effect	**Baseline BVAR**	Minnesota prior	Koop-Korobilis prior	Average effect
Real GDP								
Basel III episode	-1.5	-1.6	-2.3	-1.8	-0.9	-0.9	-0.2	-0.7
EBA episode	-0.2	-0.7	-1.1	-0.7	-0.1	-0.0	-0.9	-0.3
SMM/CA episode	-1.7	-1.3	-2.4	-1.8	-0.3	-0.4	-0.4	-0.4

	Out-of-sample exercise				In-sample exercise			
	Baseline BVAR	Minnesota prior	Koop-Korobilis prior	Average effect	**Baseline BVAR**	Minnesota prior	Koop-Korobilis prior	Average effect
Loans to NFCs								
Basel III episode	-0.9	-2.3	-2.1	-1.8	-1.8	-1.4	-0.8	-1.3
EBA episode	-3.0	-3.2	-3.6	-3.3	-0.8	-0.9	-3.0	-1.6
SMM/CA episode	-4.0	-2.5	-3.5	-3.3	-1.0	-1.1	-2.1	-1.4

Notes: Cumulated effects over the forecast horizon; GDP is expressed in real terms. NFCs stands for non-financial firms. Differences between forecasts conditional on the actual path of the Tier 1 ratio (policy scenario) and the counterfactual path (no-policy scenario).

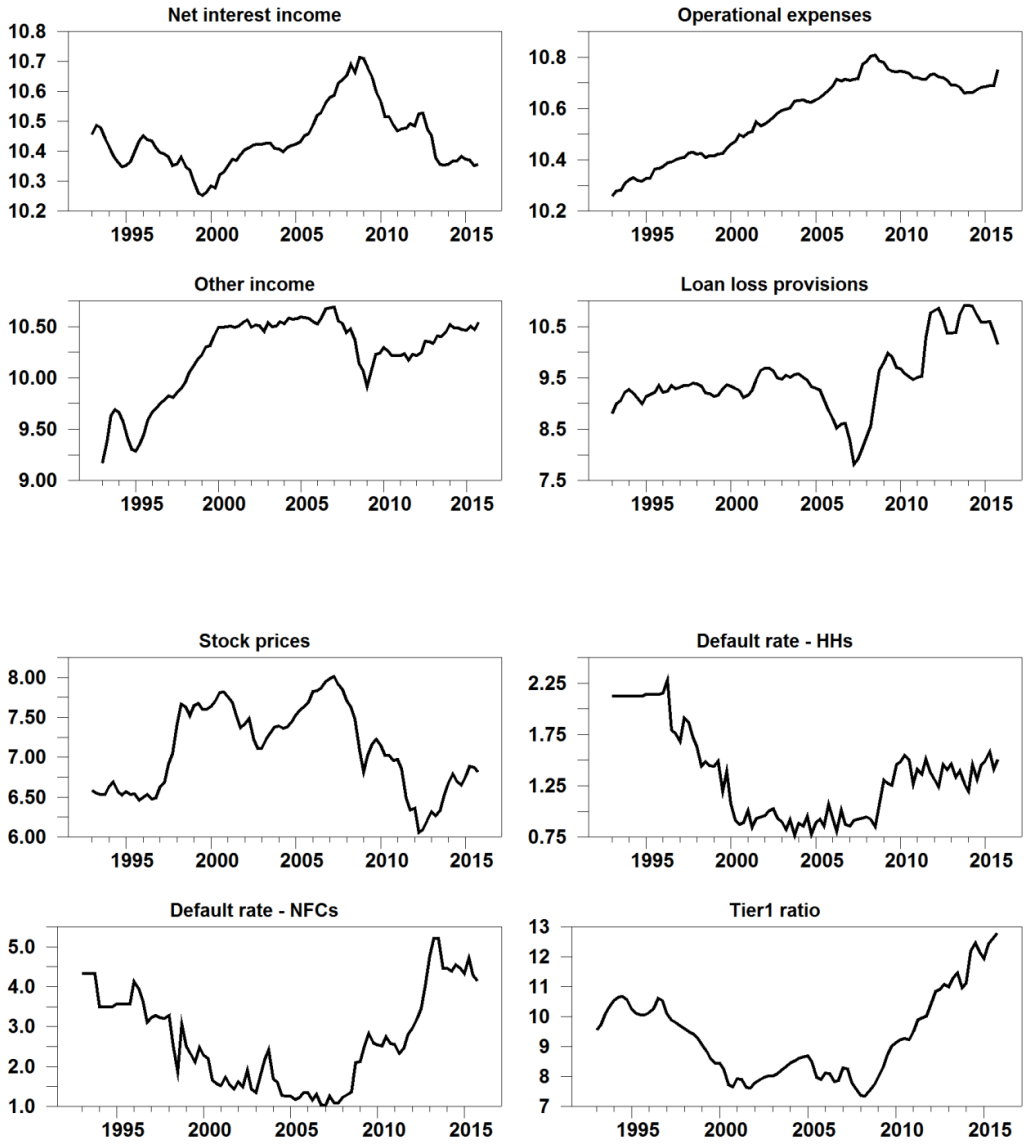
Appendix A - Data

Figure A-1: Data employed in the empirical analysis



Notes: Log–levels, except for interest rates, default rates and Tier1 ratio (pecentage values).

Figure A-1 (Cont.): Data employed in the empirical analysis



Notes: Log–levels, except for interest rates, default rates and Tier1 ratio (pecentage values).