Model-based approach for scenario design: stress test severity and banks' resiliency*

Paolo Nicola Barbieri†, Giuseppe Lusignani ‡, Lorenzo Prosperi §, Lea Zicchino¶

October 31, 2019

Abstract

After the financial crisis, evaluating the financial health of banks under stressed scenarios has become common practice among supervisors. According to supervisory guidelines, the adverse scenarios prepared for stress tests need to be severe but plausible. The first contribution of this paper is to propose a model-based approach to assess the severity of the scenarios. To do so, we use a Large Bayesian VAR model based on the Italian Economy where potential spillovers between the macroeconomy and the aggregate banking sector are explicitly considered. We show that the 2018 exercise has been the most severe so far, in particular due to the path of GDP, the stock market index and the 3-month Euribor rate. Our second contribution is an evaluation of whether the resilience of the Italian banking sector to adverse scenarios has increased over time (for example, thanks to improved risk management practices induced by greater awareness of risks that come with performing stress test exercises). To this scope, we construct counterfactual exercises by recalibrating the scenarios of the 2016 and 2018 exercises so that they have the same severity as the 2014 exercise. We find that in 2018 the economy would have experienced a smaller decline in loans compared to the previous exercises. This implies that banks could afford to deleverage less, i.e. maintain a higher exposure to risk in their balance sheets. We interpret this as evidence of increased resilience.

Keywords: Bayesian VAR, forecasting, bank stress tests, scenario analysis & design, banking system
JEL: E30, C11, C33, C53, G21

---

*We are thankful to Emanuele de Meo and Federica Orsini for their past work on this project. Andrea Nobili, Rita Romeo, Maurizio Pierigé and Giacomo Tizzanini for insightful comments.

†University of Gothenburg and Prometeia SpA

‡University of Bologna and Prometeia SpA

§Prometeia SpA, corresponding author: `lorenzo.prosperi@prometeia.com`

¶Prometeia SpA

1 Introduction

Given the experience gathered during the financial crisis, the European Banking Authority (EBA) decided to update its guidelines on stress testing to assist institutions in identifying risks as well as their potential mitigants. In particular, supervisors observed that in many instances stress testing did not appear to be sufficiently integrated into institutions' risk management frameworks or senior management decision-making. In other instances, supervisors observed that risk concentrations and second-round effects were not considered in a meaningful fashion BCBS (2009a). One of the consequences of the lessons learned from the financial crisis was that the scenarios provided by EBA for the stress testing exercises became more severe. Or at least they were meant to be more severe. One fundamental issue is, in fact, that it may be difficult to evaluate how severe a scenario is, given the large number of variables involved. Moreover, since the start of the stress testing rounds banks have taken risk management actions to reduce their sensitivity to adverse shocks. Were these actions successful in making banks more resilient?

We propose an operational approach for scenario design and banks' resiliency evaluation consistent with the guidelines of the regulators for the construction of stress scenarios. In particular, our contribution is twofold. First, we propose an approach to measure the severity of a stress test scenario defined by EBA (and apply it to the stress tests conducted in 2014, 2016, 2018). We focus on a restricted set of variables of scenarios that are specific to the Italian economy. Second, we investigate whether the resiliency of the Italian banking sector to adverse shocks has increased over time (from the 2014 stress test to the 2018 one).

In our work, we give an interpretation of the guidelines of the Regulator, and therefore our definitions need to be clarified.

In the 2017 stress test guidelines, the European Banking Authority (EBA) defines the severity of a stress test scenario as

> *"[...] the degree of severity of the assumptions or the deterioration of the scenario (from baseline to an adverse scenario) expressed in terms of the underlying macroeconomic and financial variables (or any other assumptions)* (EBA, 2018)

A stress test scenario also needs to be plausible in order to allow the evaluation of a bank's financial position under a severe scenario that has some probability to occur BCBS (2009a). Therefore, not only a scenario has to be severe in terms of deviation of its main variables, but it has also to be regarded as likely to materialize in respect to the consistency of the relationship of each macro-financial input variables with their current trend (EBA, 2018). In designing our approach to evaluate stress test scenarios we stayed consistent with the Regulators' definition and tried to develop an operational approach by measuring the severity of an alternative scenario based on its likelihood of realization. Such probability of realization depends on the baseline scenario associated with each stress test and on the volatility surrounding such scenario. In our approach, we define a scenario on a variable as more or less severe according to the probability of realization of the path of the macro-financial input variables. This means that in our definition the greater the severity of the scenario the lower will be its overall probability, consistently with the guidelines of the regulators[1]. The EBA guidelines are clear in defining the severity of a variable but give no suggestion on how to evaluate the overall severity of the scenario. We therefore try to provide a unique and operational approach to assess the severity of the stress test scenario as a whole.

Resiliency on the other hand is generally defined as the

> *"[...] ability to absorb shocks arising from financial and economic stress, whatever the source, thus reducing the risk of spillover from the financial sector to the real economy"* (BCBS, 2009b)

Resiliency is therefore the ability to absorb and adapt to shocks, rather than contribute to them. As such, the ultimate goal of stress testing should be to evaluate if a banking system becomes more or less resilient in terms of: (1) the recovery after a negative shock and (2) its ability to dampen such negative shock instead of amplifying it. However, differently from severity, the Regulators' guidelines on resiliency are much less precise and usually refer to the capital shortfall after the shock. In other words, a more resilient banking sector is usually one with adequate capital position or lower capital depletion after a shock. As with severity, we provide an operational approach to evaluate resiliency, by measuring the impact on banks' balance sheets of different stress tests that are equally severe. In particular, in order to understand how the capability of the Italian banking sector to absorb shocks evolved over time we sterilize the effect of the different severity of the stress test exercises conducted since 2014 by building a counterfactual stress test with the same degree of severity. We are therefore able to compare the responses of the banking variables across time. Moreover, we claim that the impact on capital ratios is not a sufficient statistic to evaluate banks' resiliency. Instead, banks should not contribute to increase the size of the shock. As such, it is important also to evaluate other factors, like continuing to lend in adverse scenarios. Indeed, a bank that strongly reduces credit to the private sector to meet capital requirements might generate potential "second-round" effects due to the impact of its response on the real economy, exacerbating the size of the shock. Therefore, we claim that a more resilient banking sector is the one which not only has low capital shortfall in an adverse scenario (i.e. absorption of shock) but is also able to sustain the domestic credit market (i.e. reduce spillover effects).

We investigate the issues of severity and resilience with Prometeia Italian Banking System Scenario Evaluation (IBASE) model. The IBASE is a Large Bayesian VAR model (LBVAR) that includes macro-financial variables (e.g. GDP, inflation, market interest rates, etc.) and aggregate bank balance sheet variables (loans, funding, bank interest rates, capital ratio, etc.). In the model bank and macro-financial variables are closely interconnected. In particular, bank variables affect macro-financial variables, a feature that is absent in traditional stress testing models. Despite the limited scale of our model, any potential feedback among variables is allowed and we show that it is a valid tool for scenario design in macroprudential stress testing. We support our claim that the model is able to represent the interconnections between macro-financial and bank variables by means of impulse response analysis and forecasting performance evaluation. In particular, with impulse response analysis we show that bank variables react to different shocks in an intuitive way.

[1] In the remainder of the paper, with the term ''stress test severity" we refer to the severity of the scenario

Also, the forecasting performance of the model is good both in terms of Mean Absolute Error (MAE) and accuracy, especially for stock variables (loans).

The model allows us to compare all the recent EBA stress test scenarios in terms of severity. To do so, we estimate the IBASE up to the starting date of each exercise and we simulate the model conditional on the EBA baseline scenario. We measure severity by computing the percentile of the marginal simulated distribution in which the path of each variable in the adverse scenario is located. Even if a measure of severity for each variable is informative, we would like to have an overall assessment of the likelihood of the scenario. Theoretically, this should be measured by calculating the joint probability of realization of the adverse paths. However, using this approach, the EBA stress test scenario would have a zero probability of realization. A novel contribution of this paper is to propose an aggregate measure of severity. Having measured the severity of each variable in the EBA scenario (the percentile of the marginal simulated distribution), we define the severity of the overall scenario as the weighted average of the percentiles of each variable, where the weights are given by the contribution of the shock of each variable to the variance of the bank aggregates. As a result, in assessing the overall severity of the scenario we assign a higher weight to shocks that are more relevant in shaping the banking system reaction in our model. To anticipate the results, we find that the 2018 exercise was the most severe of the three considered, in particular due to the profiles of GDP, stock market index and 3-month euribor rate in the adverse scenario. The other issue we want to investigate is whether the resiliency of the Italian banking sector has increased over time. However, looking at the stress test results published by the EBA does not give us an answer. The reason is that the response of key bank variables (e.g. capital ratios and loans) might differ across exercises simply because the three scenarios (2014, 2016 and 2018) have a different degree of severity. To measure resiliency, we build counterfactual exercises by recalibrating the scenarios of the 2016 and 2018 exercises so that they have the same severity of the 2014 exercise. Under these new artificial scenarios, we can evaluate the response of the banking system at different points in time to now comparable stress scenarios. We find that in 2018 the economy would have experienced a lower decline in loans compared to the previous exercises. We take this result as evidence that the resiliency of the banking sector to adverse stress scenarios has increased: banks can accommodate a lower decline in loans, i.e. maintain a higher exposure to risk in their balance sheets. This comes at the expense of capital ratios. The reduction in Tier 1 ratio in 2018 would have been lower compared to official scenario but still larger than in the previous exercises.

The paper is organized as follows. In section 2 we briefly review the existing literature. In section 3 we describe the data used for estimating the model. In section 4 we present the methodology, in particular the model estimation strategy, the analysis conducted to validate the model and the approach used to measure severity and to construct counterfactual stress tests. The results of the different exercises are presented in section 5 and in Section 6 we run some robustness check. Section 7 concludes.

2 Related Literature

To analyse the issues at hand we draw from several strands of the literature.

First, the Prometeia IBASE model is closely related to the recent literature on medium- and large-scale Bayesian VAR models designed to address and overcome the *curse of dimensionality* (Bańbura et al., 2015, 2010, De Mol et al., 2008, Giannone et al., 2012). More specifically, this paper relates to other attempts to use this class of model to study the interaction between monetary policy, the real economy and the banking sector (Giannone et al., 2012, Altavilla et al., 2015) and to other contributions that analyse the same issues in a data-rich-envinronment (Boivin et al., 2018, Von Borstel et al., 2016, Dave et al., 2013). Large BVAR has been applied to the Italian credit market in Conti et al. (2018) to study the impact of bank capital shocks on credit supply and economic activity.

Secondly, there is a growing literature providing alternative approaches for stress testing as, according to many, traditional methodology might not represent the most efficient early warning device, but is more effective as a crisis management and resolution tool (Borio et al., 2014, Arnold et al., 2012). According to Dees and Henry (2017), traditional stress tests have several limitations. First of all, the static balance sheet hypothesis makes the exercises too conservative. In practice banks react to adverse conditions by deleveraging, making straight capital increases or working out non-performing loans. Moreover, macro-financial shocks are treated as exogenous to the banking sector, ignoring any potential feedback. Finally, traditional approaches ignore any interactions between different sectors in the economy. There have been several attempts to develop novel methodology to give supporting information to the supervisor authority. Hoggarth et al. (2005) was one of the first paper to suggest a VAR approach to run a stress test on banks, accounting not only for the transmission of macroeconomics shocks to bank variables but also for potential feedback effects from banks' balance sheets to the macroeconomy. To address the interaction between German banks and the real sector Dovern et al. (2010) also employ a VAR analysis and find that the level of stress in the banking sector is strongly affected by monetary policy shocks, giving credit to the active behavior of central banks observed during periods of financial market crises. Hirtle et al. (2016) develop a framework for assessing the impact of macroeconomic conditions on the U.S. banking sector, using the Capital and Loss Assessment under Stress Scenario (CLASS) model. The CLASS model is a top-down capital stress testing framework that uses public data, simple econometric models, and auxiliary assumptions to project the effect of macroeconomic scenarios on U.S. banking firms. The authors find that the U.S. banking industry's vulnerability to under-capitalization (i.e. the capital gap under the crisis scenario) has declined. For the Euro Area, a similar top-down approach, the STAMP€ framework, has been proposed by Henry et al. (2013) and later by Dees and Henry (2017). Similar to these papers, our analysis embeds a dynamic balance sheet approach and considers potential spillover effects between the banking sector, financial markets and the real economy. Although our approach focuses on a limited set of variables compared to the aforementioned papers, we develop a methodological tool to provide additional information and guidance to more detailed supervisory models of components of bank revenues and expenses. Among other attempts to develop novel methodologies for stress testing, Acharya et al. (2014) compare the capital shortfall measured by the regulatory stress test to the one measured by a benchmark methodology (i.e. the V-Lab stress test) employing only publicly available market data. When capital shortfalls are measured relative to risk-weighted assets (RWAs), the ranking of financial institutions is not well correlated to the ranking obtained with their alternative methodology, while the correlation increase when required capitalization is a function of total assets. They also find that the banks that appeared to be best capitalized relative to RWAs do not fare better than the rest during the sovereign debt crisis in 2011-12.

Finally, this paper is connected with the strand of literature on scenario design and on the evaluation of the severity of stress test scenarios.According to Henry et al. (2013) there are three approaches to calibrate the exogenous shocks and can be used jointly to define the scenario.

1. **ad-hoc:** Ad-hoc calibration without recourse to any model or historical distribution of risk factors.
2. **model-free:** Shock size calibrated on historical distributions in a ‘’model-free” non-parametric environment[2]
3. **model-based:** Shock size calibrated on the residuals of a dynamic parametric model

Depending on which approach is used the definition of severity of a scenario might differ. Durdu et al. (2017), for example, measure the severity of the Federal Reserve Board’s Comprehensive Analysis and Review (CCAR) scenario from 2013 to 2017 by using a methodology which relies on a comparison of the scenarios provided in the CCAR with historical stressful episodes, in order to derive a severity score. Similarly Yuen (2015) measures the severity associated with the 2009 stress test for U.S. bank holding companies (BHCs), known as the Supervisory Capital Assessment Program[3] (SCAP) by comparing them with he 2008 recession and creating a score based on relative rankings. The methodology applied in these two papers can be considered as part of the model-free approach to measure severity. They don’t measure the severity as the probability of realization of the adverse scenarios, but instead as the deviation between adverse and baseline scenarios. Breuer et al. (2009) proposes an alternative approach in order to rank variables according to severity across different stress tests; by also considering their joint comovement in the scenarios using the Mahalanobis distance[4].This paper uses a model-based approach but measures severity using a distance metric instead of looking at probabilities of realization. Lastly, Bonucchi and Catalano (2019) propose a model-based approach to calculate the joint probability of the whole scenarios starting from a general structural macroeconometric model and provide an application to assess the severity and plausibility of the 2016 and 2018 EBA stress tests for Italy. Our methodology also follows a model-based approach, but our severity measure is based

[2]In Henry et al. (2013) financial shocks to stock and bond prices are calibrated in this way using the copula approach to account for the dependence across asset classes.

[3]Since conducting the SCAP in 2009, the Federal Reserve System has conducted annual stress tests on the U.S. banking system, the CCARs. In each CCAR, the Federal Reserve Board generates an adverse macroeconomic scenario and requires BHCs to submit at least one adverse scenario that is related to their own specific portfolios and risk profiles. However, at least for the 2013 CCAR analyzed by Yuen (2015), there is no precise information on what should be the appropriate severity.

[4]Mahalanobis distance is given by

$$Maha(r) = \sqrt{(r-\mu)^T \cdot Cov^{-1} \cdot (r-\mu)}$$

which is simply the distance of the test point r from the center of mass μ divided by the width of the ellipsoid in the direction of the test point. Intuitively it can be interpreted as the number of standard deviations of the multivariate move from μ to r.

on the percentile of the distribution of the variables in stress scenarios. Moreover, we propose a measure of aggregate severity by weighting different percentiles calculated on marginal distributions.

3 Data

The dataset include monthly information on the Italian banking sector from January 1999 to March 2019. The time interval covered allows us to include several recessions periods as well normal times in the estimation. In particular we are able to include three major crisis: (1) the early 2000s dot-com bubble recession; (2) the Global Financial Crisis of 2008-09 and the Sovereign Debt Financial Crisis of 2011-2012.

In the benchmark model we include 23 variables: (1) seven macroeconomics and financial variables: Italian Real GDP; consumer price inflation; one measure of short-term interest rate, the 3-month Euribor; two measure of long-term interest rate, the 5-year euro interest rate swap and the 10-year Italian government bond yield and a risk measure of the Italian economy, the 10-year BTP-Bund sovereign spread, the Italian stock market index; (2) seven variables related to the credit market: the cost and quantity of (net) loans to non-financial firms (NFC) and households (HH); the amount of (net) loans to other intermediaries[5], the amount of bad loans and the markup on short-term loans[6], which is supposed to be a synthetic measure on how the Italian banking sector is able to profit from the emission of new (short-term) loans; (3) six measures of bank funding and liabilities: the stock and interest rate on bonds and bank deposits, divided in current accounts and all other type of deposits (both short and longer-term ones) and the amount of funds obtained by Italian banks from the ECB; (4) the stock of Italian debt bonds held by banks and the Tier 1 ratio[7]. We use the Denton-Cholette (Denton, 1971) method to get a monthly frequency version of Real GDP from R software package *tempdisagg*[8].

Since there is no monthly Tier 1 capital ratio series available for the Italian banking sector we had to construct one. To do so we collected all available data on Tier 1 capital and risk-weighted assets (RWA) of the Italian banks for any semester from 2000 onward, from the statistical appendix of the Economic Bulletin of the Bank of Italy[9]. Then we exploit two high-frequency (i.e. monthly) proxies for Tier 1 capital and RWA in order to reconstruct the intra-semester missing months, keeping all the end-of-semester data equal to the official one. The high-frequency proxy for the Tier 1 capital is the monthly stock of capital and reserves from Bank of Italy statistics Banks and Money: National Data[10]. For the RWA we constructed a proxy for the standard RWA, using Bank of Italy data for all the sub-components in the computation. Then the standard benchmark was adjusted to account for the Italian banks that specifically stated that they moved to the internal methods for RWA's computation[11]. The two proxies were used to augment the frequency of

[5] Including, among others, financial and insurance firms, central government.

[6] Measured as the differential between the average rate on loans under one year and the minimum rate on the stock of new loans under 1 year.

[7] Measured as the amount of Tier 1 equity of Italian banks divided by Risk Weighted Assets (RWA)

[8] See `http://CRAN.R-project.org/package=tempdisagg`

[9] `https://www.bancaditalia.it/pubblicazioni/bollettino-economico/`

[10] `https://www.bancaditalia.it/pubblicazioni/moneta-banche/`

[11] In order to collect such information we looked at the balance sheets of the 10 largest Italian banks from 2013 to 2018.

the Bank of Italy's series using Chow et al. (1971) method for temporal disaggregation. Finally, the Tier 1 ratio was computed as the ratio between the Tier 1 capital and the RWA.

An alternative approach to include Tier 1 ratio as an endogenous variable in the IBASE is to calculate the evolution of this variable using the bank variables that enter into its definition. We choose not to use this approach for several reasons. The first is the lack of data for all the balance sheet items necessary for the computation of capital which would have forced us to use several series that needed to be reconstructed and in most cases would have been very poorly explained by an econometric model. This would have reduced the explanatory power of the IBASE significantly, so we decided to focus on reconstructing the numerator and denominator of the Tier 1 ratio. We followed the recent contribution from Conti et al. (2018) who run a counterfactual analysis on the effect of regulatory shocks to bank capitalization on Italian data, validating the use of the Tier 1 ratio as an endogenous variable in these types of analysis. Conti et al. (2018) not only employed an estimation strategy very similar to ours (i.e. LBVAR) but their results on Tier 1 capital were robust to several model specification and different estimation procedures, giving us confidence in using the same strategy. We also we investigated the forecasting explanatory power of the IBASE for the Tier 1 ratio: it was among the best-performers, thus supporting our choice (see Table 4). Finally, according to variance decomposition analysis, more than half of the variance of the Tier 1 ratio at 3-years horizon is explained by shocks from other variables. This suggests that the variables included in the system help in explaining the dynamics of the Tier 1 ratio.

Apart from macroeconomic variables and the Italian stock market index, the source for all the other variables is the Bank of Italy[12]. In the model all variables enter in log-levels with the exception of inflation, interest rates, unemployment rate and the Tier 1 ratio which are expressed in percentages. Figures 1 and 2 provide a graphical representation of all the variables in the model, while Table 1 contains the variables names and the labels used throughout the paper.

[Figure 1 about here.]

[Figure 2 about here.]

[Table 1 about here.]

4 Methodology

4.1 The Large Bayesian VAR model

Let $Y_t = (y_{1,t}, y_{2,t} \dots y_{n,t})'$ be the (large) vector including the n (with $n = 23$) variables. We consider the following $VAR(p)$ model:

$$Y_t = c + A_1 Y_{t-1} + ... + A_p Y_{t-p} + u_t \tag{1}$$

[12] More specifically from the "Bank and Money: National Data", a monthly publication of statistics on monetary policy, banks' balance sheets and bank interest rates. Most of the statistics are harmonized at the Eurosystem level.

where Y_t is an $n \times 1$ vector of endogenous variables; $A_1, \ldots, A_p$ are $n \times n$ matrices of coefficients; $c = (c_1, \ldots, c_n)'$ is an n dimension vector of constants and u_t is a normally distributed multivariate white noise with covariance matrix Ψ (i.e. $u_t \sim \mathcal{N}(0, \Psi)$).

Since we are dealing with a large dimensional vector of information, standard econometric techniques could incur in a problem of over-fitting due to the large number of parameters. The problem of parameter proliferation prevents us from conduction reliable inference with large dimensional system (i.e. *the curse of dimensionality*).

Therefore, we choose to estimate the IBASE with a Bayesian VAR (BVAR) framework, which is particularly useful when dealing with a large number of variables since it helps to overcome the curse of dimensionality via the imposition of prior beliefs on the parameters (Bańbura et al., 2010, 2015, Giannone et al., 2012). The idea behind such method is to combine the likelihood coming from the complex and highly parametrized VAR model with a prior distribution for the parameters which is naive but parsimonious.

In setting the prior for our baseline estimation, we start from the so-called Minnesota prior, (Litterman et al., 1979), which has been shown to be a reliable approach to reduce the estimation uncertainty without introducing substantial bias (De Mol et al., 2008, Bańbura et al., 2010). The basic principle behind the Minnesota prior (Litterman et al., 1979) is that each endogenous variable follows an independent random walk process with drift, such as

$$Y_t = c + Y_{t-1} + u_t \tag{2}$$

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. Such prior specification incorporates the belief that more recent lags should provide more reliable information than the more distant ones and that own lags should explain more of the variation of a given variable than the lags of some other variables in the equation.

However, since we are setting the IBASE to perform structural analysis, we need to consider the possible correlation among the residual of different variables. This means that Litterman's assumption of a fixed and diagonal covariance matrix is somewhat problematic. To overcome this problem, we impose a Normal inverted Wishart prior, retaining the principles of the Minnesota ones (Kadiyala and Karlsson, 1997, Bańbura et al., 2010). We consider a conjugate prior distribution 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 account for correlations among the residuals of different equations and depart from the Litterman's standard assumption of a fixed and diagonal covariance matrix.

The prior parameters are chosen so that

$$E(A_{ij,k}) = \begin{cases} \delta_i, & \text{if } j = 1, k = 1 \\ 0, & \text{otherwise} \end{cases} \qquad V(A_{ij,k}) = \begin{cases} \frac{\lambda^2}{k^2}, & j = i, \\ \nu \frac{\lambda^2}{k^2} \frac{\sigma_i^2}{\sigma_j^2}, & \text{otherwise} \end{cases} \tag{3}$$

The hyperparameter δ_i characterises the integration order of the associated variable i. The hyperparameter λ 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. For $\lambda = 0$ the posterior equals the prior and the data do not influence the estimates. If $\lambda = \infty$, on the other hand, posterior expectations coincide with the Ordinary Least Squares (OLS) estimates. To calibrate such hyperparameter we follow a method similar to that of Bańbura et al. (2010), applied to all the banking variables contained in the dataset, but differently from Bańbura et al. (2010) we validate the λ value from an out-of sample analysis at 60-months after the last observation available, and choose the value corresponding to the lowest relative Means Square Error (MSE).

The factor k^2 is the rate at which prior variance decreases with increasing lag length and σ_i^2/σ_j^2accounts for the different scale and variability of the data. The coefficient $\nu \in (0, 1)$ governs the extent to which the lags of other variables are less important than the own lags. To ensure that the prior parameters of the Normal inverted Wishart are chosen so that the prior expectations and the variance of B coincide with the one of a Minnesota we impose $\nu = 1$.

We include an additional prior. To better understand it, it is useful to rewrite the VAR equation in error correction form

$$\Delta Y_t = c + \Pi Y_{t-1} + B_1 \Delta Y_{t-1} + \cdots + B_{p-1} \Delta Y_{t-p+1} + \varepsilon_t \tag{4}$$

with $B_s = -A_{s+1} - \cdots - A_p$, $s = 1$ and $\Pi = A_1 + \cdots + A_p - I_n$. We set a prior that shrinks Π to zero. More precisely, following Bańbura et al. (2015), we set a prior centered around one for the sum of the coefficients on own lags for each variable, and equal to zero for the sum of coefficients on other variables' lags. The tightness of this prior on the "sum of coefficients" is controlled by the hyperparameter τ. As τ goes to infinity the prior becomes flat while, as it goes to zero, we approach the case of exact differencing, which implies the presence of a unit root in each equation.

We implement these priors by augmenting the system with dummy observations that is equivalent to imposing the Normal inverted Wishart prior (see Bańbura et al. (2010) for methodological details). In particular, the estimation of the IBASE in a multivariate regression setting using dummy observations is done in the following way:

$$Y_* = X_* \hat{B} + U_* \qquad U \sim \mathcal{N}(0, \hat{\Psi}) \tag{5}$$

where Y_* is the matrix of original endogenous variable augmented with dummy observations and X_* the vector of exogenous variables augmented with dummy observations, $\hat{B}$ are estimated coefficients in the model and $\hat{\Psi}$ is the estimated variance covariance matrix.

4.2 Impulse-Response Analysis

To better understand the ability of the model to capture the effects of adverse shocks on banking variables, we implement impulse response analysis. An impulse response function measures the time profile of the effect of shocks at a given point in time on the (expected) future values of variables in a dynamical system. In particular, we investigate the responses of the variables of the systems to adverse shocks on: 1) spread BTP-Bund 2) GDP 3) Italian stock Market Index, 4) 5-years Euro Area interest rate swap. The analysis is carried on in two different ways:

- **Generalized Impulse Response**, as in Pesaran and Shin (1998). In contrast with standard impulse response analysis, that requires orthogonalization using the Cholesky decomposition, this approach is invariant to the ordering of the variables. More precisely, when the economy is hit by a shock on a specific variable, the immediate reaction on the other variable is extracted by using the historical distributions of the errors among variables.

- **Conditional Impulse Response**. In impulse response analysis, each variable in the system is endogenous and responds to exogenous shocks from all the other variables. As a result, the 3-month Euribor rate and 5-year Euro Swap, that are aggregate euro area variables, might respond to shocks arising in Italy. For example, if Italian GDP slows down, short term interest rates might decline because of an expansionary monetary policy measure from the ECB. To better gauge the response of the variables without any potential intervention from the monetary authority we provide an alternative approach to estimate impulse responses by sterylizing the impact on the 3-month Euribor and 5-year Swap. Following the approach of Bańbura et al. (2015) and Conti et al. (2018), for each adverse shock we produce the conditional impulse responses in the following way:

  - Estimate the full-sample model
  - Generate an H-period ahead unconditional forecast to generate a "baseline" scenario
  - Generate a conditional forecast in which the "adverse shock variable" is set equal to the baseline scenario plus one standard deviation of residuals for this variable at initial time and 3-month Euribor and 5-year Swap are equal to the baseline scenario for $h \in \{1, \ldots, H\}$. Conditional forecasts are generated by applying the Kalman Smoother following the approach in Durbin and Koopman (2002) as in Bańbura et al. (2015)

To better assess the importance of each single shock calibrated in the adverse EBA scenario on the banking sector, we provide some evidence using Variance-Decomposition. In particular Forecast Error Variance Decomposition (FEVD) tells us how much of the forecast error variance of each of the variables can be explained by exogenous shocks to the other variables. More precisely, we define $\theta_{i,j}(h)$ as the proportion of the h-step ahead forecast error variance of variable i which is accounted for by the innovations in variable j in the VAR.

$$\theta_{i,j}(h) = \frac{\sigma_{ii}^{-1} \sum_{l=0}^{h} \left(\mathbf{e}_i' \Phi_l \Psi \mathbf{e}_j\right)^2}{\sum_{l=0}^{h} \left(\mathbf{e}_i' \Phi_l \Psi \Phi_l' \mathbf{e}_i\right)} \qquad i, j = 1, \ldots, n$$

where σ_{ii} is the $i-th$ element of the diagonal of Ψ, $\mathbf{e}_i$ is a $n \times 1$ vector of zero elements except for a one in position i, Φ_l is the dynamic multiplier calculated from the vector of lag coefficients $A_1, \ldots, A_p$. The output of FEVD is also used to create the aggregate synthetic severity index, as described in section 4.3.1.

4.3 Stress test analysis

4.3.1 Evaluation of the severity

In this section we describe in detail the approach that has been used to assess the severity of the three stress test scenarios. To begin with, we measure the severity of the scenarios by calculating realization probabilities implicit in the IBASE model. This approach differs from other contributions in the literature, which measure severity in a model-free environment. We claim that relying on model-based implied probabilities is adequate for two reasons

1. A stress test is commonly described as the evaluation of a bank's financial position under a severe but plausible scenario to assist in decision making within the bank (BCBS, 2009a). As a result the definition of severity in the supervisory framework is strictly related to the notion of likelihood.

2. While two scenarios might be equally severe when looking at deviations from the baseline scenario, they might be different in terms of probability of realization. For example, a 50 basis point shock on the Euribor in 2018 might be more or less severe compared to the same shock in 2014. More precisely, this might happen because when evaluating the shock in 2014, the model is estimated on a shorter information set (up to the date before the start of the exercise) compared to the same exercise in 2018.

Our approach has also drawbacks. A severity measure based on the probability of realization is model dependent and, depending on the complexity of the model, cannot be easily replicated. Moreover, EBA stress test scenarios are defined as shocks on a wide set of global and country-specific macrofinancial variables. The IBASE is estimated on the variables of the Italian economy with additional European financial variables. Consequently, we can only feed the shocks on this restricted set of variables, ignoring the additional contribution of shocks originating from other countries or sectors. However, a more detailed description of the different channels poses serious identification issues that requires the introduction of additional restrictions in the model. To be more specific, in our exercise we feed the EBA scenarios defined on the following set of variables: GDP, $EUR3M$, $BTP.10Y$, $SWAP.5Y$, UN, $INFL$, $STOCK.MARKET$ (See Table 1 for definitions). Through the paper, we refer this set of variables as ‘’input variables”, while banking variables are sometimes defined as ‘’output variables”.

We now describe in details each step involved in the methodology adopted to measure the severity of the three stress test considered in the analysis (2014, 2016 and 2018). For $T \in \{2014, 2016, 2018\}$

1. **Estimate the model up to the date of the exercise**: We estimate the IBASE from T_0 to $T-1$, where T_0 is the starting year of the data (1999).

2. We produce $S = 10000$ 3-year ahead simulations on the variables of the systems conditional on the baseline scenario provided by the EBA. In particular for $s \in \{1, \ldots, S\}$

   (a) **Sample coefficients from posterior distribution**: Consider the estimation of the IBASE in a multivariate regression setting using dummy observations.

$$Y_* = X_* \hat{B}_{|T-1} + U_* \qquad U \sim \mathcal{N}(0, \hat{\Psi}) \tag{6}$$

Using a Gibb's sampler, we sample a vector of coefficient B^s and a variance-covariance matrix Ψ^s, from Normal/Inverted Wishart prior distribution

$$vec(B^s_{|T-1})|\Psi \sim \mathcal{N}(vec(\hat{B}_{|T-1}), \Psi^s \otimes \left(X'_* X_*\right)^{-1}), \Psi^s \sim iW(\tilde{S}, T_d + T + 2 - k)$$

where T_d is the number of artificial time dummy observation, k is the number of endogenous variables in the system.

(b) **Conditional Forecasts on the EBA baseline Scenario**: Using $B^s_{|T-1}$ and Ψ^s, we run forecast exercise by conditioning the central path to the baseline EBA scenario as in (Bańbura et al., 2015). Following their approach, the VAR system can be cast in state space representation as below

Measurement Equation

$$Z_t = CS_t + \nu_t \qquad \nu_t \sim \mathcal{N}(0, R) \tag{7}$$

Transition Equation

$$S_{t+1} = GS_t + \omega_t \qquad \omega_t \sim \mathcal{N}(0, H) \tag{8}$$

where $Z_t = Y_t$, $S_t = [Y_t, \ldots, Y_{t-p+1}, c]$, $C = [I_k, 0_{k \times kp}]$, $R = 0_k$, $G_{[1:k,]} = \left[A^s_1, \ldots, A^s_p, I_n\right]$, $G_{[(k+1):(k+1)(p-1),1:k(p-1)]} = I_k$, $G_{[(kp+1):k(p+1),(kp+1):k(p+1)]} = I_k$,$H_{[1:k,1:k]} = \Psi^s$ In this way, the problem of finding the path of specific variables conditioned on the path of other variables can be understood as a Kalman filtering problem, i.e. estimating the states of the system when a set of observations are observed. We followed the standard approach of (Durbin and Koopman, 2002), that applies the Kalman filter to a modified state space representation. We can therefore derive point conditional forecast based on sampled coefficients and variance-covariance matrix $B^s_{|T-1}$ and Ψ^s.

(c) **Draw disturbances around the baseline scenario**: To include additional sources of uncertainty deriving from future shocks, we also draw one set of disturbances for 3 years from the measurement equation from multivariate normal distribution[13]. Finally, we generated a set of alternative paths, $Y_{T-1+h,s}$, of the variables in the system

3. **Measure of Severity**: We compute the severity of the stress test exercise on each single input variable as the probability at $T-1$ that the target variable is equal or below (or above depending on the variable considered) the level in the stress scenarios at horizon h. More precisely.

$$SEV^k_{T-1+h} = \text{Prob}\left(Y^k_{T-1+h} < \tilde{Y}^k_{T-1+h}\right) \qquad k \in \underline{\mathcal{I}} = \{GDP, STOCK.MARKET, INFL\} \tag{9}$$

[13] While this looks as a separate step from the previous one, it is actually implemented in the Kalman filter procedure.

$$SEV^k_{T-1+h} = \text{Prob}\left(Y^k_{T-1+h} > \tilde{Y}^k_{T-1+h}\right) \qquad k \in \bar{\mathcal{I}}\{EUR3M, BTP.10Y, SWAP.5Y, UN\}$$

4. **Conditional Forecasts on the EBA adverse Scenario**: Using the estimated coefficients of the model, we run forecast exercises by conditioning the central path to the adverse EBA scenario as in (Bańbura et al., 2015), in order to track the response of the output variables.

As described above, uncertainty around the baseline EBA scenario is generated from two different sources: (1) the uncertainty connected with the parameters' realization (2) future realization of the shocks (Monte Carlo). As a robustness check, in section 6.2 we show the result of the analysis when we only consider uncertainty arising from future realization of the disturbances.

The definition of severity proposed above corresponds to the probability of realization of a variable calculated from its marginal distribution. If we had to measure the severity of the whole scenario, the best approach would be to calculate the joint realization probability as

$$SEV_{T-1+h} = \left(\bigcap_{k\in\underline{\mathcal{I}}} \text{Prob}\left(Y^k_{T-1+h} < \tilde{Y}^k_{T-1+h}\right)\right) \bigcap \left(\bigcap_{k\in\bar{\mathcal{I}}} \text{Prob}\left(Y^k_{T-1+h} > \tilde{Y}^k_{T-1+h}\right)\right) \tag{10}$$

However the computation of this joint probability poses serious practical issues. First, the larger the set of variables included in the stress test input scenarios, the lower the probability of realization, if the variables are not perfectly correlated. Second, the model generates scenarios in which variables are somewhat correlated. As an example, we produced a scatterplot of generated scenarios for Real GDP and 3-months Euribor at 3-year horizon from the 2018 exercise (see figure 3). The model generates scenarios in which these two variables are positively correlated: this happens essentially because in the estimation sample the ECB responded to a slowdown in GDP and inflation by cutting rates. In the same scatter we draw a line where we included the adverse scenarios defined by the EBA for these two variables. It can be noticed that there are no scenarios generated by the model where Real GDP is lower and Euribor is larger than the levels provided by EBA for these variables. This implies that using this approach to measure aggregate severity would deliver inconclusive results for the comparison of severity across different exercises.

[Figure 3 about here.]

To overcome this limitation, we propose an alternative approach. We measure a synthetic aggregate severity index as a weighted average of single-variable marginal probabilities of realization defined in 9. In particular, we weigh the probability of each variable by considering its contribution to the aggregate variance of banking variables. In particular, we define the weight of an input variable k at horizon h, $\omega_k(h)$ as

$$\omega_k(h) = \frac{\tilde{\omega}_k(h)}{\sum_{m\in I} \tilde{\omega}_m(h)} \tag{11}$$

$$\tilde{\omega}_k(h) = \sum_{i \in \mathcal{B}} \frac{\theta_{i,k}(h)}{\sum \sum_{m \in \mathcal{B}, n \in 1,\dots,n} \theta_{m,n}(h)} \tag{12}$$

Finally, the synthetic aggregate severity is computed as

$$SSEV_{T-1+h} = \sum_{k \in I} \omega_k(h) SEV_{T-1+h} \tag{13}$$

4.3.2 Resiliency evaluation: balance sheet effects from a counterfactual stress test

The strategy implemented in this paper to check whether the resiliency of the Italian banking sector has increased over time relies on two points. The first one is to estimate the model up to the date prior to the start of the exercise starts thus using a recursive sample. In this way, since the exercises are run every two years, the model parameters incorporate any potential effort that the banking system has implemented to make their balance sheets more robust to adverse shocks. Second, we constructed a counterfactual stress test scenario with the same severity and deviations from baseline (i.e. we use the 2014 stress test as a benchmark). This allow us to track the response of balance sheet variables at different dates to scenarios that are comparable in terms of severity. In this way we can evaluate whether the banking sector became more or less resilient according to the definition we presented in Section 1[14].

With simulated scenarios and probability of realization at hand, we can easily generate counterfactual stress tests. The intuition is to reproduce an artificial path of the input variables in 2016 and 2018 that are consistent with the probability of realization of the 2014 scenarios. To do so we proceed as follows for scenario $T \in \{2016, 2018\}$

1. For each input variable k and each horizon h, we calculate an alternative path $\hat{Y}^k_{T-1+h}$ as the percentile of the simulated distribution corresponding to the probability level in 2014. In particular,

$$\hat{Y}^k_{T-1+h} = \left\{ y \in \left\{ Y^k_{T-1+h,s} \right\}_{s=1,\dots,S} | \, \text{Prob}\left(Y^k_{T-1+h,s} \leq y \right) = \text{Prob}\left(Y^k_{2014-1+h} \leq \tilde{Y}^k_{2014-1+h} \right) \right\} \qquad k \in \underline{I} \tag{14}$$

$$\hat{Y}^k_{T-1+h} = \left\{ y \in \left\{ Y^k_{T-1+h,s} \right\}_{s=1,\dots,S} | \, \text{Prob}\left(Y^k_{T-1+h,s} \geq y \right) = \text{Prob}\left(Y^k_{2014-1+h} \geq \tilde{Y}^k_{2014-1+h} \right) \right\} \qquad k \in \bar{I} \tag{15}$$

[14]Since the model is estimated on different samples, not only the sensitivity of the variables to the lags but also the variance-covariance matrix of the disturbances might change. This implies that, for example, a 5% probability shock on GDP can correspond to different deviations from the baseline across different exercises. Since in the counterfactual exercise we want to interpret the different responses of banking variables across exercises as the effect of the derisking/hedging/capital adequacy decisions of the sector, we decided to use re-estimated lag parameters $A_1, \dots, A_p$ as the posterior mean to simulate parameters, while the posterior mean of the variance-covariance matrix of disturbances is the one estimated in 2018

2. **Conditional Forecasts on the Counterfactual Adverse Scenario**: Using the estimated coefficients of the model, we run forecast exercises by conditioning the central path to the counterfactual adverse scenario calculated in the previous step following the methodology in (Bańbura et al., 2015), in order to track the response of the output variables.

5 Results

5.1 Model estimation

Before presenting the results on the IBASE performance, on the severity of the stress test and on the counterfactual analysis, we are going to discuss all the main parameters used in order to estimate the LBVAR. First, the out-of-sample calibration of the λ parameter gives us a value equal to 0.05, which is a consistent value according to the LBVAR related literature (Conti et al., 2018, Sims and Zha, 1998). Given such value for λ we impose $\tau = \kappa \times \lambda$ with $\kappa = 10$ (such value choice will be discussed in Section 5.3, based on several forecasting performances exercises). In order to set the prior on δ_i we estimate an autoregressive integrated moving average (ARIMA) univariate model for each endogenous variable and for different orders of integration, choosing the one that minimizes the conditional sum-of-squares (CSS). The order of integration for each endogenous variable is presented[15] in Table 1.

For the lag order, we choose a parsimonious value equal to one, which was the value minimizing the Bayes information criterion (BIC) (Schwarz et al., 1978) according to the formula

$$BIC = n \cdot \ln\left(\widehat{\sigma_e^2}\right) + k \cdot \ln(n) \tag{16}$$

where $\widehat{\sigma_e^2}$ is the error variance, n is the number of observations and k the number of endogenous variables. As an additional robustness check we run the results from the estimation of the IBASE with a different lag value (i.e. four) which was selected applying a variety of lag selection processes (see Section 6.1).

5.2 Impulse-Response and Variance Decomposition

We now comment the response of the variables to each shock. Following a one-off 15 bp increase in the spread BTP-Bund (see figure 4), the Italian economy slows down and Real GDP is 0.2% lower than in the baseline scenario after 3 years from the shock. Net loans to households and firms are also dampened by almost 0.5% and 1% respectively, while bad loans increase. For bank interest rates, results differ when considering conditional vs generalized impulse responses. In the case of GIRF, interest rates on loans and bank bonds decline. This happens essentially because short term interest rates decline as the model captures a response from the ECB to a slowdown in economic activity. When these effects are shut down, interest rates on loans go up. This happens because the cost of funds for banks is now higher and the probability

[15]When the procedure select orders of integration greater or equal to one, we set $\delta_i = 1$ and zero otherwise.

of default, especially for firms, increases. Therefore banks charge higher interest rates to compensate for the higher cost of funds and the additional risk.

[Figure 4 about here.]

In figure 5 we present the results for a positive shock to Real GDP by 0.1%. In this case, net loans to firms increase, while the impact on household lending is muted. Moreover the stock of bad loans is around 0.5% lower at the through. Instead interest rates on loans are higher even when the effects on euro area interest rates are sterilized. This result is consistent with a credit demand shock, where higher demand for loans from firms and households results in higher interest rates charged by banks.

[Figure 5 about here.]

When stock prices are hit by a positive shock (5%), the spread between Italian and German bond yield decreases (see figure 6). The shock also stimulates lending, especially to firms, and fosters a reduction in the stock of bad loans. The effect on bank interest rates are different, depending on the methodology. When standard GIRF are used, interest rates increase after the shock because of the responses of the monetary authority to improved macroeconomic conditions resulting in higher short term interest rates. In the conditional case, bank interest rates decline because of improved creditworthiness of banks and firms that is reflected in lower risk premia.

[Figure 6 about here.]

Similar to a stock market shock, an increase in the 5-year swap rate induces a positive reaction of loans and reduces risk premia on Italian sovereign bonds and bank interest rates (see figure 7). This happens because a positive shock on swap rates carries information of improved macroeconomic conditions. In the calibrated adverse scenario, higher swap rates compared with the baseline scenario are supposed to be harmful for the banking sector, a result that seems not to be supported by the impulse response analysis. However, a positive shock on interest rates when the economy is improving (as implicit in the impulse response analysis) or when the economy slows down has a very different effect on the banking sector as it is evident when we feed the EBA scenario to the model.

[Figure 7 about here.]

In table 2 we report the FEVD for a selection of bank variables in response to shocks from the variables in the EBA stress test scenarios at different time horizons (1 to 3 years ahead), with the model estimated on the full sample. Interestingly shocks on market interest rates play a dominant role in determining the variability of response variables. In particular market rates explain more than 50% of the variability of loan rates and bank bond rates at 3-year horizon, but also explain a large portion of variability (above 10%) in loans. More generally stock variables and the Tier 1 Ratio seem to be less affected by shock variables, essentially because they are more strongly influenced by their own variability. Finally, stock market shocks are also relevant, especially for loans.

[Table 2 about here.]

5.3 Forecasting Performances

In this section we present the analysis on the forecasting performance of the IBASE. To do so we evaluate the model out-of-sample from December 2008 to March 2016 for a total of 88 iterations. We select a starting date, around the mid-point of the data, to guarantee a sufficiently long dataset from the first iteration. We then evaluate the model on a 3-year horizon, with the final date of the out-of-sample analysis chosen consequently and set, for the last iteration, equal to the last observation we have (i.e. March 2019). Starting from 2008 makes our forecasting exercise particularly challenging since we include two recessions period: (1) the Global Financial Crisis of 2008-09 and (2) the Sovereign Debt Financial Crisis of 2011-2012.

For each out-of-the-sample iteration we calibrate the hyperparameter λ following the same calibration method described in Section 4.1. However we change the tightness of the prior on the "sum of coefficients" setting the corresponding hyperparameter τ to five different values $\tau = \kappa \times \lambda$ where $\kappa \in \{10, 20, 50, 100, 1000\}$, in order to support our initial choice of tightness.

For each iteration we also check the stability of the model by verifying that the unit root of the correspondent LBVAR model lies inside the unit circle. In Figure 8 we show the unit roots and the λ values, from which it is clear that the more unstable estimates are the ones associated with the two recession periods.

[Figure 8 about here.]

The performance analysis is conducted on quantitative forecast precision and direction accuracy. For quantitative forecast errors we compute the ratios of mean absolute errors (MAE) of the IBASE versus different benchmarks (Random Walk (RW), Random Walk with Trend (RWT) and AR(1)) for all values of τ on a 3-year horizon; in addition to this we also report a measure of forecasting performance that is the ability of the model to forecast the direction of the endogenous variables, measured as the number of correct directional forecasts over the total number of (stable) forecasts. Before comparing the IBASE with the benchmark models for all endogenous variables, in Table 3, we present the number of stable iterations, average MAE and direction accuracy across variables for all five values of τ in order to support our choice for $\tau = 10$ and then present for that specific values the MAE and direction for all endogenous variables.

We support the choice of $\tau = 10$ for two main reasons. First, Table 3 shows that in terms of direction of the forecast such value clearly outperform all the other values, also being among the best performers in terms of MAE; the only downside of choosing $\tau = 10$ it is represented by its stability ratio, however, from the graphical inspection of Figure 8 we already established that the majority of unstable episodes corresponds to the two financial crises. Second, we set a value equal to 10 for the degree of shrinkage following the standard approach used by the literature (Bańbura et al., 2010).

[Table 3 about here.]

Having established our choice for the τ parameter, tables 4 presents the IBASE performances for some selected bank variables. The IBASE outperforms all benchmark models for many of the bank stock variables such as: bank bonds, sovereign bonds (against AR(1)), bad loans, net loans to non-financial corporations and households, although for the latter variable our model overperforms only the random walk with trend. As for interest rates the IBASE is not able to clearly outperform all the other benchmark models even if it scores not so distant from the unity. However, the sample used for the analysis covers two major recessions that created unprecedented financial turmoil and therefore pose many challenges for the ability of an econometric model to capture interest rates' movements, that were driven by a range of unconventional monetary policy measures. Lastly the IBASE model is able to outperform all selected benchmarks for the Tier 1 ratio. This is an important results given the pivotal importance that such indicator has in the stress tests.

[Table 4 about here.]

Finally, table 5 presents the directions results for some selected bank variables. Similar to the performance analysis the IBASE is more accurate in forecasting the direction of the stock variables and the Tier 1 ratio rather than the interest rates. Overall the IBASE proves to be an efficient LBVAR model, especially suited for bank-stock variables and Tier 1 ratio.

[Table 5 about here.]

5.4 Severity evaluation

Table 6 presents the deviation from the baseline (first lines) and the probabilities of realization for the three stress test considered, over the 3-years horizon (second line). Is it interesting to note that in terms of GDP the deviation from baseline are more severe in the 2018 stress test that has the lowest probability of realization. Similarly to what happens with GDP for many of the other macro-financial input variables the 2018 exercise produces the highest deviations from the baseline scenario; however the associated probabilities of realization are not as low as for GDP. Moreover, we find that the 2018 exercise had been the most severe also for the 3-month Euribor and stock market, however the scenario for these variables seems more likely compared to the one for GDP. Instead, the 2014 exercise was the most severe for the BTP-Bund spread (at least on impact).

Looking at output variables it can be noticed that for loans the deviations from the baseline calculated by the model, are overall very similar for the three stress tests while the probability of realization is lower (and very similar in size) for the 2016 and 2018 stress tests. For bad loans the latest stress test entails the highest deviation from baseline associated with very high probability. This could be explained by the recent disposal of bad loans (from 2016 onward) by the Italian banking sector which decreased the amount of bad loans; hence the 2018 deviations are the highest, although associated with a decreasing and smaller stock. As we might expect from an adverse scenario, holdings of sovereign bonds increase (with a very high probability), especially for the last stress test. This is line with the empirical findings by Acharya and Steffen (2015), that document the large increase in sovereign exposures among undercapitalized banks during the European Debt Crisis and offer different explanations for this phenomenon. Bank interest rates (on loans and deposits) increase in all three scenarios, although more strongly in the 2018 ones, as a direct consequence of the increase (by scenario design) in the 3-month Euribor and the 5-year swap rate. Lastly, as expected, the Tier 1 ratio decreases in all three adverse scenarios, although more strongly in the 2018 one. The larger fall in the capital ratio in the 2018 exercise is associated with the strongest increases in bad loans and interest rates. Since the interest rate on loans increases but the stock of loans decreases and the bad loans increase, the net effect of such scenario is a reduction in bank capitalization and hence in the Tier 1 ratio. The reduction in the Tier 1 ratio in the adverse scenario is however very limited compared to the average results across different banks in traditional stress tests. The main reason for this difference is the dynamic vs static balance sheet approach. According to our exercise, in response to negative shocks banks reduce their risky exposures instead of raising new capital, a result that has also been found by other macroprudential stress test approaches (Dees and Henry, 2017).

[Table 6 about here.]

To conclude on severity evaluation analysis, in Figure 9 we show the graph of the synthetic aggregate severity (SSEV) presented in Section 4.3.1. As expected, the 2018 stress test has the lowest SSEV, highlighting the fact that the probability of realization of the 2018 stress test, weighted for its contribution to the aggregate variance of bank variables, is the lowest. Figure 9 also gives the rationale to run a counterfactual analysis standardizing the severity of all three stress tests, this is because, even when weighted, none of the three aggregate "severities" are closely comparable; with the only exception for the second year deviations from the 2014 and 2016 stress test.

[Figure 9 about here.]

5.5 Resiliency evaluation: balance sheet effects from a counterfactual stress test

The results shown in Table 6, confirm that for some but not all input and output variables the 2018 deviations were the largest and associates with a lower probability of realization. Comparing the scenarios from the three stress tests it seems that all of them were designed to include very unlikely and extreme GDP deviations, probably to mimic the Financial Crisis, while the probability of realization for all the other input variables were higher. However, we can only look and compare the three stress tests in terms of deviation and probability of realization but, without further work, we are not able to draw any conclusion on whether the resiliency of the Italian banking sector has increases over time.

To say something about this, we rescaled the 2016 and 2018 stress tests to the same level of severity of the 2014 exercise and look at what would have happened. By having the same degree of severity across all three exercises and comparing the results with those in Table 6, we are able to verify whether the Italian banking sector has become more or less resilient to the same adverse shocks. Indeed, model coefficients are estimated until the date before the beginning of the exercise. This implies that, for example, in 2018 we evaluate the impact of the counterfactual shock with a model that covers recent years, were risk management actions have been taken by the banks to improve their resiliency. Table 7 presents the deviations from the baseline (first lines) and the probabilities (only for the 2014 stress test) of the counterfactual stress test exercises. We are not discussing the counterfactual changes in the input variables since they were substituted, in the 2016 and 2018, by the deviations of the 2014 adverse scenario and we already discussed the rankings of such scenarios before. We focus instead on the output variables. Looking at the loans it is clear that, by imposing the same degree of severity, we obtain smaller deviations, especially for the 2018 stress test. Therefore, there has been an increase in resiliency of the Italian banking sector to the adverse shock. In particular, with shocks that are comparable to those in 2014, Italian banks can now afford to derisk their balance sheets less. Bad loans instead increase more in these new scenarios compared to 2014. As for government bonds the counterfactual analysis suggests that they would have increased more; this can be easily reconciled with the fact that in 2014 the deviation for the 10-years Italian bonds yields, and the sovereign spread, were the highest. For the interest rate on loans the counterfactual analysis results in higher rates for both NFCs and households, as a consequence of the increase in short- and long-term market rate (i.e. 3-month Euribor and 5-year swap). Lastly, we turn our attention to the Tier 1 capital ratio. The results of the counterfactual analysis shows that resiliency measured in terms of Tier 1 ratio slightly declined in 2018. Unfortunately in the IBASE we don't model all the balance sheet items necessary to interpret the impact on Tier 1 ratio. One possible explanation for the lower resiliency in 2018 for this variables is that banks did less to derisk their balance sheets as a result of smaller decline in loans as discussed above.

To conclude, by relying on counterfactual adverse scenarios that are comparable in terms of severity to the first EBA exercise, we find that Italian banks respond by allowing for larger decline in the Tier 1 ratio and a smaller decline in net loans. We interpret this as an increase in resiliency over time.

[Table 7 about here.]

6 Robustness check

6.1 The model with more lags

As a robustness check we present the results from the estimation of the IBASE with a different lag structure. In order to decide which lag value to use, we employed several identification criteria, different from the BIC used in the baseline model. More precisely, we used four different information criteria: (1) Akaike information criterion (AIC) (Akaike, 1974); (2) Hannan-Quinn information criterion (HQ) (Hannan and Quinn, 1979);(3) Schwarz Criterion (SC) (Schwarz et al., 1978) and (4) Final Prediction Error (FPE)

(Akaike, 1969). We set the maximum lag value equal to

$$l_{max} = \frac{t-1}{i-2}$$

where t is the number of monthly observations used in the LBVAR estimation and i the number endogenous variables. By averaging the results from all these tests we set the number of lags equal to four. To reduce the computational burden we generate confidence bands around the baseline scenario only considering the uncertainty coming from shocks' realization (i.e. Monte Carlo).

Table 8 present the stress tests deviations and probabilities for the input variables from the IBASE estimated with four lags. If we compare the probability associated with the three stress test from Table 8 we notice that they are qualitatively similar to the benchmark ones of Table 6. There are some small differences in particular for unemployment rate and interest rates, for which using a higher lag structure results in a higher probability. As for the probability associated with the Real GDP and Italian stock market the results from Table 8 are smaller than those obtained by estimating the IBASE with only one lag. Overall we don't notice any major differences thus supporting the choice of using, as a benchmark model the IBASE estimated with one lag.

[Table 8 about here.]

6.2 Parameters vs Shock Uncertainty

In section 4.3.1 we describe the procedure to generate uncertainty around the baseline scenario. Our benchmark results rely on two sources of uncertainty: 1) the uncertainty connected with the parameters' realization (2) and the uncertainty due to the future realization of the shocks (Monte Carlo). In this section, we show the importance of the first source of uncertainty in generating confidence bands for a selection of variables. Figure 10 presents the simulated distributions conditional on the central path of the EBA baseline scenarios for a selection of variables. Simulated paths are generated at 1- to-3-year horizon with the model estimated until December 2017. As it can be noticed, accounting for both sources of uncertainty contributes to generate more probability mass for more extreme events, especially at longer horizons. In particular, the distance between the 99.9% and the 0.1% percentile is around 50% larger for loans at the 3-year horizon and 30% larger for Real GDP. This result is explained by larger second moments of the simulated distribution when accounting for both sources of uncertainty, but also by larger leptokurtosis. This implies that simulated paths in our benchmark setup do not follow a normal distribution as suggested by Jarque Bera test statistics. We claim then that accounting for both types of uncertainty is important to better capture the likelihood of adverse and rare events.

[Figure 10 about here.]

7 Conclusion

In this paper we propose a model-based approach to analyze the stress tests carried out by the EBA on banks. In particular, we investigate whether 1) the severity of the adverse scenarios has increased from the first exercise to the last one, and 2) the resiliency of the Italian banking sector has improved. We argue that these two concepts need to be considered separately. We define severity as the probability of realization of adverse scenarios of input variables, while resiliency depends on how strongly banking variables react to these shocks and how they are able to dampen the spillover effects to the real economy.

To address these issues we used the Prometeia IBASE model, an econometric model for the Italian economy, where banking and macro-financial variables are closely interrelated. As such, our approach departs from traditional stress test exercises on several ways. First, we consider feedback effects from the banking sector to the real economy. Second, our setup is consistent with a dynamic balance sheet approach: banks can deleverage/derisk in response to negative shocks as opposed to the static balance sheet approach imposed. Severity is measured on each variable included in the exercise by calculating percentiles from conditional forecasting simulations of the model. We find that in general the adverse scenarios on Italian Real GDP are very severe, while the scenarios on financial variables (stock market and market interest rates) are more likely. Moreover, we find that the 2018 exercise had been the most severe for Real GDP, 3-month Euribor and stock market, while the 2014 exercise was the most severe for the BTP-Bund spread (at least on impact). We also find that the joint realization probability of the EBA adverse scenarios is extremely low, as such it is not possible to give an overall assessment of the severity of the exercises. We therefore propose a novel approach. We calculate a synthetic aggregate severity index by averaging the marginal probability of realization of the shocks according to their contribution on the variability of bank variables. The index so constructed shows that the last exercise was the most severe.

To measure the resiliency of Italian banks we run a counterfactual stress test exercise. Since the exercises are not comparable in terms of probability of realization we use the model to generate alternative adverse scenarios for the 2016 and 2018 that have the same severity as the 2014 ones. Resiliency is assessed by feeding these shocks to the IBASE model estimated up to the date when the exercise begins. In this way, when evaluating the exercises in 2016 and 2018 we are able to capture the effect of the risk management actions put in place to reduce the exposure to the shocks with the model's parameters. In the 2016 and 2018 counterfactual exercises we find that Italian banks respond by reducing loans to the private sector by a smaller amount allowing for a stronger decline in their Tier 1 ratio. We interpret this result as an increase in the resiliency of the banking sector over time.

Our paper contributes to the policy discussion on how to properly design stress test scenarios. First, we show that the static vs dynamic balance sheet assumption makes a lot of difference for evaluating banks resiliency as also stated in Dees and Henry (2017). In our approach, we show that banks would react to negative shocks by reducing risky exposures in their balance sheet, as such the decline in capital ratios would be lower than in EBA stress tests (with static balance sheets). Second, we show that according to the IBASE model, the EBA scenarios are extremely unlikely when considering the joint probability of realization of the whole scenario.

While our approach relies on a limited set of variables at the aggregate levels compared to the detailed analysis of the EBA exercise, we argue that our approach can be used in a more complex environment as the STAMP€ and CLASS framework do. In particular, we can potentially consider cross-country spillovers by modeling interlinkages in a Bayesian context as in Canova and Ciccarelli (2004) or in a GVAR/IVAR fashion (Dees et al., 2007, De Meo et al., 2018). Moreover, the aggregate responses of bank variables to the shocks can be projected on single banks while still considering the potential spillovers from the banking sector to the aggregate economy as in Gross et al. (2016). Finally, the potential cross-sector interlinkages could work as an additional propagation channel of adverse macroeconomic shocks as in Castrén and Rancan (2014). We leave these extensions to future research.

References

Acharya, V., R. Engle, and D. Pierret (2014). Testing macroprudential stress tests: The risk of regulatory risk weights. *Journal of Monetary Economics 65*, 36–53.

Acharya, V. V. and S. Steffen (2015). The "greatest" carry trade ever? Understanding eurozone bank risks. *Journal of Financial Economics 115*(2), 215–236.

Akaike, H. (1969). Fitting autoregressive models for prediction. *Annals of the institute of Statistical Mathematics 21*(1), 243–247.

Akaike, H. (1974). A new look at the statistical model identification. In *Selected Papers of Hirotugu Akaike*, pp. 215–222. Springer.

Altavilla, C., M. Darracq Pariès, and G. Nicoletti (2015). Loan supply, credit markets and the euro area financial crisis. Technical report, ECB Working Paper, No. 1861.

Arnold, B., C. Borio, L. Ellis, and F. Moshirian (2012). Systemic risk, macroprudential policy frameworks, monitoring financial systems and the evolution of capital adequacy. *Journal of Banking & Finance 36*(12), 3125–3132.

Bańbura, M., D. Giannone, and M. Lenza (2015). Conditional forecasts and scenario analysis with vector autoregressions for large cross-sections. *International Journal of Forecasting 31*(3), 739–756.

Bańbura, M., D. Giannone, and L. Reichlin (2010). Large Bayesian vector auto regressions. *Journal of Applied Econometrics 25*(1), 71–92.

BCBS (2009a). Principles for sound stress testing practices and supervision. Technical report, Basel Committee on Banking Supervision.

BCBS (2009b). Strengthening the resilience of the banking sector. *BIS Consultative Document*.

Boivin, J., M. P. Giannoni, and D. Stevanović (2018). Dynamic effects of credit shocks in a data-rich environment. *Journal of Business & Economic Statistics*, 1–13.

Bonucchi, M. and M. Catalano (2019). How severe are the EBA macroeconomic scenarios for the Italian Economy? A joint probabilistic approach. *Prometeia working papers*.

Borio, C., M. Drehmann, and K. Tsatsaronis (2014). Stress-testing macro stress testing: does it live up to expectations? *Journal of Financial Stability 12*, 3–15.

Breuer, T., M. Jandacka, K. Rheinberger, M. Summer, et al. (2009). *How to find plausible, severe, and useful stress scenarios.* Österr. Nationalbank.

Canova, F. and M. Ciccarelli (2004). Forecasting and turning point predictions in a Bayesian panel VAR model. *Journal of Econometrics 120*(2), 327–359.

Castrén, O. and M. Rancan (2014). Macro-Networks: An application to euro area financial accounts. *Journal of banking & finance 46*, 43–58.

Conti, A. M., A. Nobili, F. M. Signoretti, et al. (2018). Bank capital constraints, lending supply and economic activity. Technical report, Bank of Italy, Economic Research and International Relations Area.

Dave, C., S. J. Dressler, and L. Zhang (2013). The bank lending channel: a FAVAR analysis. *Journal of Money, Credit and Banking 45*(8), 1705–1720.

De Meo, E., L. Prosperi, G. Tizzanini, and L. Zicchino (2018). Forecasting Macro-Financial Variables in an International Data-Rich Environment Vector Autoregressive Model (iDREAM). *Prometeia working papers*.

De Mol, C., D. Giannone, and L. Reichlin (2008). Forecasting using a large number of predictors: Is Bayesian shrinkage a valid alternative to principal components? *Journal of Econometrics 146*(2), 318–328.

Dees, S. and J. Henry (2017). Stress-Test Analytics for Macroprudential Purposes: Introducing STAMP€. *Satellite Models 13*.

Dees, S., F. d. Mauro, M. H. Pesaran, and L. V. Smith (2007). Exploring the international linkages of the euro area: a global VAR analysis. *Journal of applied econometrics 22*(1), 1–38.

Denton, F. T. (1971). Adjustment of monthly or quarterly series to annual totals: an approach based on quadratic minimization. *Journal of the American Statistical Association 66*(333), 99–102.

Diebold, F. X. and R. S. Mariano (2002). Comparing predictive accuracy. *Journal of Business & economic statistics 20*(1), 134–144.

Dovern, J., C.-P. Meier, and J. Vilsmeier (2010). How resilient is the German banking system to macroeconomic shocks? *Journal of Banking & Finance 34*(8), 1839–1848.

Durbin, J. and S. J. Koopman (2002). A simple and efficient simulation smoother for state space time series analysis. *Biometrika 89*(3), 603–616.

Durdu, C. B., R. M. Edge, D. Schwindt, et al. (2017). Measuring the Severity of Stress-Test Scenarios. Technical report, Board of Governors of the Federal Reserve System (US).

EBA (2018, July). *Guidelines on institution's stress testing.* European Banking Authority.

Giannone, D., M. Lenza, H. Pill, and L. Reichlin (2012). The ECB and the interbank market. *The Economic Journal 122*(564), F467–F486.

Giannone, D., M. Lenza, and L. Reichlin (2012). Money, credit, monetary policy and the business cycle in the euro area. *Centre for Economic Policy Research (CEPR).*

Gross, M., C. Kok, and D. Żochowski (2016). The impact of bank capital on economic activity-Evidence from a Mixed-Cross-Section GVAR model. *ECB Working Paper*.

Hannan, E. J. and B. G. Quinn (1979). The determination of the order of an autoregression. *Journal of the Royal Statistical Society: Series B (Methodological) 41*(2), 190–195.

Henry, J., C. Kok, A. Amzallag, P. Baudino, I. Cabral, M. Grodzicki, M. Gross, G. Halaj, M. Kolb, M. Leber, et al. (2013). A macro stress testing framework for assessing systemic risks in the banking sector. *ECB Occasional Paper* (152).

Hirtle, B., A. Kovner, J. Vickery, and M. Bhanot (2016). Assessing financial stability: the capital and loss assessment under stress scenarios (CLASS) model. *Journal of Banking & Finance 69*, S35–S55.

Hoggarth, G., S. Sorensen, and L. Zicchino (2005). Stress tests of UK banks using a VAR approach. *Bank of England working paper no. 282*.

Kadiyala, K. R. and S. Karlsson (1997). Numerical methods for estimation and inference in Bayesian VAR-models. *Journal of Applied Econometrics 12*(2), 99–132.

Litterman, R. B. et al. (1979). Techniques of forecasting using vector autoregressions. Technical report.

Pesaran, M. H. and Y. Shin (1998). Generalized impulse response analysis in linear multivariate models. *Economics letters 58*(1), 17–29.

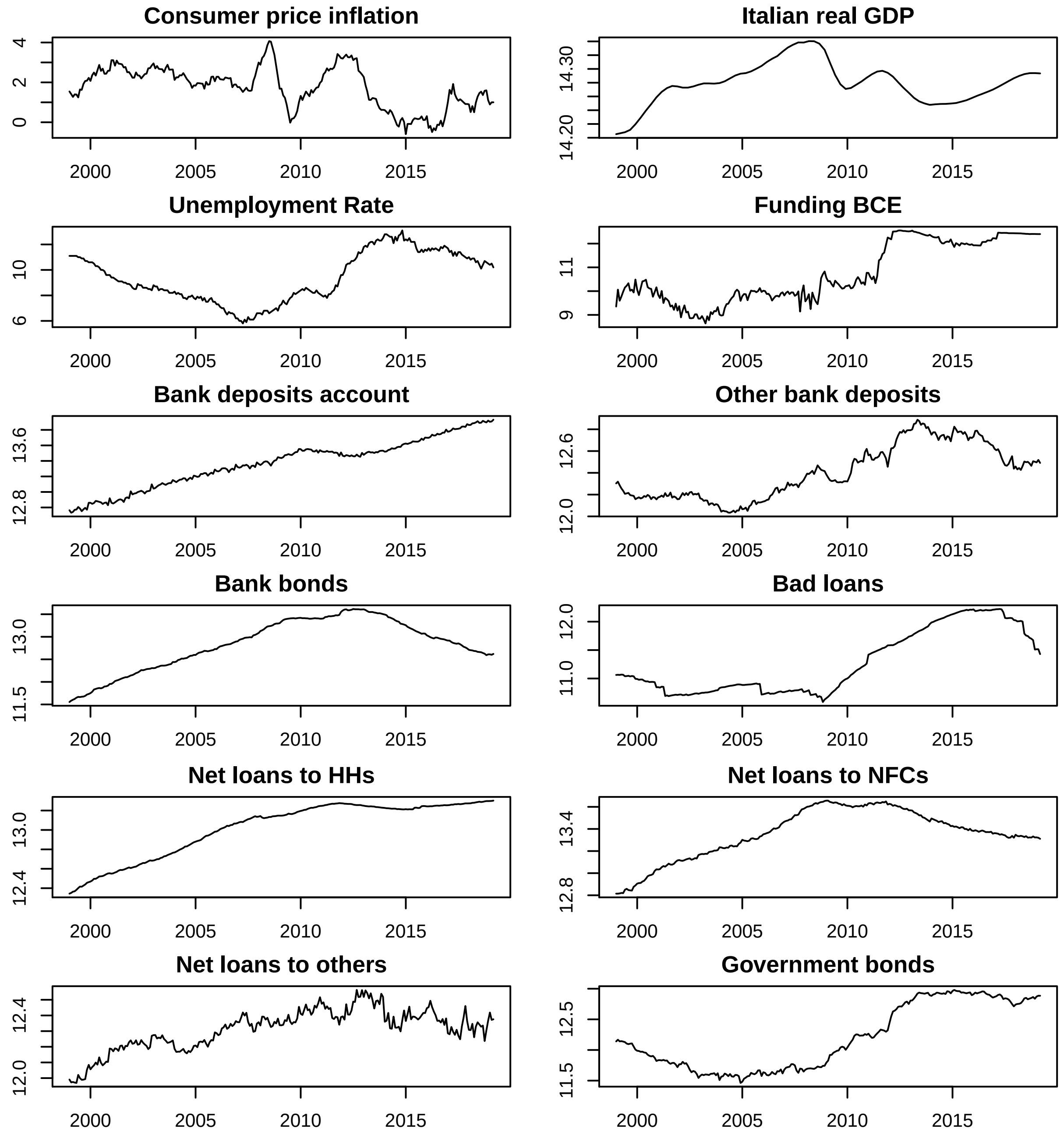
Schwarz, G. et al. (1978). Estimating the dimension of a model. *The annals of statistics 6*(2), 461–464.

Sims, C. A. and T. Zha (1998). Bayesian methods for dynamic multivariate models. *International Economic Review*, 949–968.

Von Borstel, J., S. Eickmeier, and L. Krippner (2016). The interest rate pass-through in the euro area during the sovereign debt crisis. *Journal of International Money and Finance 68*, 386–402.

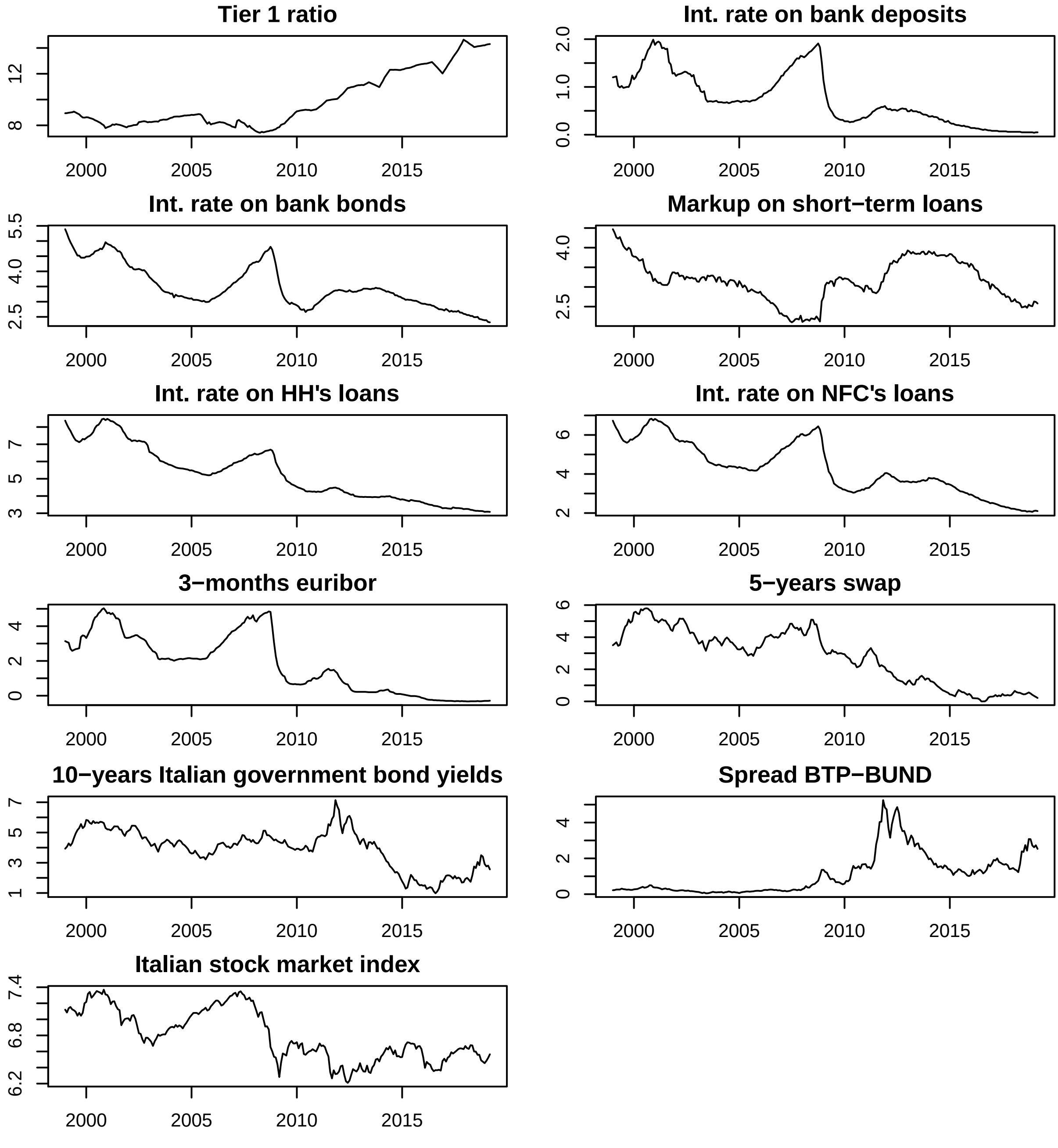
Yuen, K. (2015). Determining the Severity of Macroeconomic Stress Scenarios. *Supervisory Staff Reports, Federal Reserve Bank of New York*.

Figure 1: Variables for the empirical analysis



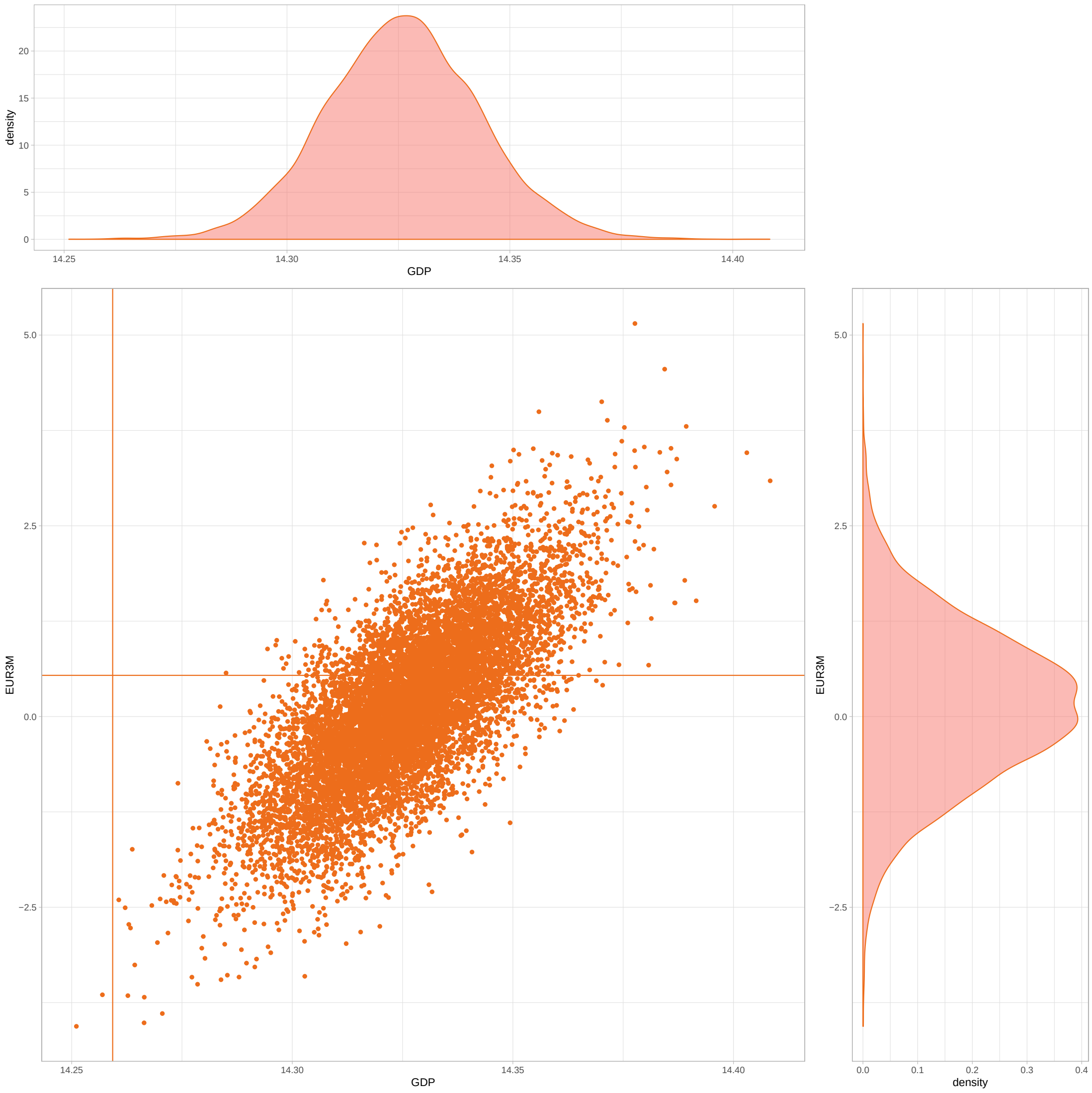
Note: All variables enter in log-levels with the exception of inflation, interest rates, unemployment rate and the Tier 1 ratio which are expressed in percentages. Banking macroeconomic variables are specific to Italian economy.

Figure 2: Variables for the empirical analysis (cont.)



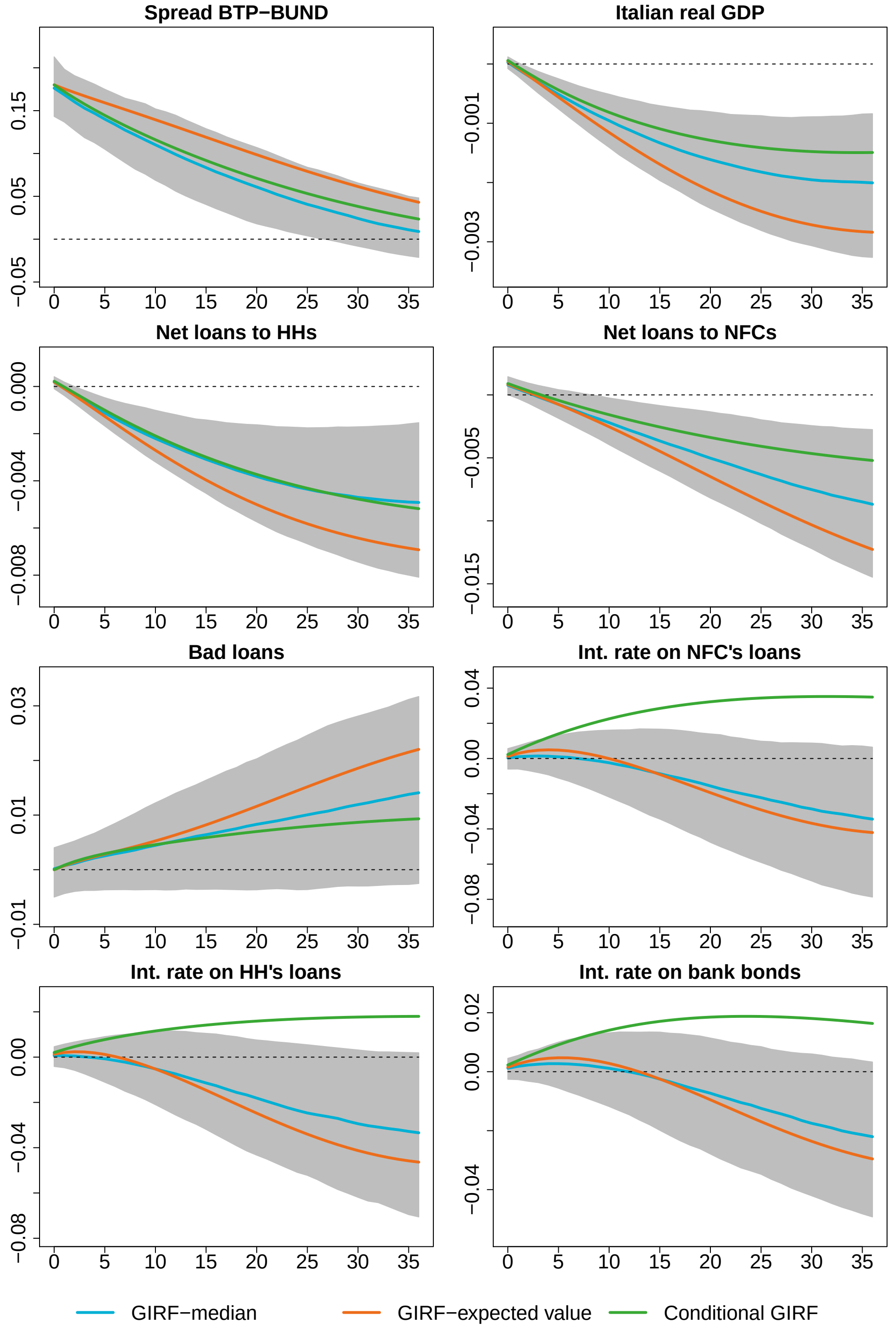
Note: All variables enter in log-levels with the exception of inflation, interest rates, unemployment rate and the Tier 1 ratio which are expressed in percentages. Banking macroeconomic variables are specific to Italian economy.

Figure 3: Multivariate distribution of Italian Real GDP and Euribor 3m at 3 years horizon in the 2018 exercise



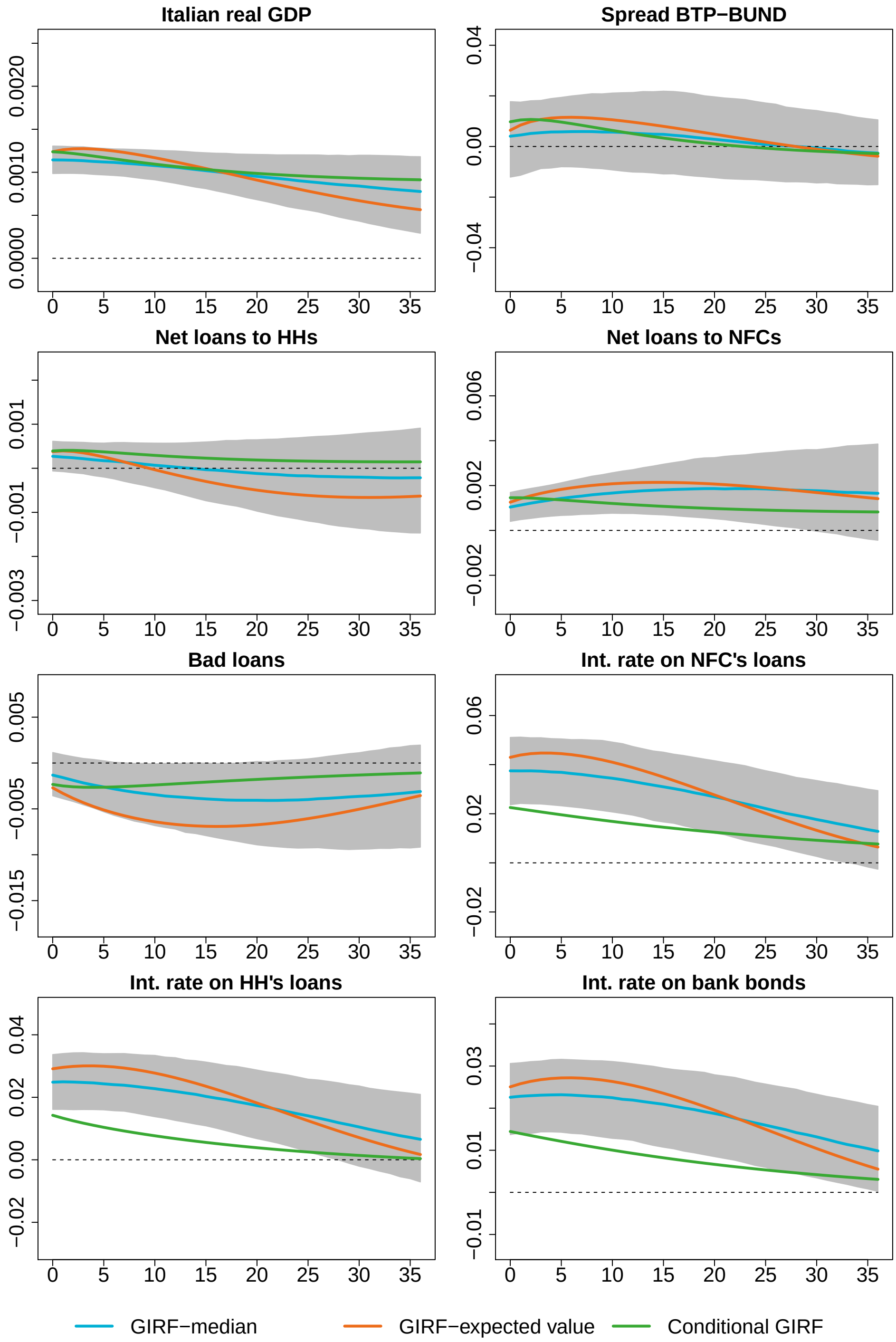
Note: The figure shows the scatter plot of simulated scenarios for Italian Real GDP and 3-month Euribor for the 2018 stress tests at 3-year horizon. The vertical line represents the adverse scenario of the 2018 stress test for Real GDP while the horizontal one for the 3-month Euribor.

Figure 4: Responses of to a shock in the Spread BTP Bund



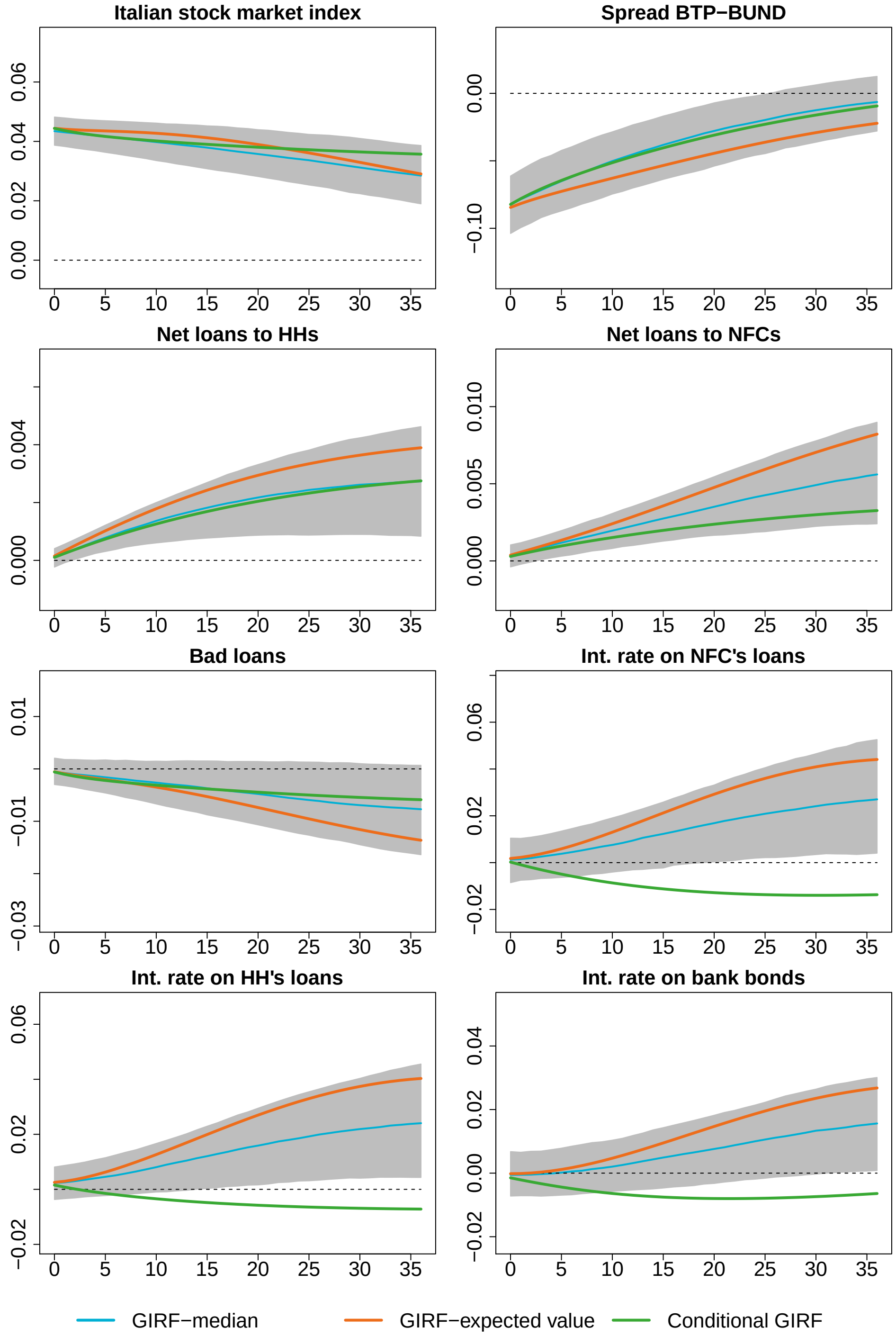
Note: The figure represents the impulse response function to a 15bp increases in the spread BTP-BUND and the corresponding 90% confidence interval from bootstrap (1000 draws) for spread BTP-BUND, Real GDP, net loans stock and interests rate to HHs and NFCs, bad loans and bank bonds' interest rate. The prior on the sum of coefficients has been added with the hyperparameter $\tau = 10\lambda$. The blue line represents the median of all bootstrapped responses; the orange line is the GIRF from the estimated model and the green line is conditional GIRF as explained in Section 4.2.

Figure 5: Responses to a shock in Italian Real GDP



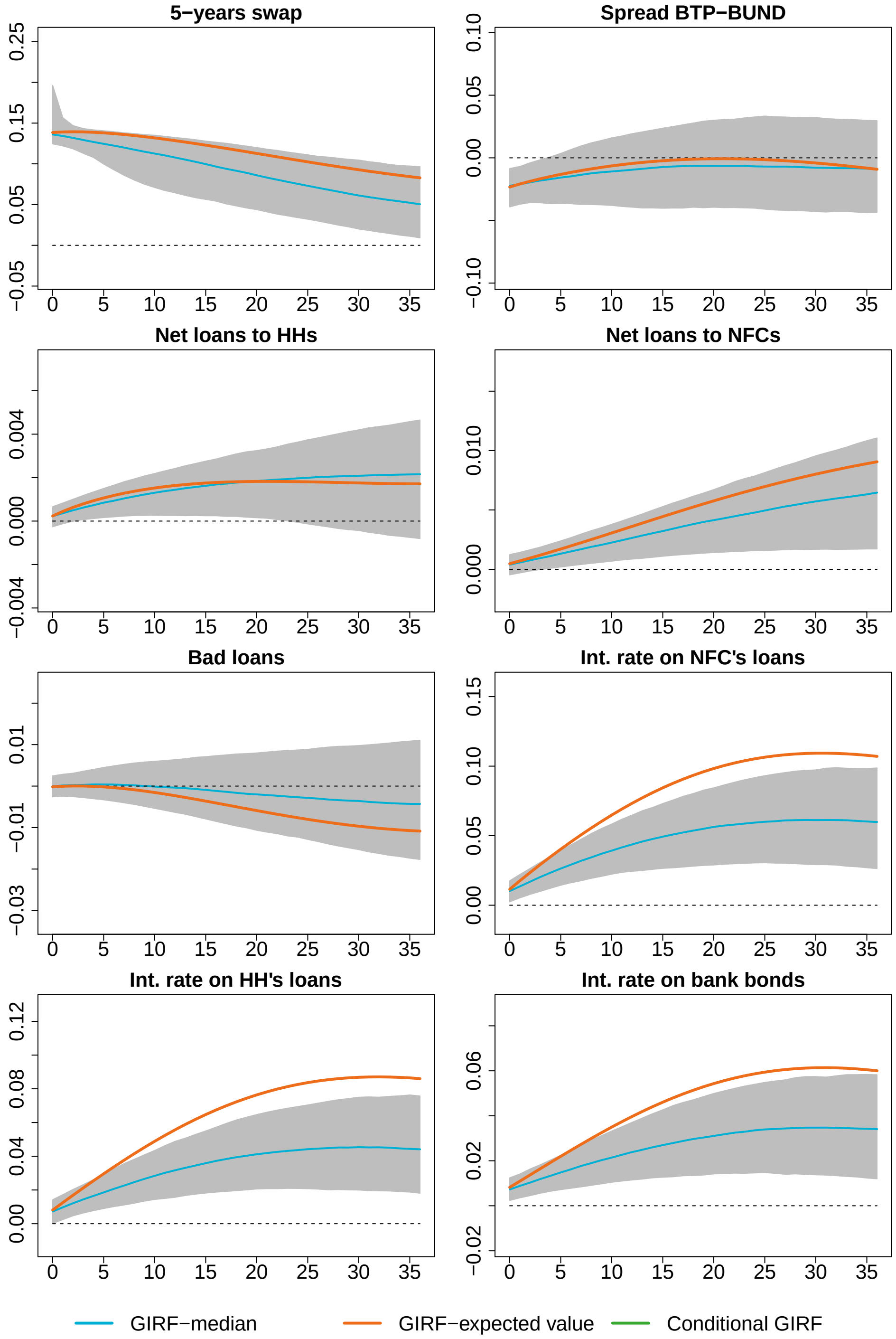
Note: The figure represents the impulse response function to a 0.1% drop in Italian Real GDP and the corresponding 90% confidence interval from bootstrap (1000 draws) for spread BTP-BUND, Real GDP, net loans stock and interests rate to HHs and NFCs, bad loans and bank bonds' interest rate. The prior on the sum of coefficients has been added with the hyperparameter $\tau = 10\lambda$. The blue line represents the median of all bootstrapped responses; the orange line is the GIRF from the estimated model and the green line is conditional GIRF as explained in Section 4.2.

Figure 6: Responses to a shock in Italian Stock Price index



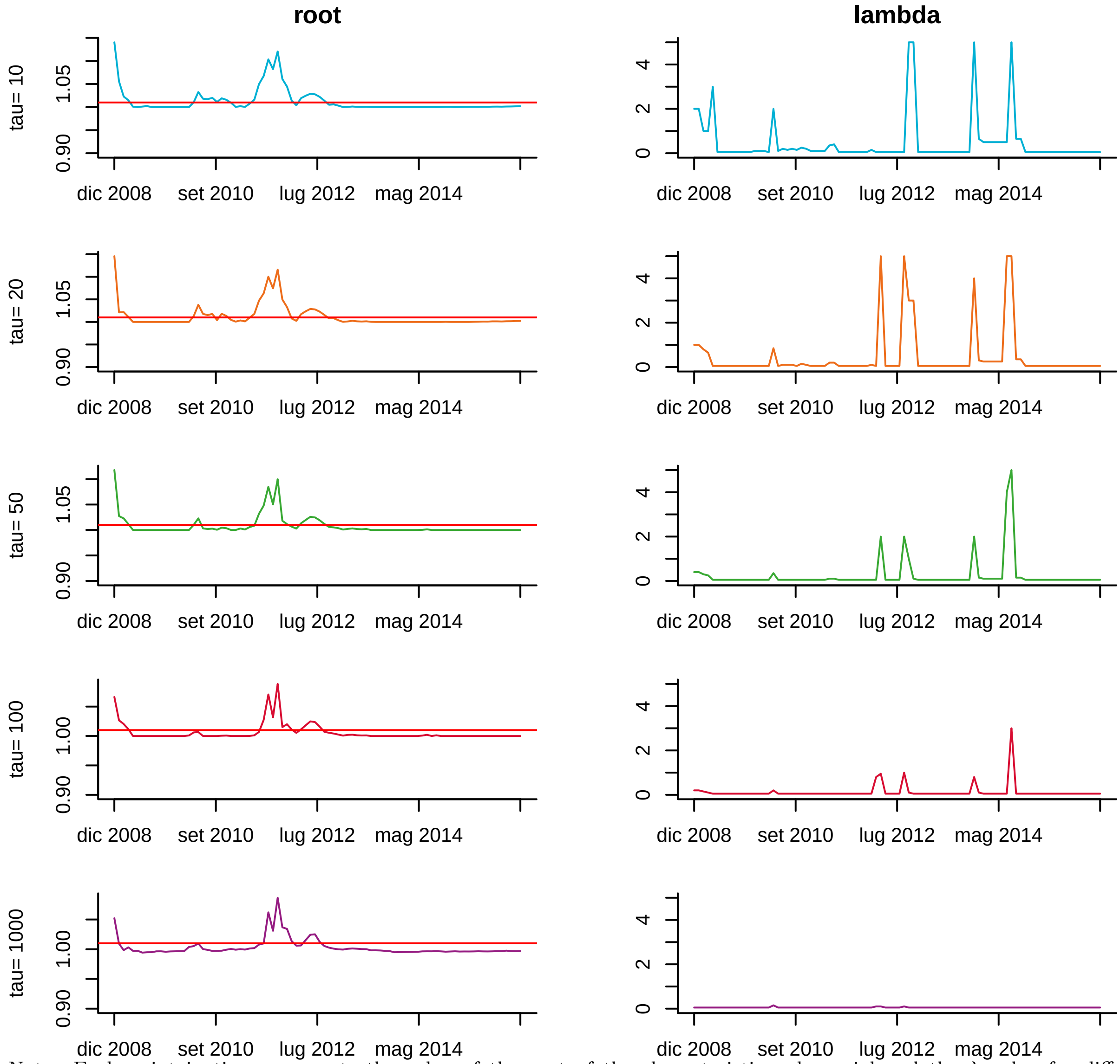
Note: The figure represents the impulse response function to a 5% increase in Italian stock prizes and the corresponding 90% confidence interval from bootstrap (1000 draws) for spread BTP-BUND, Real GDP, net loans stock and interests rate to HHs and NFCs, bad loans and bank bonds' interest rate. The prior on the sum of coefficients has been added with the hyperparameter $\tau = 10\lambda$. The blue line represents the median of all bootstrapped responses; the orange line is the GIRF from the estimated model and the green line is conditional GIRF as explained in Section 4.2.

Figure 7: Responses to a shock in 5-years swap rates



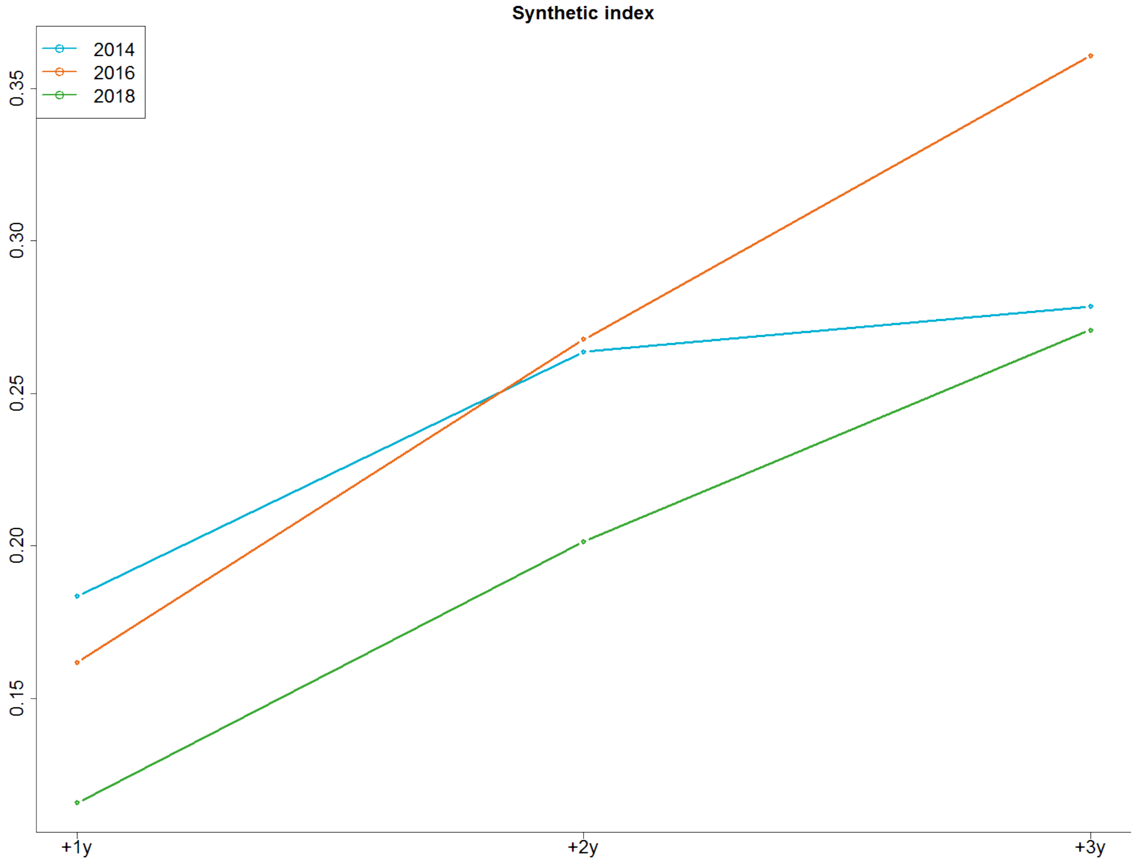
Note: The figure represents the impulse response function to a 15bp increase in 5-year swap rate and the corresponding 90% confidence interval from bootstrap (1000 draws) for spread BTP-BUND, Real GDP, net loans stock and interests rate to HHs and NFCs, bad loans and bank bonds' interest rate. The prior on the sum of coefficients has been added with the hyperparameter $\tau = 10\lambda$. The blue line represents the median of all bootstrapped responses; the orange line is the GIRF from the estimated model and the green line is conditional GIRF as explained in Section 4.2.

Figure 8: Root of the characteristic polynomial (left) and λ (right) values associated with each model estimation for different τ



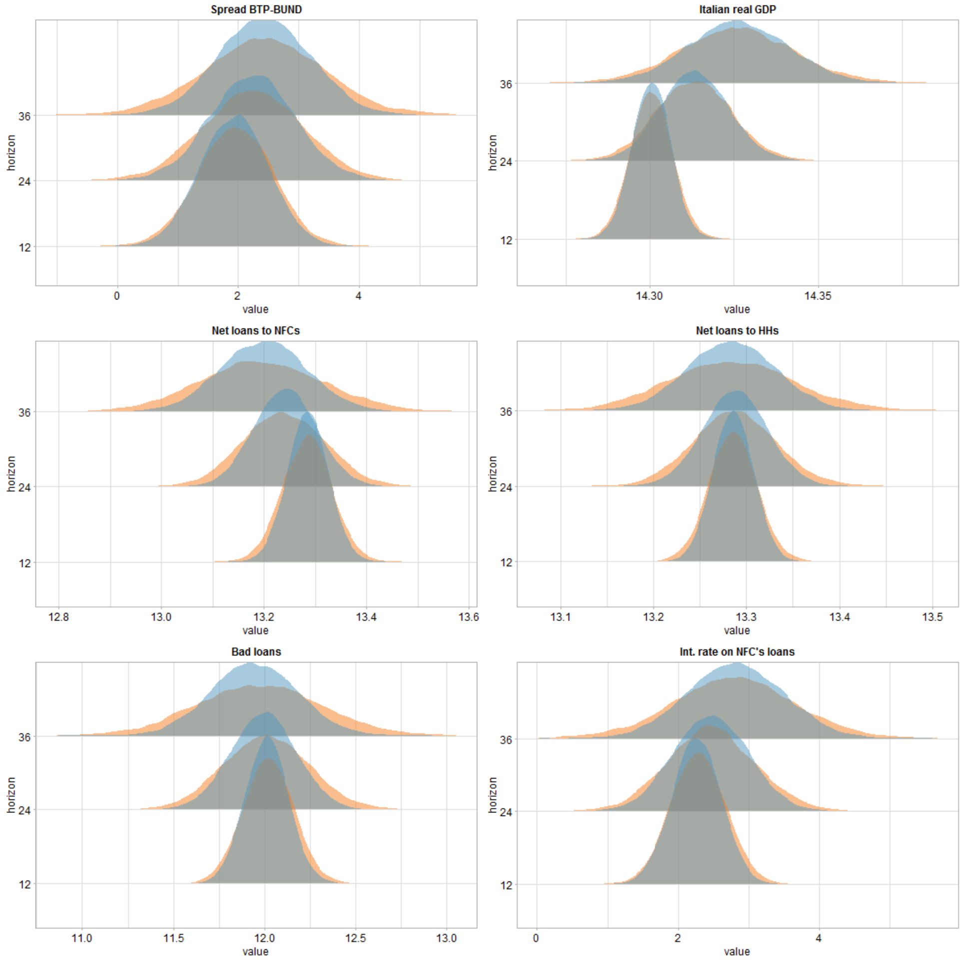
Note: Each point in time represents the value of the root of the characteristic polynomial and the λ value for different out-of-sample intervals. The red line on the left-panel graphs separates the stable model estimations from the unstable ones.

Figure 9: Synthetic aggregate severity measures for the three stress tests



Note: The graph shows the synthetic aggregate severity index for the three stress tests computed according to Section 4.3.1

Figure 10: Simulated distribution for selected variables at different horizon with and without parameter uncertainty



Note: The graph shows for a selection of variables the simulated distribution at different horizons generated by the model with data available until 2017:12. Central forecast are conditioned on the path of available variables in the EBA baseline scenario. The orange area represents the distribution generated accounting for both shocks' and parameters' uncertainty, while the blue area is the distribution generated accounting for shocks' uncertainty only.

Table 1: Variables names, labels and orders of integration

name	label	δ_i
Consumer price inflation	INFL	0
Italian real GDP	GDP	1
Unemployment Rate	UN	2
Funding BCE	FUND.ECB	1
Bank deposits account	DEP.DA	1
Other bank deposits	DEP.OTH	1
Bank bonds	BBONDS	1
Bad loans	BLOANS	2
Net loans to HHs	LOANS.HH	2
Net loans to NFCs	LOANS.SNF	1
Net loans to others	LOANS.OTH	1
Government bonds	SOV.BONDS	1
Tier 1 ratio	T1.RATIO	1
Int. rate on bank deposits	DEP.DA.Y	0
Int. rate on bank bonds	BBONDS.Y	1
Markup on short-term loans	DIFF.Y	1
Int. rate on HH's loans	LOANS.HH.Y	1
Int. rate on NFC's loans	LOANS.SNF.Y	1
3-months euribor	EUR3M	1
5-years swap	SWAP.5Y	1
10-years Italian government bond yields	BTP.10Y	1
Spread BTP-BUND	SPREAD	1
Italian stock market index	STOCK.MARKET	1

Table 2: Variance Decomposition

		shock variable						
horizon	response variable	GDP	EUR3M	BTP.10Y	SWAP.5Y	UN	INFL	STOCK.MARKET
H=12	LOANS.HH	0.24	0.12	1.98	5.26	0.11	0.20	6.45
	LOANS.SNF	3.51	4.77	0.24	5.17	0.01	0.13	3.21
	SOV.BONDS	1.67	3.23	1.64	1.38	0.47	0.25	3.27
	BLOANS	2.48	4.97	0.96	0.10	0.37	2.84	0.58
	LOANS.SNF.Y	8.73	22.36	3.64	11.09	0.06	1.38	0.40
	LOANS.HH.Y	6.69	21.78	2.42	10.46	0.13	0.24	0.65
	BBONDS.Y	8.41	20.12	3.25	8.33	0.10	1.77	0.12
	T1.RATIO	2.46	7.96	0.21	1.06	0.56	1.78	0.46
H=24	LOANS.HH	0.29	0.77	7.24	5.12	0.26	1.14	10.51
	LOANS.SNF	2.70	8.49	1.20	11.82	0.00	0.13	7.93
	SOV.BONDS	1.05	3.52	4.33	2.54	0.37	0.82	5.74
	BLOANS	2.59	9.89	2.00	1.05	1.02	2.38	1.88
	LOANS.SNF.Y	6.25	22.96	5.95	24.35	0.15	1.28	1.79
	LOANS.HH.Y	4.60	23.54	3.47	23.54	0.27	0.15	2.54
	BBONDS.Y	6.56	23.64	4.87	18.84	0.06	1.70	1.07
	T1.RATIO	2.30	13.07	0.95	3.63	0.69	2.58	2.15
H=36	LOANS.HH	0.35	1.25	10.94	3.99	0.36	1.90	11.81
	LOANS.SNF	1.67	8.51	2.66	15.54	0.00	0.43	11.54
	SOV.BONDS	0.70	3.41	5.78	3.46	0.79	1.22	7.21
	BLOANS	1.97	11.38	3.36	2.45	1.93	1.65	3.80
	LOANS.SNF.Y	4.53	20.04	6.42	33.77	0.25	1.02	3.66
	LOANS.HH.Y	3.15	20.82	3.27	32.53	0.51	0.12	4.88
	BBONDS.Y	5.02	22.80	4.76	27.41	0.06	1.36	2.92
	T1.RATIO	1.74	14.70	1.78	6.76	0.84	3.04	4.32

Note: The table reports the percentage share of the adverse EBA scenarios in the forecast error variance for a given forecast horizon for loans to HHs and NFCs (stock and interest rates), sovereign bank bonds, bad loans, bank deposit interest rate and Tier 1 ratio. The prior on the sum of coefficients has been added with the hyperparamter $\tau = 10\lambda$.

Table 3: IBASE performance comparison with RW and AR(1) for different values of τ

			IBASE vs RW		IBASE vs RWT		IBASE vs AR(1)	
	stability	direction	MAE	RMSE	MAE	RMSE	MAE	RMSE
10	0.69	0.52	0.96	0.89	1.25	1.14	1.17	1.06
20	0.72	0.48	0.96	0.90	1.25	1.14	1.17	1.07
50	0.78	0.47	0.95	0.90	1.25	1.16	1.15	1.05
100	0.82	0.48	0.94	0.88	1.26	1.16	1.15	1.04
1000	0.88	0.46	0.95	0.92	1.25	1.18	1.13	1.06

Note: The table represents average stability, direction, MAE and RMSE performances for different value of τ, across variables. The stability is given by the percentage of stable model iteration while the direction is measured as the number of correct directional forecasts over the total number of (stable) forecasts.

Table 4: IBASE performance comparison with RW, RWT and AR(1) for $\tau = 10$

variable	IBASE vs RW +1y	+2y	+3y	mean	IBASE vs RWT +1y	+2y	+3y	mean	IBASE vs AR(1) +1y	+2y	+3y	mean
BBONDS	**1.57**	**1.61**	**1.63**	**1.59**	**2.75**	**2.72**	**2.87**	**2.78**	**2.27**	**2.11**	**2.19**	**2.21**
BLOANS	**1.59**	**1.11**	0.83	**1.4**	**1.41**	**1.02**	0.85	**1.26**	**1.68**	**1.58**	**1.56**	**1.64**
LOANS.HH	0.95	0.7	0.51	0.81	**1.72**	**1.63**	**1.69**	**1.7**	0.82	0.58	0.57	0.77
LOANS.SNF	**1.72**	**1.55**	**1.02**	**1.41**	**3.75**	**3.66**	**2.55**	**3.09**	**2.88**	**2.71**	**1.84**	**2.35**
LOANS.OTH	0.67	0.51	0.48	0.63	0.7	0.67	0.78	0.76	0.62	0.4	0.38	0.56
SOV.BONDS	0.76	0.72	0.65	0.78	0.84	0.88	0.83	0.89	**1.52**	**1.76**	**1.73**	**1.58**
T1.RATIO	**1.22**	**1.64**	**1.51**	**1.38**	**1.09**	**1.39**	**1.17**	**1.18**	**1.45**	**1.63**	**1.58**	**1.48**
DEP.DA.Y	0.57	0.62	0.37	0.53	0.43	0.51	0.31	0.42	0.58	0.63	0.38	0.54
BBONDS.Y	0.6	0.77	0.64	0.66	0.46	0.66	0.52	0.54	0.59	0.74	0.61	0.65
LOANS.HH.Y	0.62	0.67	0.56	0.66	0.48	0.54	0.38	0.53	0.45	0.34	0.22	0.43
LOANS.SNF.Y	0.63	0.78	0.61	0.7	0.57	0.67	0.47	0.59	0.66	0.79	0.63	0.71
Mean	0.99	0.97	0.8	0.96	**1.29**	**1.3**	**1.13**	**1.25**	**1.23**	**1.21**	**1.06**	**1.17**

Note: The table represents the ratio between the MAE of different benchmark models (random walk, random walk with trend and AR(1)) and the IBASE model for different time horizons and for selected banking variables. Bold numbers correspond to value of the ratio above one, while underlined values corresponds to combinations of horizon and variables where we reject the null hypothesis of the Diedbold-Mariano test (Diebold and Mariano, 2002) (at the 10% confidence interval) in favor of the IBASE.

Table 5: IBASE direction accuracy for $\tau = 10$ and different time horizon

	direction			
	+3m	+1y	+2y	+3y
BBONDS	0.66	0.57	0.59	0.51
BLOANS	0.91	0.69	0.63	0.41
LOANS.HH	0.52	0.55	0.54	0.50
LOANS.SNF	0.63	0.59	0.45	0.50
LOANS.OTH	0.59	0.55	0.61	0.59
SOV.BONDS	0.59	0.54	0.42	0.44
T1.RATIO	0.56	0.57	0.42	0.44
DEP.DA.Y	0.49	0.35	0.24	0.20
BBONDS.Y	0.52	0.40	0.26	0.34
LOANS.HH.Y	0.71	0.54	0.51	0.30
LOANS.SNF.Y	0.68	0.42	0.42	0.27

Note: The table represents the direction accuracy for different time horizons. Direction accuracy is measured as the number of correct directional forecasts over the total number of (stable) forecasts.

Table 6: Adverse shock (deviation from baseline) and realization probabilities (%, in parentheses) for all variables

variable	2014			2016			2018		
	+1y	+2y	+3y	+1y	+2y	+3y	+1y	+2y	+3y
GDP	-0.02	-0.04	-0.06	-0.02	-0.04	-0.06	-0.02	-0.05	-0.07
	(0.41)	(0.02)	(0.07)	(0.07)	(0.02)	(0.07)	(0.02)	(0)	(0.02)
INFL	0.03	-0.27	-1.2	-1.01	-1.58	-2.5	-0.02	-0.63	-1.7
	(52.67)	(32.13)	(2.9)	(4.16)	(2.21)	(0.79)	(48.92)	(15.99)	(0.99)
UN	0.31	1.31	2.4	0.29	1.19	2.2	0.3	1.11	2.2
	(73.67)	(94.13)	(97.13)	(69.33)	(89.9)	(95.49)	(69.23)	(88.28)	(95.71)
EUR3M	0.19	0.11	0.06	0.24	0.18	0.06	0.49	0.43	0.39
	(65.2)	(55.72)	(51.77)	(69.23)	(60.65)	(52.49)	(83.51)	(71.04)	(65.35)
SWAP.5Y	1.07	0.8	0.84	0.48	0.45	0.24	0.53	0.46	0.44
	(97.68)	(85.02)	(81.62)	(81.23)	(71.3)	(60.03)	(84.27)	(73.15)	(68.63)
BTP.10Y	2.08	1.51	1.49	1.13	1.07	0.89	1.33	1.33	1.17
	(99.95)	(97.39)	(94.81)	(95.78)	(88.41)	(80.04)	(98.11)	(94.28)	(89.05)
SPREAD	1.23	0.7	0.38	0.9	0.72	0.5	1.11	1	0.67
	(97.67)	(81.49)	(66.9)	(91.67)	(78.91)	(68.05)	(96.22)	(88.4)	(75.21)
STOCK.MARKET	-0.24	-0.2	-0.23	-0.36	-0.3	-0.18	-0.45	-0.39	-0.29
	(19.87)	(37.88)	(40.95)	(7.21)	(23.4)	(36.62)	(3.62)	(16.08)	(29)
LOANS.HH	-0.02	-0.06	-0.08	-0.02	-0.06	-0.09	-0.02	-0.06	-0.08
	(25.99)	(12.01)	(13.1)	(20.21)	(10.89)	(11.87)	(17.53)	(10.58)	(13.23)
LOANS.SNF	-0.01	-0.06	-0.09	-0.02	-0.06	-0.09	-0.02	-0.06	-0.08
	(43.79)	(26.25)	(23.18)	(34.64)	(25.44)	(25.09)	(31.65)	(25.75)	(26.97)
BLOANS	0.04	0.08	0.12	0.06	0.17	0.29	0.09	0.21	0.33
	(55.59)	(59.08)	(59.18)	(60.8)	(71.91)	(75.1)	(72.86)	(79.68)	(80.9)
SOV.BONDS	0.01	0.03	-0.01	0.03	0.06	0.04	0.06	0.15	0.21
	(50.93)	(52.71)	(48.89)	(58.14)	(58.69)	(53.6)	(65.18)	(70.72)	(69.01)
LOANS.TOT.Y	0.05	0.07	-0.01	0.02	-0.01	-0.04	0.2	0.24	0.24
	(57.67)	(57.38)	(52.25)	(51.24)	(49.37)	(48.83)	(69.79)	(67.08)	(63.61)
BDEPOSITS.Y	0.33	0.5	0.42	0.28	0.3	0.2	0.24	0.23	0.16
	(81.55)	(84.49)	(75.09)	(84.08)	(78.5)	(66.61)	(87.22)	(79.18)	(67.39)
T1.RATIO	-0.04	0.02	-0.07	-0.14	-0.13	-0.14	-0.36	-0.65	-1.01
	(62.41)	(69.36)	(66.09)	(46.35)	(52.22)	(53.04)	(32.24)	(30.73)	(27.98)

Note: The table represents the difference between the IBASE forecast conditional on the adverse EBA stress tests scenario and the baseline one for all three stress tests. The model is estimated up until the last month of the year before the stress test begins (i.e. 2013:12, 2015:12 and 2017:12). The probability of realization in brackets are derived according to Section 4.3.1.

Table 7: Counterfactual shock (deviation from baseline, rescaled to 2014's probability level)

variable	2014			2016			2018		
	+1y	+2y	+3y	+1y	+2y	+3y	+1y	+2y	+3y
GDP	-0.02	-0.04	-0.06	-0.02	-0.04	-0.06	-0.02	-0.04	-0.06
	(0.41)	(0.02)	(0.07)	-	-	-	-	-	-
INFL	0.03	-0.27	-1.2	0.08	-0.33	-1.83	0.05	-0.27	-1.35
	(52.67)	(32.13)	(2.9)	-	-	-	-	-	-
UN	0.31	1.31	2.4	0.36	1.45	2.49	0.37	1.47	2.47
	(73.67)	(94.13)	(97.13)	-	-	-	-	-	-
EUR3M	0.19	0.11	0.06	0.17	0.09	0.04	0.23	0.05	0.04
	(65.2)	(55.72)	(51.77)	-	-	-	-	-	-
SWAP.5Y	1.07	0.8	0.84	1.07	0.82	0.89	1.09	0.73	0.83
	(97.68)	(85.02)	(81.62)	-	-	-	-	-	-
BTP.10Y	2.08	1.51	1.49	2.21	1.79	1.8	2.22	1.71	1.57
	(99.95)	(97.39)	(94.81)	-	-	-	-	-	-
SPREAD	1.23	0.7	0.38	1.4	1.03	0.75	1.39	1.16	0.8
	(97.67)	(81.49)	(66.9)	-	-	-	-	-	-
STOCK.MARKET	-0.24	-0.2	-0.23	-0.22	-0.13	-0.12	-0.21	-0.13	-0.1
	(19.87)	(37.88)	(40.95)	-	-	-	-	-	-
LOANS.HH	-0.02	-0.06	-0.08	-0.02	-0.06	-0.09	-0.01	-0.04	-0.06
	(25.99)	(12.01)	(13.1)	-	-	-	-	-	-
LOANS.SNF	-0.01	-0.06	-0.09	-0.01	-0.05	-0.09	-0.01	-0.04	-0.08
	(43.79)	(26.25)	(23.18)	-	-	-	-	-	-
BLOANS	0.04	0.08	0.12	0.05	0.16	0.26	0.11	0.25	0.43
	(55.59)	(59.08)	(59.18)	-	-	-	-	-	-
SOV.BONDS	0.01	0.03	-0.01	0.03	0.09	0.08	0.05	0.16	0.24
	(50.93)	(52.71)	(48.89)	-	-	-	-	-	-
LOANS.TOT.Y	0.05	0.07	-0.01	0.08	0.13	0.16	0.16	0.3	0.2
	(57.67)	(57.38)	(52.25)	-	-	-	-	-	-
BDEPOSITS.Y	0.33	0.5	0.42	0.28	0.4	0.33	0.16	0.19	0.08
	(81.55)	(84.49)	(75.09)	-	-	-	-	-	-
T1.RATIO	-0.04	0.02	-0.07	-0.12	-0.01	0.04	-0.25	-0.37	-0.5
	(62.41)	(69.36)	(66.09)	-	-	-	-	-	-

Note: The table represents the difference between the IBASE forecast conditional on the adverse EBA stress tests scenario and the baseline one for the only 2014 exercise.The model is estimated up until the last month of the year before the stress test begins (i.e. 2013:12, 2015:12 and 2017:12). The probability of realization in brackets are derived according to Section 4.3.1, only for the 2014 exercise.

Table 8: Adverse shock (deviation from baseline) and realization probabilities (%, in parentheses) for all variables with four lags

variable	2014			2016			2018		
	+1y	+2y	+3y	+1y	+2y	+3y	+1y	+2y	+3y
GDP	-0.02	-0.04	-0.06	-0.02	-0.04	-0.06	-0.02	-0.05	-0.07
	(0.16)	(0)	(0)	(0.03)	(0)	(0.01)	(0)	(0)	(0)
INFL	0.05	-0.21	-1.2	-0.94	-1.49	-2.5	-0.03	-0.61	-1.7
	(54.84)	(32.43)	(0.37)	(9.28)	(3.45)	(0.11)	(47.64)	(11.65)	(0.06)
UN	0.3	1.3	2.4	0.29	1.19	2.2	0.29	1.1	2.2
	(73.23)	(95.37)	(99.09)	(72.85)	(93.65)	(97.92)	(73.06)	(92.7)	(98.59)
EUR3M	0.32	0.26	0.06	0.35	0.26	0.06	0.58	0.51	0.39
	(78.27)	(66.2)	(53.51)	(79.04)	(65.14)	(53.32)	(90.29)	(79.01)	(70.54)
SWAP.5Y	1.19	0.9	0.84	0.55	0.48	0.24	0.59	0.52	0.44
	(99.83)	(94.62)	(91.42)	(89.11)	(78.81)	(63.19)	(90.72)	(81.07)	(74.02)
BTP.10Y	2.1	1.55	1.49	1.14	1.1	0.89	1.29	1.31	1.17
	(100)	(99.54)	(99.22)	(98.24)	(93.8)	(87.53)	(99.15)	(97.28)	(94.56)
SPREAD	1.12	0.69	0.49	0.81	0.68	0.5	0.86	0.74	0.51
	(98.46)	(85.17)	(75.11)	(93.51)	(83.14)	(73.87)	(95.18)	(87.57)	(76.99)
STOCK.MARKET	-0.24	-0.2	-0.23	-0.36	-0.3	-0.18	-0.43	-0.38	-0.29
	(9.97)	(23.36)	(25.28)	(2.97)	(14.54)	(29.52)	(1.05)	(7.35)	(19.06)

Note: The table represents the difference between the IBASE forecast conditional on the adverse EBA stress tests scenario and the baseline one for all three stress tests. The model is estimated up until the last month of the year before the stress test begins (i.e. 2013:12, 2015:12 and 2017:12). The probability of realization in brackets are derived according to Section 4.3.1. The model is estimated with four lags.