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MACROECONOMIC AND CREDIT FORECASTS IN A SMALL ECONOMY DURING CRISIS: A LARGE BAYESIAN VAR APPROACH

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Abstract

We examine the ability of large-scale vector autoregressions (VARs) to produce accurate macroeconomic (output and inflation) and credit (loans and lending rates) forecasts in Greece, during the latest sovereign debt crisis. We implement recently proposed Bayesian shrinkage techniques and we evaluate the information content of forty two (42) monthly macroeconomic and financial variables in a large Bayesian VAR context, using a five year out-of-sample forecasting period from 2008 to 2013. The empirical results reveal that, overall, large-scale Bayesian VARs, enhanced with key financial variables and coupled with the appropriate level of shrinkage, outperform their small- and medium-scale counterparts with respect to both macroeconomic and credit variables. The forecasting superiority of large Bayesian VARs is particularly clear at long-term forecasting horizons. Finally, empirical evidence suggests that large Bayesian VARs can significantly improve the directional forecasting accuracy of small VARs with respect to loans and lending rates variables.

Keywords: Forecasting; Bayesian VARs; Crisis; Financial variables.

JEL Classifications: E27; E51,

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1. Introduction

The recent experience from the Greek crisis in 2008-2013 and the related financial support programs designed jointly by the International Monetary Fund (IMF), the European Central Bank (ECB) and the European Commission (EC) have highlighted, if nothing else, the importance of economic projections as an essential ingredient for the implementation of strategic policy action plans. In the aftermath of the Greek austerity program, the controversy regarding the accuracy of economic growth forecasts (e.g. see Kiriakidis and Kargas, 2013) and their relation with the planed fiscal consolidation (e.g. see Blanchard and Leigh, 2013) has also underlined the significance of academic efforts to develop robust econometric models that can provide policy makers with accurate economic forecasts.

Since the seminal contribution of Sims (1980), vector autoregressive (VAR) models have been established as a standard forecasting tool in empirical macroeconomics. VAR models gained popularity mainly due to their simplicity and their ability to fit the data and produce accurate forecasts (Karlsson, 2013). Nevertheless, the rich parameterization, even in medium-scale VARs, poses limitations to real-world applications. Researchers usually either restrict themselves to working with a small number of endogenous variables at a time, or impose some kind of shrinkage to circumvent over-fitting the data and imprecise forecasting. Bayesian VAR methods and especially the so-called *"Minnesota"* prior approach proposed by Doan et al. (1984) and Linterman (1986) is a convenient and relatively simple way to shrink the VAR parameters towards a predetermined representation of the data set, e.g. a unit root process, reduce parameter uncertainty and improve forecasting accuracy (Karlsson, 2013).[1]

Recently, Banbura et al. (2010) popularized the use of a modified Minnesota prior in forecasting applications that involve VAR models with a large number of variables (even greater than 100). The authors showed that large-scale VARs can outperform their factor-based counterparts in forecasting employment, inflation and interest rates for the US economy.[2] A key point in their study is that the parameters' shrinkage becomes tighter as the size of the VAR model becomes larger, successfully controlling for over-fitting. They also

[1] Alternatively, factor methods have also been used in studies that involve a large number of variables (e.g. see Stock and Watson, 2002, 2006 among others)

[2] The authors also show that models with more than 20 variables can hardly improve forecasting performance.

argue that the high level of shrinkage does not affect the ability of the model to exploit the information content of a large set of macroeconomic variables, because most of these variables are nearly collinear, meaning that they share common information.

In the same vein, Koop (2013) examined the forecasting performance of medium- and large-scale VARs using various versions of the Minnesota prior and other non-conjugate priors. Their empirical evidence, based on a US macroeconomic dataset, suggest that medium-scale VARs (up to 20 variables) combined with a simple Minnesota prior produce superior GDP, inflation and interest rates forecasts. Gupta and Kabundi (2010) also show that large Bayesian VARs outperform the theoretical dynamic stochastic general equilibrium (DSGE) models in a forecasting exercise regarding the South African economy. Finally, Carriero et al. (2009, 2012) have successfully implemented the Banbura's et al. (2010) approach in forecasting large panels of exchange rates and government bond yields, respectively.

Against this background, we aim to contribute to this growing VAR literature in the following ways. First, we examine the ability of large Bayesian VARs to deliver accurate forecasts in Greece during the latest twin –sovereign debt and banking- crises (Gibson et al., 2014a).[3] Hence, we utilize a data set of 42 monthly macroeconomic and financial variables and we compare the forecasting ability of various small-, medium- and large-scale VARs. To our knowledge, this is the first time that the large Bayesian VAR forecasting methodology is implemented in a small, relatively-closed, Euro area economy during such a challenging economic environment. In particular, almost the full out-of-sample forecasting period covers the 2008-2013 crises, which were characterized by severe economic contraction, negative credit expansion and high level of systemic stress in the financial sector (see Fig. 1).[4]

[Insert Figure 1 about here]

Second, our study concentrates on forecasting both macroeconomic (economic activity and inflation) and credit (outstanding loans and lending rates) variables rather than solely on macroeconomic forecasting as the majority of the previous studies. Researchers and policy

[3] See Provopoulos (2014) for the origins of Greek crisis and Gibson et al. (2014a) for an overview of the crisis in the Euro area.
[4] Successive recession may be attributed to reduced internal demand (due to increased unemployment and reduced salaries) and weak dynamics in exports (due to firms' reduced ability to access credit channels) (Kiriakidis and Kargas, 2013).

makers should be particularly interested in accurate credit forecasting, because credit and its pricing play a crucial role in economic growth prospects (Hristov et.al., 2012; Kiriakidis and Kargas, 2013, p. 767). They are also key inputs in stress testing exercises conducted by supervisory authorities in order to assess the resilience of the banking systems (e.g. see Bank of Greece, 2014, p.11).

Third, we lay particular emphasis on the information content of financial variables and their ability to produce accurate macroeconomic and credit forecasts. The uncertainty regarding the Greek debt viability, towards the end of 2009, resulted in sharp increases in sovereign bond, money market and CDS spreads and stock volatility. The financial systemic stress index (FSSI) of Louzis and Vouldis (2013) in Fig. 1 synopsizes the aforementioned phenomena and clearly depicts the escalation of systemic risk during the 2008-2013 period. [5] Nonetheless, empirical evidence presented so far suggest that, during the pre-crisis period, markets mispriced the Greek sovereigns and failed to account for Greece's deteriorating fundamentals (Gibson et al., 2012, 2014b).[6] Therefore, given this background, an effort to examine the forecasting ability of financial variables is of great interest. We proceed with two alternative ways: First, we implement a marginal approach, that is, we add the composite FSSI to a baseline VAR and examine whether it can improve its forecasting ability.[7] Second, the full set of the individual FSSI components along with some additional financial variables are incorporated into medium- and large-scale Bayesian VARs.

Fourth, we try to address the fact that in many real-world situations, and especially during prolonged periods of recession, economists and policy makers pay more attention to the direction of change of the target variables. Therefore, we evaluate the forecasting performance of the various VAR specifications taking into account not only their ability to minimize the magnitude of the forecasting errors but also their ability to deliver accurate directional forecasts. The former is assessed via the conventional mean squared forecast error commonly used in related studies (Carriero et al., 2009, 2012; Banbura et al., 2010; Koop, 2013), whereas the latter is assessed via the non-parametric Pesaran and Timmerman (1992)

[5] The FSSI is a composite systemic stress index which applies the insights from standard portfolio theory to summarize stress measures of different market segments into an aggregate index. The time varying cross-correlations among stress measures are the key feature of FSSI and form the mechanism which captures the systemic nature of stress. For an alternative version of FSSI see also Louzis and Vouldis (2012).

[6] See also the discussion in Kazanas and Tzavalis (2014).

[7] For a recent example of the marginal approach see Caraiani (2014).

test. An adjusted mean squared forecast error that combines both approaches is also implemented (Moosa and Burns, 2012). The evaluation process is also enriched with the model confidence set (MCS) approach of Hansen et al. (2003, 2011), which statistically determines a specific set of models that cannot be outperformed by its counterparts.

Finally, this is the first study that empirically compares two alternative data-driven approaches that determine the level of the parameters' shrinkage imposed in large VARs. In particular, we implement the method proposed by Banbura et al. (2010), where the shrinkage is related to the size of the VAR model, and the method of Carriero et al. (2009), which is based on a more dynamic, real-time process.

The remainder of the paper is organized as follows. Section 2 presents the econometrics of the large Bayesian VARs, while Section 3 describes the data set utilized in this study. In Section 4, we present the empirical analysis and we discuss the forecasting results. Section 5 summarizes and concludes this study.

2. Large Bayesian VAR methodology

2.1. Notation and preliminaries

Assume that $\boldsymbol{y}_t = (y_{1,t}, y_{2,t},..., y_{n,t})'$ is a vector of n random variables with $t=1,..,T$ being the number of observations. Then, a *p-th* order VAR model is written as:

$$\boldsymbol{y}_t = \boldsymbol{c} + \boldsymbol{A}_1\boldsymbol{y}_{t-1} + \boldsymbol{A}_2\boldsymbol{y}_{t-2} + ... + \boldsymbol{A}_p\boldsymbol{y}_{t-p} + \boldsymbol{\varepsilon}_t \qquad (1)$$

where $\boldsymbol{c} = (c_1,...c_n)'$ is a vector of constant terms, $\boldsymbol{A}_l$ with $l=1,\dots p$ is an $n \times n$ coefficient matrix and $\boldsymbol{\varepsilon}_t = (\varepsilon_{1,t},...,\varepsilon_{n,t})'$ is a vector of Gaussian error terms with covariance matrix $E(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t') = \boldsymbol{\Psi}$, i.e. $\boldsymbol{\varepsilon}_t \sim$ i.i.d $N(\boldsymbol{0}, \boldsymbol{\Psi})$.

It is also convenient to re-write a VAR(p) model in matrix form (e.g. see Koop and Korobilis, 2010):

$$\boldsymbol{Y} = \boldsymbol{X}\boldsymbol{B} + \boldsymbol{E} \qquad (2)$$

where $\boldsymbol{Y}$ is a $T \times n$ matrix with its *t-th* row given by $\boldsymbol{y}_t'$, $\boldsymbol{X}$ is a $T \times k$ matrix with $k = 1 + np$ being the total number of coefficients in each equation and its *t-th* row given by $(1, \boldsymbol{y}_{t-1}', ... \boldsymbol{y}_{t-p}')$, $\boldsymbol{B} = (\boldsymbol{c}, \boldsymbol{A}_1, ..., \boldsymbol{A}_p)'$ is a $k \times n$ matrix of coefficients and $\boldsymbol{E}$ is a $T \times n$ matrix of error terms with its *t-th* row given by $\boldsymbol{\varepsilon}_t'$. Defining $\boldsymbol{b} = vec(\boldsymbol{B})$ it can be shown that the likelihood function of a VAR model in Eq. (2) can be written as (e.g. see Kadiyala and Karlsson, 1997, p. 101):

$$L(\boldsymbol{b}, \boldsymbol{\Psi}) \propto N\left(\boldsymbol{b} \middle| \hat{\boldsymbol{b}}, \boldsymbol{\Psi} \otimes (\boldsymbol{X}'\boldsymbol{X})^{-1}\right) \times iW(\boldsymbol{\Psi} | \boldsymbol{S}, T - k - n) \qquad (3)$$

Where $\hat{\boldsymbol{B}} = (\boldsymbol{X}'\boldsymbol{X})^{-1} \boldsymbol{X}'\boldsymbol{Y}$ is the standard ordinary least squares (OLS) estimates and $\hat{\boldsymbol{b}} = vec(\hat{\boldsymbol{B}})$, iW is the inverted Wishart distribution with scale parameter $\boldsymbol{S} = (\boldsymbol{Y} - \boldsymbol{X}\hat{\boldsymbol{B}})'(\boldsymbol{Y} - \boldsymbol{X}\hat{\boldsymbol{B}})$ and $T - k - n$ degrees of freedom.

2.2. Priors, posteriors and forecasting using large Bayesian VARs

The most widely used prior in large Bayesian VAR literature is a modified version of the Minnesota prior proposed by Banbura et al. (2010) and also employed by Carriero et al. (2009, 2012) and Koop (2013). The simplicity of the original Minnesota prior, developed by Doan et al. (1984) and Linterman (1986), is due to the fact that it treats the covariance matrix of error terms in (1) as known and diagonal, i.e. $\boldsymbol{\Psi} = \boldsymbol{\Sigma}_\varepsilon = diag(\sigma_1^2, \ldots, \sigma_n^2)$ leading to simple posterior inference. In practice, the diagonal elements of $\boldsymbol{\Sigma}_\varepsilon$ are replaced with OLS estimates, $\hat{\sigma}_1^2, \ldots, \hat{\sigma}_n^2$, coming from an AR(p) model for each of the n variables. Since $\boldsymbol{\Sigma}_\varepsilon$ is considered as fixed we only have to specify the prior distribution for $\boldsymbol{A}_l$, *l=1,…p*. We assume that $\boldsymbol{A}_1, ..., \boldsymbol{A}_p$ are independently and normally distributed conditional on $\boldsymbol{\Sigma}_\varepsilon$ with first and second moments defined as:

$$E\left[(\boldsymbol{A}_l)^{ij}\right] = \begin{cases} \delta_i & \text{if } i = j, l = 1 \\ 0 & \text{if } i \neq j, l \neq 1 \end{cases} \text{ and } Var\left[(\boldsymbol{A}_l)^{ij}\right] = \begin{cases} \dfrac{\lambda^2}{l^2} & \text{if } i = j \\ \dfrac{\lambda^2}{l^2} \dfrac{\sigma_i^2}{\sigma_j^2} & \text{if } i \neq j \end{cases} \qquad (4)$$

The prior beliefs formulated in Eqs. (4) imply an AR(1) process for each of the i = $1,\ldots,n$ variables, i.e. $y_{i,t} = c_i + \delta_i y_{i,t-1} + \varepsilon_{i,t}$. Own lags of order greater than one (p>1) and lags of other variables are assumed to have no contribution in explaining the variation of a given variable. The choice of the value of δ_i depends on the assumption we make regarding the persistence of $y_{i,t}$. Thus, for highly persistent (or unit root) processes we can set values close (or equal) to 1, while for less persistent (or white noise) processes we can set values close (or equal) to 0.

The shrinkage parameter λ in the covariance matrix controls for the overall tightness of the prior distribution and is chosen by the researcher. The lower the value of λ, i.e. as $\lambda \to 0$, the tighter the prior, meaning that the role of prior beliefs on posterior estimates is maximized while that of the data is minimized. On the contrary, as $\lambda \to \infty$ the prior becomes loose and posterior estimates depend more on data. For the extremes, $\lambda = 0$ and $\lambda = \infty$, the posterior equals the prior and OLS estimates, respectively. The structure of the covariance matrix also implies that prior parameter variances become tighter around zero as the lagged length, l, increases. The rationale is that the long lagged variables are less important than short ones and thus, parameters' prior distributions should be tighter around prior means, which are set to zero by default. Finally, the ratio σ_i^2 / σ_j^2 accounts for the different scale and variability of the data.

Nonetheless, the assumption of a fixed and diagonal covariance matrix may be too restrictive if we wish to allow for possible correlation among errors terms, $\varepsilon_{i,t}$. Banbura et al. (2010) relax these assumptions and work with a normal inverted Wishart prior given by (see also Kadiyala and Karlsson, 1997):

$$\boldsymbol{b} | \boldsymbol{\Psi} \sim N(\underline{\boldsymbol{b}}, \boldsymbol{\Psi} \otimes \underline{\boldsymbol{V}}) \text{ and } \boldsymbol{\Psi} \sim iW(\underline{\boldsymbol{S}}, \underline{v}) \tag{5}$$

where $\underline{\boldsymbol{b}} = vec(\underline{\boldsymbol{B}})$, $\underline{\boldsymbol{V}}$, $\underline{\boldsymbol{S}}$ and $\underline{v}$ are prior hyperparameters chosen by the researcher. Normal inverted Wishart is a natural conjucate prior, meaning that it comes from the same family of distributions along with the likelihood and the posterior, and it can be shown that it arises from a fictitious prior dataset (Koop, 2013). Banbura et al. (2010) implement this technique in order to impose hyperparameters in Eq. (5) that replicate the prior beliefs specified in Eq. (4). In particular, the authors propose the use of the following $\underline{T}$ dummy observations:

$$\underline{\boldsymbol{Y}} = \begin{pmatrix} diag(\delta_1\sigma_1,\ldots,\delta_n\sigma_n)/\lambda \\ \boldsymbol{0}_{(np-n+1)\times n} \\ diag(\sigma_1,\ldots,\sigma_n) \end{pmatrix}, \ \underline{\boldsymbol{X}} = \begin{pmatrix} \boldsymbol{J}_p \otimes diag(\sigma_1,\ldots,\sigma_n)/\lambda & \boldsymbol{0}_{(np)\times 1} \\ \boldsymbol{0}_{1\times(np)} & \omega \\ \boldsymbol{0}_{n\times(np)} & \boldsymbol{0}_{n\times 1} \end{pmatrix} \qquad (6)$$

where $\boldsymbol{J}_p = diag(1,\ldots,p)$, $\boldsymbol{0}_{a\times b}$ is an $a\times b$ matrix of zeros, σ_i are replaced with OLS estimates as in Minnesota prior and ω in $\underline{\boldsymbol{X}}$ is usually a small number which determines the prior for the constant terms.[8] The structure of $\underline{\boldsymbol{Y}}$ also implies a zero prior mean for the constant term. The prior hyperparameters are defined as: $\underline{\boldsymbol{B}} = (\underline{\boldsymbol{X}}'\underline{\boldsymbol{X}})^{-1}\underline{\boldsymbol{X}}'\underline{\boldsymbol{Y}}$, $\underline{\boldsymbol{V}} = (\underline{\boldsymbol{X}}'\underline{\boldsymbol{X}})^{-1}$, $\underline{\boldsymbol{S}} = (\underline{\boldsymbol{Y}} - \underline{\boldsymbol{X}}\,\underline{\boldsymbol{B}})'(\underline{\boldsymbol{Y}} - \underline{\boldsymbol{X}}\,\underline{\boldsymbol{B}})$ and $\underline{v} = \underline{T} - k$ and it is easy to verify that they coincide with the prior beliefs described in (4). The hyperparameter $\underline{\boldsymbol{S}}$ is also constructed to replicate the errors covariance matrix, $\boldsymbol{\Sigma}_\varepsilon$, of the Minnesota prior.

Posterior inference is simple if we augment the actual data with the dummy observations presented in Eq. (6). The new data set is defined as $\tilde{\boldsymbol{Y}} = (\boldsymbol{Y}', \underline{\boldsymbol{Y}}')'$, $\tilde{\boldsymbol{X}} = (\boldsymbol{X}', \underline{\boldsymbol{X}}')'$, $\tilde{\boldsymbol{E}} = (\boldsymbol{E}', \underline{\boldsymbol{E}}')'$ with sample length $\tilde{T} = T + \underline{T}$ and an augmented regression of the form: $\tilde{\boldsymbol{Y}} = \tilde{\boldsymbol{X}}\boldsymbol{B} + \tilde{\boldsymbol{E}}$. Then, the posterior distribution becomes:

$$\boldsymbol{b}|\boldsymbol{\Psi},\boldsymbol{Y} \sim N(\tilde{\boldsymbol{b}}, \boldsymbol{\Psi}\otimes\tilde{\boldsymbol{V}}) \text{ and } \boldsymbol{\Psi}|\boldsymbol{Y} \sim iW(\tilde{\boldsymbol{S}}, \tilde{v}) \qquad (7)$$

where $\tilde{\boldsymbol{b}} = vec(\tilde{\boldsymbol{B}})$, $\tilde{\boldsymbol{B}} = (\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{X}})^{-1}\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{Y}}$, $\tilde{\boldsymbol{V}} = (\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{X}})^{-1}$, $\tilde{\boldsymbol{S}} = (\tilde{\boldsymbol{Y}} - \tilde{\boldsymbol{X}}\tilde{\boldsymbol{B}})'(\tilde{\boldsymbol{Y}} - \tilde{\boldsymbol{X}}\tilde{\boldsymbol{B}})$ and $\tilde{v} = T + \underline{v}$. As pointed out in Koop (2013), the use of natural conjugate priors has the following two advantages, especially when we work with large VARs: (a) the analytical solutions presented here simplify the Bayesian inference and forecasting, avoiding time-consuming posterior simulations and (b) posterior mean and variance estimates require only the inversion of the $(k\times k)$ square matrix $\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{X}}$. Thus, even in cases with a high number of variables (*n*) and lags (*p*) the inversion of $\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{X}}$ is still feasible, enabling posterior inference.

Given the mean posterior estimates of the parameter vector, $\boldsymbol{B}$, it is easy to derive one-step-ahead point forecasts as: $E(\boldsymbol{y}_{T+1}|\boldsymbol{Y}) = \boldsymbol{x}_{T+1}\tilde{\boldsymbol{B}}$ where $\boldsymbol{x}_t$ is the *t-th* row of $\boldsymbol{X}$. For forecasting horizons longer than one, we follow Carriero et al. (2009) and Koop (2013) and

[8] As $\omega \to 0$ the prior for the constant terms becomes relatively non-informative.

we implement a direct forecasting methodology. Therefore, for each forecasting horizon *h*, with $h > 1$ we estimate the regression $\boldsymbol{y}_t = \boldsymbol{x}_{t-h+1}\boldsymbol{B}_h + \boldsymbol{\varepsilon}_t$ and we use the posterior mean estimates of parameter matrix $\boldsymbol{B}_h$ in order to produce h-step-ahead forecasts given by $E(\boldsymbol{y}_{T+h}|\boldsymbol{Y}) = \boldsymbol{x}_{T+1}\tilde{\boldsymbol{B}}_h$. Direct forecasting implies that for each forecasting horizon a different set of parameters is employed. It is also evident that the applied methodology converts multi-step forecasting into a one-step-ahead forecasting for which we have analytical expressions for the forecasting density.[9]

3. The data set

We use a data set which includes 42 monthly variables spanning from 2002:11 to 2013:8 and are listed in Tables A.1 to A.3 in the Appendix. We follow Koop (2013) and we apply all necessary transformations in order to achieve stationarity for all variables, which are also standardized. After these transformations we impose a zero prior mean for all coefficients, i.e. we set $\delta_i = 0$ for *i=1,…,n*, since we assume a white noise process across variables.

Following Ciccarelli et al. (2010) and Hristov et al. (2012) we define as the "*Baseline*" model a small-scale VAR which includes five variables: two fundamental macroeconomic variables (aggregate output and price level), two credit variables (loan volumes and lending rates) and a monetary policy rate. Table A.1 in the appendix presents the proxies used for each of the above-mentioned variables.[10, 11] As already mentioned, we choose to concentrate on the forecasting ability of the proposed VAR models with regard to the macroeconomic variables, i.e. Industrial Production Index (IPI) and Consumer Price Index (CPI), and the credit variables, i.e. loans and lending rates.

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[9] E.g. see Koop (20013, p. 180) for details.

[10] We use the industrial production index as a proxy for the aggregate output as in Caraiani (2014), since it is the only index of economic activity for Greece available at a monthly frequency. The industrial production index is also one of the main determinants of the Greek GDP (Kiriakidis and Kargas, 2013).

[11] We use the Euro OverNight Index Average (EONIA) as a proxy for the monetary policy stance in the Euro-zone. The EONIA rate is defined as the average of overnight rates for unsecured interbank lending in Euro area. The Governing council of the European Central Bank (ECB) determines the range of fluctuation of the EONIA rate which is given by the range [deposit facility rate, marginal lending facility rate]. The EONIA rate is considered an efficient proxy of the monetary policy stance in the Euro area, as compared with other money market instruments such as the Euribor, the overnight interest swap (OIS) rate on EONIA rate or the repo rates (see the discussion in Ciccarelli et al. (2010) and Gerlach and Lewis (2013)).

Table A.2 presents a set of eighteen (18) variables which follows, as close as possible, the set of variables used in the medium-scale VARs in related studies (e.g. see Banbura et al. (2010, p. 89) and Table BII in Koop (2013, p. 201)). In general, Table 2 includes monetary aggregates (e.g. M1, M2, Foreign reserves) and variables from other aspects of the economy such as producer prices, labor market, housing market, imports, exports, stock market, interest and exchange rates. We should, however, keep in mind that there is limited availability of monthly macroeconomic data for the Greek economy. More specifically, income, consumption and capacity utilization variables, used in related studies, were hard to find at the frequency or for the time period we are interested in. Thus, we choose to use other proxies for these variables, such as retail sales and consumer confidence indicators for the income and consumption variables, respectively, and economic - business sentiment indicators for the capacity utilization.

In Table A.3, we list an additional set of nineteen (19) *financial* variables that are also used to predict the four target variables. Most of these variables are key stress components of the FSSI developed for Greece by Louzis and Vouldis (2013). Although we could have extended the set of variables in Table 2 so as to include further sectoral variables, as in Banbura et al. (2010) or Koop (2013), we chose to focus more on the informational content of additional financial variables.[12] Next, we explain the rationale behind this choice. First, empirical evidence in Banbura et al. (2010) and Koop (2013) indicate that a larger set with sectoral variables cannot considerably improve the forecasting performance. Second, assessing the forecasting ability of various market-based risk measures (such as spreads and volatilities) and other financial variables is especially interesting for the Greek case. We should recall that Greece was under hard pressure by markets, especially during the outbreak of the debt crisis in early 2010. Thus, employing a number of key financial variables in our analysis enables us to assess the informational content of financial variables as well as the overall signaling of financial markets regarding the future evolution of macro and credit conditions in Greece.

Table 1 presents the combinations of variables included in each of the five VAR models employed in this study. First, we estimate the five-variable baseline specification. Along with the baseline model, we also consider the baseline model augmented with the FSSI

[12] As already mentioned there are also data availability issues, which pose limitations to this kind of analysis.

(*Baseline plus FSSI*). By doing this we are able to investigate the forecasting ability of a composite index, which summarizes the informational content of a large set of financial variables, taking also into account the systemic nature of risk.[13] Next we estimate two medium-scale models: the *Medium* model which is the baseline specification plus the Table A.2 variables and the *Medium-Financial* which is defined as the baseline model plus the Table A.3 variables. Finally, the *Large* model is defined as the baseline plus Tables A.2 and A.3 variables Therefore, we consider two small-scale models, two medium-scale models and one large-scale model containing all 42 variables. For all models we use 3 lags, i.e. p=3.

[Insert Table 1 about here]

4. Empirical analysis

We implement a rolling window of approximately six years of monthly data, that is seventy (70) monthly observations, to produce out-of-sample forecasts. In particular, the out-of-sample period spans from $T_0 = 2008{:}9$ to $T = 2013{:}8$ covering almost the full five-year period of recession in Greece (2008 – 2013). We provide empirical evidence for four forecasting horizons, i.e. for h=1, 3, 6 and 12 months ahead.

The remainder of this section is structured as follows. In Section 4.1, we describe the methods used for choosing the shrinkage hyperparameter λ and we present the empirical results. Section 4.2 presents the forecast evaluation measures, while in Section 4.3 we discuss the forecasting results.

4.1. Choosing the shrinkage hyperparameter λ

The shrinkage hyperparameter, λ, plays a crucial role in large dimension Bayesian VAR applications. As discussed in Banbura et al. (2010) and formally showed in De Mol et al. (2008), λ should be chosen in relation to the number of the variables used in the VAR model. For the *Baseline* and the *Baseline plus FSSI* models with five and six parameters, respectively, we impose no shrinkage, i.e. $\lambda \to \infty$, and thus parameter estimates coincide with the OLS estimates. Nonetheless, in larger systems we should enforce tighter priors

[13] This can be considered as analogous to the use of principal components applied by Banbura et al. (2010, p. 80).

(smaller λ) in order to avoid over-fitting. Here, we employ two distinct data-driven methodologies for selecting λ which are described below.

The first method, proposed by Banbura et al. (2010) (BGR hereafter), selects the hyperparameter λ on the basis of the in-sample fit of large-scale VARs, which has to be as close as possible to the in-sample fit of small-scale VARs. We define the in-sample period as the first seventy (70) observations, from 2002:11 to 2008:8, for which the '*Fit*' for each model *m*, and forecasting horizon *h*, is defined as follows:

$$Fit_m^h(\lambda) = \frac{1}{4}\sum_{i=1}^{4}\frac{msfe_m^h(i,\lambda)}{msfe_{Baseline}^h(i,0)} \tag{8}$$

where $msfe_m^h(i,\lambda)$ is the mean squared forecast error (MSFE) (see Section 4.2) for model *m* with *m* = *Medium*, *Medium-Financial* and *Large* and forecasting horizon *h*, with *h* = 1, 3, 6 and 12. The *msfe* is computed for each of the four variables of interest, *i*, with *i* = Loans, Lending rates, IPI and CPI and for a given level of λ. Then, it is normalized by the $msfe_{Baseline}^h(i,0)$ which is the MSFE produced by the Baseline model using the prior ($\lambda = 0$). Finally, the normalized MSFE measure is averaged across the four target variables. We employ grid search methods in order to choose the value of λ which minimizes the following criterion:

$$\lambda_{m,h}^{*} = \arg\min_{\lambda}\left|Fit_m^h(\lambda) - Fit_{Baseline}^h(\infty)\right| \tag{9}$$

In Table 2 we present the BGR results across forecasting horizons. The empirical findings are in line with the results presented by Banbura et al. (2010) indicating that $\lambda \to 0$ as the VAR system becomes larger. Hence, the in-sample fit of large VARs is retained as close as possible to the fit of small VaRs.

[Insert Table 2 about here]

Carriero et al. (2009) (CKM hereafter) proposed an alternative method for choosing λ, which is based on a real-time process described in the following steps. First, we choose a range of values for λ over which we estimate the respective VAR models. We use the VAR coefficient estimates to produce forecasts at τ point in time, with $\tau \in (T_0, T-1]$, and compute the sum of squared forecasting errors over the four variables of interest, i.e.

$SFE_h^m(\tau,\lambda) = \sum_{i=1}^{4} FE_{i,h}^m(\tau,\lambda)$. Second, in the next period, $\tau+1$, we chose that value of the hyperparameter λ which minimizes the $SFE_h^m(\tau)$ in the previous period τ , i.e.:

$$\lambda_{m,h}^*(\tau+1) = \arg\min_{\lambda}\left\{SFE_h^m(\tau,\lambda)\right\} \tag{10}$$

where *m* = *Medium*, *Medium-Financial* and *Large* and *h* = 1, 3, 6 and 12. We follow Carriero et al. (2009) and we use the same a grid of values for $\lambda(t)$, $\lambda(t) \in 10^{-4} \times [0.01, 0.1, 0.5, 1, 1.5, 2, 2.5, 5]$, which implies a tighter prior compared to the one implied by the values presented in Table 2. This means that we circumvent the over-fitting problems, but we also put more weight on prior beliefs than the BGR method.

Fig. 2 depicts the time-varying hyperparameter over the full out-of-sample period and across forecasting horizons. The most striking feature of Fig. 2 is that the $\lambda(t)$ parameter remains close to the lower bound of the predetermined grid of values over consecutive rolling estimations, during the beginning of the Greek sovereign debt crisis in late 2009. This phenomenon is more intense in the *Medium-Financial* and *Large* VARs that include financial variables. This is probably an indication that financial data were relatively uninformative during the outbreak of the crisis and thus the selected $\lambda(t)$ parameter put more weight on prior beliefs and less on data. Moreover, the results also support the findings of Gibson et al. (2012, 2014b), who argue that financial markets during the pre-crisis period did not carry information that reflected the actual macroeconomic conditions in Greece.

[Insert Figure 2 about here]

4.2. Forecasting evaluation

We assess the forecasting performance of the models using three categories of forecasting evaluation metrics: (a) the standard mean squared forecast error (MSFE), (b) two directional accuracy measures and (c) an adjusted MSFE that takes into account both the magnitude of the forecasting errors and the directional accuracy of the models. Next, we briefly discuss the evaluation measures employed in this study.

The MSFE for the variable *i* at forecasting horizon *h* produced by the model $m = 1,\ldots,\mathrm{M}_0$ is given by:

$$MSFE = \frac{1}{T_{out}} \sum_{t=1}^{T_{out}} \left(y_{i,t+h} - \hat{y}^{m}_{i,t+h} \right)^2 \quad (11)$$

where $\hat{y}^{m}_{i,t+h} = E\left(y^{m}_{i,t+h} \middle| \mathbf{Y}\right)$, $T_{out} = T - T_0$ is the number of out-of-sample forecasts, i = *Industrial Production index*, *CPI*, *Loans* and *Lending rates* and h = 1, 3, 6 and 12. We follow the standard practice in the literature and we present the results for the MSFE metric relative to MSFE produced by a random walk model (e.g. see Koop, 2013). We also compute the bias of the forecast errors in order to evaluate the ability of a model to produce forecasts that are close to the average level of the target variable (Giannone et al., 2014).[14]

In a plethora of real world applications, practitioners and policy makers are much more interested in predicting the direction of change of the target variables than in minimizing the magnitude of the forecasting errors (see the discussion in Moosa and Burns, 2014). A typical direction accuracy (DA) measure is defined as follows (Moosa and Burns, 2014):

$$DA = \frac{1}{T_{out}} \sum_{t=1}^{T_{out}} a_t \quad \text{where } a_t = \begin{cases} 1 \text{ if } \hat{y}^{m}_{i,t+h} \times y_{i,t+h} > 0 \\ 0 \text{ if } \hat{y}^{m}_{i,t+h} \times y_{i,t+h} < 0 \end{cases} \quad (12)$$

We also apply a non-parametric test for the evaluation of the directional forecasting performance proposed by Pesaran and Timmerman (1992) (hereafter PT).[15] Granger and Pesaran (2000) proposed a convenient form for the PT test statistic that is given by:

$$PT = \frac{\sqrt{T_{out}}\,(H - F)}{\left(\hat{\pi}(1-\hat{\pi}) / \pi(1-\pi)\right)^{1/2}} \quad (13)$$

where H and F are the "*hit*" and "*false alarm*" rates defined as $H = \frac{\Pr\left(y^{m}_{i,t+h} > 0, \hat{y}^{m}_{i,t+h} > 0\right)}{\Pr\left(y^{m}_{i,t+h} > 0\right)}$ and $F = \frac{\Pr\left(y^{m}_{i,t+h} < 0, \hat{y}^{m}_{i,t+h} > 0\right)}{\Pr\left(y^{m}_{i,t+h} < 0\right)}$ respectively, while π and $\hat{\pi}$ are given by the probabilities $\pi = \Pr\left(y^{m}_{i,t+h} > 0\right)$ and $\hat{\pi} = \Pr\left(\hat{y}^{m}_{i,t+h} > 0\right)$.[16] The null hypothesis is that of no directional

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[14] The bias is computed as the mean of the forecasting errors: $bias = \frac{1}{T_{out}} \sum_{t=1}^{T_{out}} y_{i,t+h} - \hat{y}^{m}_{i,t+h}$

[15] For recent applications of the PT test see Moosa and Burns (2014), Lahiri and Wang (2013) and Nyberg (2011).

[16] In order to compute the PT test in Eq. (10) we define the following quantities: $I^{f}_{t} = 1\left(\hat{y}^{m}_{i,t+h} > 0\right)$, $I_t = 1\left(y^{m}_{i,t+h} > 0\right)$, $\hat{I}^{++} = \sum_{t=1}^{T_{out}} 1\left(I^{f}_{t} = 1, I_t = 1\right)$, $\hat{I}^{+-} = \sum_{t=1}^{T_{out}} 1\left(I^{f}_{t} = 1, I_t = 0\right)$, $\hat{I}^{-+} = \sum_{t=1}^{T_{out}} 1\left(I^{f}_{t} = 0, I_t = 1\right)$ and

predictability, meaning that the hit rate, i.e. the probability of correctly predicting the sign of a positive return, does not differ significantly from the false alarm rate, i.e. the probability of wrongly predicting the sign of a negative return. Therefore, under the null hypothesis the forecast series are assumed to have no predictive ability for the sign of changes of the realized series and the PT statistic is asymptotically distributed as standard normal.

Moosa and Burns (2012) proposed the adjusted MSFE (AMSFE) which is a combined measure that accounts for both the directional accuracy and the magnitude of the forecast errors. The AMSFE scales the conventional MSFE with the confusion rate (CR), defined as $CR = 1 - DA$, and is computed as follows:

$$AMSFE = \frac{CR}{T_{out}} \sum_{t=1}^{T_{out}} \left(y_{i,t+h} - \hat{y}_{i,t+h}^{m} \right)^2 \quad (14)$$

The MSFE and AMSFE evaluation metrics can provide us with a consistent ranking of the competing models, but they cannot reassure that the differences among the various forecasting models are statistically significant. Hence, for these two measures, we also employ the Model Confidence Set (MCS) technique of Hansen et al. (2003, 2011) in order to construct a set of models, $\mathsf{M}_{1-a}^{*} \subseteq \mathsf{M}_0$, that has statistically superior predictive ability at a given confidence level.

Assuming an initial set of $\mathsf{M} = \mathsf{M}_0$ models, the MCS method is based on a specific loss function, $L_{m,t}$ with $m = 1,...,\mathsf{M}$, and applies an iterative process of sequential Equal Predictive Ability (EPA) tests of the form:

$$H_{0,\mathsf{M}_0} : E\left(d_{mk,t}\right) = 0 \text{ for all } m,k \in \mathsf{M} \quad (15)$$

where $d_{mk,t} = L_{m,t} - L_{k,t}$ is the loss differential between models *m* and *k* and $L_{\bullet,t}$ is one of the MSFE or AMSFE at each point in time, *t*. A rejection of the null hypothesis indicates that a model has inferior predictive ability and should not be included in the MCS at an a significance level. The EPA test in Eq. (10) is repeated for the remaining M_{1-a} models, with

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$\hat{I}^{--} = \sum_{t=1}^{T_{out}} 1\left(I_t^f = 0, I_t = 0\right)$, where $1(\cdot)$ is an indicator function which takes the value of one if the condition in the parenthesis is satisfied and zero otherwise. Given the above definitions we compute: $H = \hat{I}^{++} / \left(\hat{I}^{++} + \hat{I}^{-+}\right)$, $F = \hat{I}^{+-} / \left(\hat{I}^{+-} + \hat{I}^{--}\right)$, $\pi = \left(1/T_{out}\right)\sum_{t=1}^{T_{out}} I_t$ and $\hat{\pi} = \left(1/T_{out}\right)\sum_{t=1}^{T_{out}} I_t^f$.

$M_{1-a} \subset M$, and this procedure continues until the null hypothesis cannot be rejected. The final set of surviving models forms the MCS at the $1-a$ confidence level, denoted by M^*_{1-a}. The models included in the MCS have equal predictive ability, but they outperform the eliminated models, while the MCS *p*-values indicate the probability of a model being a member of the MCS.[17]

4.3. Forecasting results

We discuss the forecasting results regarding the IPI and CPI in Section 4.3.1. and the results for the loans and lending rates in Section 4.3.2.. The shrinkage hyperparameter λ for the *Medium*, *Medium-Financial* and *Large* VAR models is selected according to the methods of both BGR and CKM described in Section 4.1, which means that we have in total eight (8) competing models.

4.3.1. Macroeconomic variables

Overall, the empirical results for the IPI and CPI variables (Tables 3 and 4, respectively) suggest that Bayesian VARs enriched with a large set of macroeconomic and financial variables can improve the forecasting ability of the baseline VAR models. More specifically, in the ranking summary presented in Table 5, we observe that the *Large (CKM)* model has, overall, the best forecasting performance, across forecasting horizons, followed by the *Medium-Financial (CKM)* and the *Medium (CKM)* and *Medium (BGR)* models. These findings are in line with the results of Banbura et al. (2010) and Koop (2013) and reveal that large Bayesian VARs, coupled with the appropriate level of shrinkage, can also provide more accurate macroeconomic forecasts in the case of a small economy during an economic downturn.

The empirical results also indicate that the informational content of key financial indicators can contribute to the improvement of macroeconomic forecasting when

[17] For details on MCS technique and its implementation see Hansen et al. (2003, 2011). The MCS is implemented using MULCOM 2.00 package for Ox, kindly provided by the authors. The MULCOM 2.00 package is available at http://mit.econ.au.dk/vip_htm/alunde/mulcom/mulcom.htm.

incorporated into a large-scale Bayesian VAR. By contrast, the FSSI composite index does not consistently improve the forecasting ability of the baseline model, across evaluation measures and forecasting horizons. In addition, the use of financial variables reduces the biasedness of the forecasts; the *Medium-Financial (CKM)* model produces, overall, the least biased forecasts across forecasting horizons (four out of eight cases. See Panel A of Tables 3 and 4).

[Insert Table 3 about here]

[Insert Table 4 about here]

[Insert Table 5 about here]

Moreover, the empirical evidence indicates that when we use the BGR method for choosing λ, a data set larger than the one used in *Medium* models can hardly improve models' forecasting ability. This is also in accordance with the findings of BGR and Koop (2013). By contrast, the CKM method for selecting λ gives, overall, better forecasting results irrespective of the model used, i.e., *Medium*, *Medium-Financial* or *Large*. This may be attributed to the tighter prior assumption implied by the CKM method and to its dynamic nature, which gives more flexibility in choosing the appropriate level of λ.

Furthermore, the MCS *p*-values for the MSFE results in Panel A of Tables 3 and 4 reveal that the information content of the additional variables is much more valuable in long-term than in short-term forecasts. In particular, for both macroeconomic variables under examination and for the one month ahead forecasts (h=1) the hypothesis of equal predicting ability cannot be rejected for all models, except for the *Medium-Financial (BGR)*. The whole set of models can also produce statistically equal CPI forecasts for h=3. The picture changes regarding longer term forecasts and particularly for the forecasting horizons h=3, 6 and 12 for the IPI and h=6 and 12 for the CPI. In the majority of the cases, the MCS consists of models that employ the CKM approach along with the *Medium (BGR)* model.

Another interesting evidence is that Bayesian VARs can only marginally improve the directional accuracy of the baseline models (see Panel B in Tables 3 and 4). More specifically, Bayesian VARs rank first in five out of eight cases in terms of the DA measure, across forecasting horizons and target variables. However, the null hypothesis of no directional predictability examined by the PT test cannot be rejected for the majority of the models across forecasting horizons; exceptions are the *Baseline* followed by the *Baseline plus FSSI*, *Medium (BGR)* and *Large (CKM)* models. Therefore, the overall improvement in the directional accuracy performance, implied by the DA measure for the Bayesian VARs, is not adequate to trigger the rejection of the null hypothesis of the PT test.

Finally, in Panel C of Tables 3 and 4 we present the results for the adjusted MSFE and the corresponding MCS *p*-values. Here, the *Large (CKM)* model is the indisputable winner, since it is part of the MCS in six out of eight cases, followed by the *Medium (CKM) and Medium (BGR)* models (five out of six cases). On the other hand, baseline models are included in the MCS only in two cases. This indicates that large Bayesian VARs can produce better forecasts compared to their baseline counterparts in terms of a combined evaluation measure, which assesses both the directional accuracy and the magnitude of the forecast errors. This is a significant result for policy makers that are particularly interested in forecasting the direction of target variables.

4.3.2. Credit variables

In this section, we discuss the forecasting results for loans and lending rates presented in Tables 6 and 7, respectively. The overall picture is qualitatively similar with the picture presented in Section 4.3.1 for the macroeconomic forecasts. Specifically, medium- and large-scale Bayesian VARs outperform their small-scale counterparts (*Baseline* and *Baseline plus FSSI* models) for most of the forecasting horizons and evaluation metrics employed in this study. Again, the Bayesian VAR models estimated using the CKM method are the best performers, with the *Large (CKM)* model beating its opponents in the ranking summary presented in Table 8. It is also evident that financial variables can improve the forecasting of credit variables in the context of a large-scale Bayesian VAR, whereas a composite stress index, which summarizes their informational content, does not improve the forecasting performance of small-scale VARs. This indicates the ability of large-scale VARs to extract that information and signal content of the individual financial stress components which is essential in order to improve the forecasting ability of VAR models.

[Insert Table 6 about here]

[Insert Table 7 about here]

[Insert Table 8 about here]

Moreover, the MCS results for the RMSFE in Panel A of Tables 6 and 7 give evidence in favour of the augmented Bayesian VARs for longer forecasting horizons, i.e. for h>3. For short forecasting horizons (h=1 for loans and h=1 and 3 for lending rates) small-scaled baseline VARs cannot be outperformed by their Bayesian counterparts. Nevertheless, regarding the lending rates, it is evident that none of the models can outperform the random walk model, i.e. the RMSFE is greater than one across all models and forecasting horizons. These results align with the empirical evidence suggesting that, in general, random walk models can produce fairly good interest rate forecasts (e.g. see Carriero et al., 2012 for government bond yields).

The results presented in Panel B of Tables 6 and 7, and especially the PT test results, confirm that the hypothesis of no directional predictability is hard to reject, especially for long-term forecasting horizons. Nonetheless, the picture is slightly different compared to the one presented for the macroeconomic variables. Now, Bayesian VARs clearly outperform their baseline counterparts mainly in long-term horizons. In particular, regarding the loan forecasting results, the *Large (CKM)* model rejects the null for h=1 and 3, whereas the baseline models reject the null only for h=1. As far as the lending rate is concerned, the *Medium-Financial (BGR)* and *Large (BGR)* models reject the null for h=1, 3 and 6 and h=1, 3 and 12 respectively, while baseline models reject the null only for h=1 and 3.

Given the abovementioned results, we expect that large-scale Bayesian VARs will also perform well when we use the adjusted MSFE measure which also accounts for the directional accuracy of the models. The results in Panel C of Tables 6 and 7 confirm that Bayesian VARs are, indeed, the best performers across forecasting horizons and credit variables. More specifically, the *Large (CKM)* model is the best predictor, since it is included in the MCS in seven out of eight cases, while the *Medium-Financial (CKM)* model follows. It is also worth noting that Bayesian VARs performance is improved for longer forecasting horizons, as expected.

Finally, we examine the practical value of the proposed techniques by using a real-world evaluation approach. Specifically, in Fig. 3, we compare the annual credit growth forecasts reported in the IMF country reports for Greece with the forecasts generated by the overall best performing model, i.e. the *Large (CKM)* model.[18, 19] It should be noticed that a more formal approach for this kind of evaluation requires a real-time data set, i.e. using data vintages available at the time of forecasting (see Giannone et al. 2014 for a recent example on real-time forecasting). Nonetheless, we argue that since our model includes a large number of non-revised figures, e.g. financial variables, the real-time data "problem" is somewhat alleviated and a comparison could be feasible.

The overall picture indicates that the proposed specification can improve the forecasting accuracy of IMF predictions. This outcome becomes clearer once we take into account the date of the IMF review publication and therefore the availability of the data until this date. More specifically, the three months ahead annual forecast produced by the model for 2010 is closer to the actual credit growth figure compared with the forecast reported by the IMF in September of 2010 (denoted with an asterisk in Fig. 3, see Fig. 3.B.). These two figures can be considered as directly comparable because both the IMF and the model do not use data after September of 2010. Another example is the twelve months ahead forecast for 2012 and the IMF forecasts published in December of 2011 (denoted with an empty triangle in Fig. 3, see Fig. 3.D). Both forecasting schemes use information up to twelve months before the target date (end of 2012) and thus are considered comparable. Again, the proposed specification can generate superior forecasts, with the predicted value being closer the realized value of credit growth. Therefore, the aforementioned results confirm that the improved forecasting accuracy of large Bayesian VARs can be beneficial for policy-related decisions even in a small relatively-closed economy during crisis.

[Insert Figure 3 about here]

5. Conclusions

The present study evaluates the ability of large Bayesian VARs to deliver superior macroeconomic (aggregate output and inflation) and credit (loans and lending rates) forecasts in Greece during the turbulent 2008-2013 crisis period. Overall, the empirical evidence

[18] IMF reviews do not present forecasts for the rest of the variables of interest, i.e. IPI, CPI, and lending rates (for instance, IMF reports HICP forecasts instead of CPI) and therefore a direct comparison was not feasible.
[19] The annual credit growth forecasts presented in Fig. 3 were calculated by aggregating month-to-month credit growth forecasts.

suggests that Bayesian VAR models, coupled with the appropriate level of shrinkage, are able to exploit the information content of a large set of both macroeconomic and financial variables and produce macroeconomic and credit forecasts that outperform their small-scale VAR counterparts. The forecasting superiority of large-scale VARs is clearer when we consider long-term forecasting horizons.

Moreover, we find that the directional accuracy is hard to improve, especially for long-term forecasting horizons. Nevertheless, as long as the credit variables are concerned, there is evidence that large Bayesian VARs can improve the directional forecasting performance even at long-term horizons. Furthermore, the forecasting results based on forecasting evaluation metrics that account for both the directional accuracy and the magnitude of the forecasting errors, clearly support the use of large-scale VARs for both macroeconomic and credit variables. Finally, empirical evidence are in favor of dynamic techniques for the choice of the shrinkage hyperparameter, compared to relatively more static approaches.

Our findings are of particular interest to supervisors and policy makers. In particular, we show that large-scale Bayesian VARs enriched with financial variables can enhance macroeconomic and credit forecasting in a small, relatively-closed, Euro-area economy during crisis. This may have significant implications for the design of rescue programs in related countries, since policy makers can exploit the improved forecasting accuracy when they design and implement their economic policy. Moreover, supervisors can enhance the robustness of the stress testing results based on more accurate forecasts regarding the evolution of macroeconomic and credit variables, which are key inputs in stress tests and related exercises.

Appendix

[Insert Table A.1 about here]

[Insert Table A.2 about here]

[Insert Table A.3 about here]

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Table 1 Definition of VAR models

VAR models	Number of Variables	Variables from
Baseline	5	Table 1
Baseline plus FSSI	6	Table 1 + FSSI
Medium	23	Table 1 + Table 2
Medium-Financial	24	Table 1 + Table 3
Large	42	Table 1 + Table 2+ Table 3

Table 2 Results for the shrinkage hyperparameter λ using the BGR method

	h=1	h=3	h=6	h=12
Medium	0.075	0.052	0.055	0.069
Medium-Financial	0.052	0.015	0.031	0.045
Large	0.032	0.012	0.013	0.025

Notes: The BGR refers to the method proposed in Banbura et al. (2010)

Table 3 Industrial production index (IPI) forecasting results

Panel A Forecasting results based on relative MSFE

	1 month ahead (*h*=1)					3 months ahead (*h*=3)					6 months ahead (*h*=6)					12 months ahead (*h*=12)				
	Bias	RMSFE	Rnk	MCS *p*-value		Bias	RMSFE	Rnk	MCS *p*-value		Bias	RMSFE	Rnk	MCS *p*-value		Bias	RMSFE	Rnk	MCS *p*-value	
Baseline	-0.042	0.371	5	0.354	***	-0.131	0.557	7	0.002		-0.067	0.491	7	0.025		**-0.044**	0.490	5	0.034	
Baseline plus FSSI	-0.090	0.395	7	0.125	**	-0.153	0.576	8	0.002		**-0.059**	0.543	8	0.018		-0.051	0.516	6	0.034	
Medium (CKM)	-0.102	0.307	3	0.354	***	**-0.091**	**0.301**	1	1.000	***	-0.117	0.302	3	0.670	***	-0.086	**0.313**	1	1.000	***
Medium-Financial (CKM)	**-0.034**	0.308	4	0.354	***	-0.133	0.317	3	0.153	**	-0.108	0.314	4	0.601	***	-0.113	0.317	3	0.790	***
Large (CKM)	-0.108	0.304	2	0.354	***	-0.108	0.301	2	0.909	***	-0.118	0.299	2	0.695	***	-0.081	0.316	2	0.790	***
Medium (BGR)	-0.065	**0.263**	1	1.000	***	-0.102	0.356	4	0.099	*	-0.083	**0.288**	1	1.000	***	-0.125	0.379	4	0.139	**
Medium-Financial(BGR)	-0.102	0.605	8	0.002		-0.110	0.472	5	0.013		-0.062	0.473	6	0.018		-0.472	1.298	8	0.034	
Large(BGR)	-0.083	0.383	6	0.159	**	-0.164	0.483	6	0.013		-0.192	0.389	5	0.025		-0.243	0.902	7	0.020	

Panel B Forecasting results based on direction accuracy measures

	1 month ahead (*h*=1)				3 months ahead (*h*=3)				6 months ahead (*h*=6)				12 months ahead (*h*=12)			
	DA	Rnk	PT *p*-values		DA	Rnk	PT *p*-values		DA	Rnk	PT *p*-values		DA	Rnk	PT *p*-values	
Baseline	0.617	2	0.033	‡	0.417	8	0.920		**0.550**	1	0.250		**0.667**	1	0.005	‡
Baseline plus FSSI	0.600	3	0.052	‡	0.517	3	0.385		0.533	3	0.376		0.633	2	0.016	‡
Medium (CKM)	0.550	4	0.189		0.533	2	0.376		0.517	5	0.304		0.433	6	0.881	
Medium-Financial (CKM)	0.500	6	0.781		0.467	5	0.484		0.400	8	0.923		0.367	8	0.974	
Large (CKM)	0.550	4	0.189		**0.600**	1	0.061	‡‡	0.483	6	0.478		0.450	5	0.811	
Medium (BGR)	**0.700**	1	0.001	‡	0.450	6	0.771		**0.550**	1	0.229		0.483	3	0.589	
Medium-Financial(BGR)	0.417	8	0.920		0.433	7	0.801		0.533	3	0.327		0.400	7	0.931	
Large(BGR)	0.467	7	0.721		0.500	4	0.555		0.433	7	0.817		0.467	4	0.624	

Panel C Forecasting results based on adjusted MSFE

	1 month ahead (*h*=1)				3 months ahead (*h*=3)				6 months ahead (*h*=6)				12 months ahead (*h*=12)			
	AMSFE	Rnk	MCS *p*-value		AMSFE	Rnk	MCS *p*-value		AMSFE	Rnk	MCS *p*-value		AMSFE	Rnk	MCS *p*-value	
Baseline	0.521	4	0.040		1.190	8	0.001		0.810	7	0.033		**0.599**	1	1.000	***
Baseline plus FSSI	0.578	6	0.040		1.020	7	0.002		0.928	8	0.014		0.694	4	0.684	***
Medium (CKM)	0.506	3	0.040		0.514	2	0.006		0.534	2	0.257	***	0.650	3	0.697	***
Medium-Financial (CKM)	0.564	5	0.040		0.620	3	0.006		0.691	4	0.033		0.734	6	0.527	***
Large (CKM)	0.500	2	0.040		**0.441**	1	1.000	***	0.567	3	0.166	**	0.638	2	0.749	***
Medium (BGR)	**0.289**	1	1.000	***	0.718	4	0.006		**0.475**	1	1.000	***	0.717	5	0.684	***
Medium-Financial(BGR)	1.292	8	0.000		0.980	6	0.005		0.808	6	0.015		2.855	8	0.059	*
Large(BGR)	0.752	7	0.016		0.886	5	0.006		0.807	5	0.014		1.763	7	0.027	

Notes: Rnk is the rank of the models. Bias is the mean of forecast error. RMSFE is the relative mean square forecast error defined in Eq. (11), DA is the direction accuracy measure defined in Eq. (12) and AMSFE is the adjusted mean square forecast error defined in Eq. (14). The MCS is the model confidence set of Hansen et al. (2003; 2011) and the *p*-values are calculated using the *deviation* test statistic (see also Laurent et al, 2012). A given model *i*, belongs to the MCS if its *p*-value is greater than a prespecified significance level, a , where a = 0.05, 0.10 and 0.25 . One (*), two (**) and three (***) asterisks indicate that a model belongs to the $M^*_{0.95}$, $M^*_{0.90}$ and $M^*_{0.75}$, respectively. Note that $M^*_{0.75} \subset M^*_{0.90} \subset M^*_{0.95}$. The PT is the Pesaran and Timmermann (1992) test which follows a standard normal distribution. The table presents the *p*-values of rejecting the null hypothesis of predictive failure. The symbols ‡ and ‡‡ indicate rejection of the null at 0.01 and 0.05 significance level, respectively.

Table 4 Consumer price index (CPI) forecasting results

Panel A Forecasting results based on relative MSFE

	1 month ahead (*h*=1)					3 months ahead (*h*=3)					6 months ahead (*h*=6)					12 months ahead (*h*=12)				
	Bias	RMSFE	Rnk	MCS *p*-value		Bias	RMSFE	Rnk	MCS *p*-value		Bias	RMSFE	Rnk	MCS *p*-value		Bias	RMSFE	Rnk	MCS *p*-value	
Baseline	-0.229	0.934	6	0.057	*	-0.178	0.817	7	0.137	**	-0.164	0.966	6	0.016		-0.151	0.909	7	0.029	
Baseline plus FSSI	-0.203	0.964	7	0.058	*	-0.180	0.835	8	0.137	**	-0.230	1.052	7	0.016		-0.241	0.905	6	0.063	*
Medium (CKM)	-0.168	0.609	3	0.944	***	-0.136	0.643	2	0.599	***	-0.131	**0.627**	1	1.000	***	-0.094	**0.626**	1	1.000	***
Medium-Financial (CKM)	**-0.054**	**0.600**	1	1.000	***	**-0.063**	0.674	3	0.539	***	**-0.107**	0.641	2	0.713	***	-0.293	0.682	3	0.407	***
Large (CKM)	-0.167	0.602	2	0.946	***	-0.130	**0.638**	1	1.000	***	-0.124	0.642	3	0.713	***	-0.112	0.636	2	0.415	***
Medium (BGR)	-0.224	0.618	4	0.944	***	-0.143	0.725	5	0.356	***	-0.183	0.730	4	0.050	*	-0.155	0.711	4	0.127	**
Medium-Financial(BGR)	-0.284	0.975	8	0.014		-0.151	0.784	6	0.148	**	-0.102	1.395	8	0.000		-0.169	2.234	8	0.014	
Large(BGR)	-0.254	0.725	5	0.361	***	-0.130	0.687	4	0.599	***	-0.170	0.779	5	0.050	*	**0.091**	0.802	5	0.126	**

Panel B Forecasting results based on direction accuracy measures

	1 month ahead (*h*=1)				3 months ahead (*h*=3)				6 months ahead (*h*=6)				12 months ahead (*h*=12)			
	DA	Rnk	PT *p*-values		DA	Rnk	PT *p*-values		DA	Rnk	PT *p*-values		DA	Rnk	PT *p*-values	
Baseline	0.467	8	0.584		**0.567**	1	0.083	‡‡	0.500	2	0.542		0.417	8	0.913	
Baseline plus FSSI	0.500	7	0.374		0.550	2	0.145		0.500	2	0.458		0.433	6	0.852	
Medium (CKM)	0.533	5	0.230		0.500	4	0.626		0.483	4	0.816		0.567	2	0.324	
Medium-Financial (CKM)	0.617	2	0.164		0.433	7	0.987		0.450	5	0.881		0.433	6	0.598	
Large (CKM)	0.550	3	0.119		0.500	4	0.626		0.417	6	0.969		**0.583**	1	0.067	‡‡
Medium (BGR)	**0.633**	1	0.018	‡	0.367	8	0.986		0.417	6	0.855		0.450	5	0.768	
Medium-Financial(BGR)	0.533	5	0.301		0.533	3	0.376		0.400	8	0.915		0.483	4	0.500	
Large(BGR)	0.550	3	0.119		0.483	6	0.741		**0.517**	1	0.337		0.500	3	0.584	

Panel C Forecasting results based on adjusted MSFE

	1 month ahead (*h*=1)				3 months ahead (*h*=3)				6 months ahead (*h*=6)				12 months ahead (*h*=12)			
	AMSFE	Rnk	MCS *p*-value		AMSFE	Rnk	MCS *p*-value		AMSFE	Rnk	MCS *p*-value		AMSFE	Rnk	MCS *p*-value	
Baseline	0.999	8	0.003		0.710	3	0.516	***	0.969	6	0.034		1.063	7	0.005	
Baseline plus FSSI	0.967	7	0.007		0.754	6	0.452	***	1.055	7	0.034		1.028	6	0.005	
Medium (CKM)	0.570	4	0.022		0.645	2	0.516	***	**0.650**	1	1.000	***	0.544	2	0.205	**
Medium-Financial (CKM)	0.461	2	0.884	***	0.766	7	0.220	**	0.707	2	0.237	**	0.775	3	0.005	
Large (CKM)	0.543	3	0.024		**0.640**	1	1.000	***	0.751	3	0.076	*	**0.531**	1	1.000	***
Medium (BGR)	**0.454**	1	1.000	***	0.921	8	0.067	*	0.854	5	0.034		0.784	4	0.005	
Medium-Financial(BGR)	0.912	6	0.003		0.734	5	0.452	**	1.679	8	0.000		2.315	8	0.005	
Large(BGR)	0.659	5	0.022		0.711	4	0.516	***	0.755	4	0.237	**	0.804	5	0.010	

Notes: See Table 3

Table 5 Models' ranking synopsis for the macroeconomic variables (IPI, CPI)

	h=1	h=3	h=6	h=12	Ranking based on *average* performance across forecasting horizons
Baseline	2	3	6	6	5
Baseline plus FSSI	2	6	6	3	5
Medium (CKM)	5	3	1	1	3
Medium-Financial (CKM)	2	1	3	3	2
Large (CKM)	5	1	1	1	1
Medium (BGR)	1	3	3	3	3
Medium-Financial (BGR)	8	6	6	7	8
Large (BGR)	5	6	5	7	7

Notes: For the synopsis of the forecasting performance across evaluation metrics and macroeconomic variables, we consider the MCS results for the MSFE (Panel A) and AMSFE (Panel B) measures and the PT test (Panel B). A model that manages to succeed in most of the abovementioned tests across target variables ranks first. Green, yellow and orange colors indicate the models that rank first, second and third, respectively.

Table 6 Total loans forecasting results

Panel A Forecasting results based on relative MSFE

	1 month ahead (*h*=1)				3 months ahead (*h*=3)				6 months ahead (*h*=6)				12 months ahead (*h*=12)			
	Bias	RMSFE	Rnk	MCS *p*-value	Bias	RMSFE	Rnk	MCS *p*-value	Bias	RMSFE	Rnk	MCS *p*-value	Bias	RMSFE	Rnk	MCS *p*-value
Baseline	-0.087	0.350	2	0.704 ***	-0.058	0.590	7	0.019	-0.094	0.755	7	0.001	0.049	0.789	5	0.012
Baseline plus FSSI	-0.091	**0.332**	1	1.000 ***	-0.065	0.647	8	0.018	-0.089	0.813	8	0.001	-0.021	0.931	7	0.005
Medium (CKM)	-0.010	0.369	3	0.704 ***	-0.024	**0.363**	1	1.000 ***	-0.033	0.354	2	0.176 **	-0.022	0.371	2	0.784 ***
Medium-Financial (CKM)	-0.021	0.377	5	0.681 ***	0.064	0.374	3	0.599 ***	0.013	0.369	3	0.176 **	-0.051	**0.368**	1	1.000 ***
Large (CKM)	-0.009	0.370	4	0.700 ***	**-0.010**	0.364	2	0.747 ***	-0.043	**0.348**	1	1.000 ***	-0.023	0.381	3	0.464 ***
Medium (BGR)	-0.033	0.413	6	0.495 ***	**-0.010**	0.419	6	0.028	-0.011	0.405	4	0.024	**-0.019**	0.466	4	0.062 *
Medium-Financial(BGR)	**-0.004**	0.499	8	0.287 ***	0.067	0.389	4	0.599 ***	**0.003**	0.504	5	0.004	0.289	0.798	6	0.012
Large(BGR)	-0.010	0.435	7	0.403 ***	0.012	0.406	5	0.186 **	-0.022	0.595	6	0.004	0.059	1.222	8	0.012

Panel B Forecasting results based on direction accuracy measures

	1 month ahead (*h*=1)			3 months ahead (*h*=3)			6 months ahead (*h*=6)			12 months ahead (*h*=12)		
	DA	Rnk	PT *p*-values	DA	Rnk	PT *p*-values	DA	Rnk	PT *p*-values	DA	Rnk	PT *p*-values
Baseline	**0.650**	1	0.008 ‡	0.467	6	0.683	0.450	5	0.768	0.517	2	0.405
Baseline plus FSSI	**0.650**	1	0.008 ‡	0.350	8	0.989	0.450	5	0.774	0.517	2	0.411
Medium (CKM)	0.600	4	0.063 ‡‡	0.533	3	0.278	0.550	2	0.201	0.400	8	0.936
Medium-Financial (CKM)	0.517	6	0.359	0.550	2	0.228	0.450	5	0.829	0.517	2	0.335
Large (CKM)	0.633	3	0.020 ‡	**0.600**	1	0.061 ‡‡	**0.567**	1	0.132	0.433	5	0.840
Medium (BGR)	0.450	7	0.779	0.417	7	0.900	0.517	3	0.417	0.433	5	0.854
Medium-Financial(BGR)	0.417	8	0.903	0.533	3	0.321	0.450	5	0.807	**0.567**	1	0.155
Large(BGR)	0.550	5	0.216	0.517	5	0.399	0.467	4	0.683	0.417	7	0.896

Panel C Forecasting results based on adjusted MSFE

	1 month ahead (*h*=1)			3 months ahead (*h*=3)			6 months ahead (*h*=6)			12 months ahead (*h*=12)		
	AMSFE	Rnk	MCS *p*-value	AMSFE	Rnk	MCS *p*-value	AMSFE	Rnk	MCS *p*-value	AMSFE	Rnk	MCS *p*-value
Baseline	0.335	2	0.554 ***	0.861	7	0.015	1.136	7	0.001	1.043	6	0.011
Baseline plus FSSI	**0.318**	1	1.000 ***	1.150	8	0.010	1.223	8	0.001	1.231	7	0.011
Medium (CKM)	0.403	4	0.436 ***	0.463	3	0.042	0.436	2	0.004	0.609	3	0.027
Medium-Financial (CKM)	0.498	5	0.222 **	0.461	2	0.042	0.555	4	0.001	**0.486**	1	1.000 ***
Large (CKM)	0.371	3	0.554 ***	**0.398**	1	1.000 ***	**0.413**	1	1.000 ***	0.590	2	0.027
Medium (BGR)	0.622	7	0.005	0.668	6	0.010	0.535	3	0.004	0.722	4	0.027
Medium-Financial(BGR)	0.797	8	0.000	0.496	4	0.042	0.759	5	0.001	0.946	5	0.014
Large(BGR)	0.537	6	0.068 *	0.537	5	0.019	0.869	6	0.001	1.951	8	0.011

Notes: See Table 3

Table 7 Total lending rates forecasting results

Panel A Forecasting results based on relative MSFE

	1 month ahead (h=1)				3 months ahead (h=3)				6 months ahead (h=6)				12 months ahead (h=12)			
	Bias	RMSFE	Rnk	MCS p-value	Bias	RMSFE	Rnk	MCS p-value	Bias	RMSFE	Rnk	MCS p-value	Bias	RMSFE	Rnk	MCS p-value
Baseline	**-0.008**	**1.306**	1	1.000 ***	0.033	2.665	7	0.139 **	0.065	2.827	6	0.049	0.194	3.352	6	0.006
Baseline plus FSSI	-0.012	1.438	2	0.538 ***	0.034	2.905	8	0.068 *	0.104	3.212	7	0.035	0.179	3.992	7	0.001
Medium (CKM)	-0.153	1.775	6	0.538 ***	-0.164	1.756	4	0.883 ***	-0.242	1.694	2	0.937 ***	-0.251	1.638	2	0.293 ***
Medium-Financial (CKM)	-0.029	1.661	4	0.538 ***	**-0.025**	1.674	2	0.918 ***	**-0.022**	1.707	3	0.937 ***	-0.321	1.929	4	0.293 ***
Large (CKM)	-0.147	1.746	5	0.538 ***	-0.164	1.694	3	0.918 ***	-0.239	**1.689**	1	1.000 ***	-0.262	1.650	3	0.293 ***
Medium (BGR)	-0.172	1.661	3	0.538 ***	-0.121	**1.637**	1	1.000 ***	-0.248	2.167	4	0.112 **	**-0.025**	1.316	1	1.000 ***
Medium-Financial(BGR)	-0.076	2.257	7	0.446 ***	-0.194	1.872	6	0.810 ***	-0.308	4.773	8	0.008	-0.484	5.589	8	0.006
Large(BGR)	-0.106	2.400	8	0.538 ***	-0.103	1.777	5	0.918 ***	-0.383	2.366	5	0.228 **	-0.351	3.336	5	0.055 *

Panel B Forecasting results based on direction accuracy measures

	1 month ahead (h=1)			3 months ahead (h=3)			6 months ahead (h=6)			12 months ahead (h=12)		
	DA	Rnk	PT p-values	DA	Rnk	PT p-values	DA	Rnk	PT p-values	DA	Rnk	PT p-values
Baseline	0.667	4	0.004 ‡	0.617	2	0.041 ‡	0.567	3	0.202	0.483	6	0.769
Baseline plus FSSI	0.667	4	0.003 ‡	0.617	2	0.056 ‡‡	0.517	5	0.500	0.433	7	0.916
Medium (CKM)	0.483	7	0.702	0.583	5	0.145	0.517	5	0.265	0.583	3	0.056 ‡‡
Medium-Financial (CKM)	0.583	6	0.281	0.567	7	0.428	**0.617**	1	0.092 ‡‡	0.433	7	0.727
Large (CKM)	0.467	8	0.801	0.567	7	0.248	0.517	5	0.265	0.533	4	0.142
Medium (BGR)	**0.700**	1	0.001 ‡	0.583	5	0.128	0.533	4	0.317	**0.700**	1	0.001 ‡
Medium-Financial(BGR)	**0.700**	1	0.001 ‡	0.600	4	0.098 ‡‡	**0.617**	1	0.071 ‡‡	0.500	5	0.413
Large(BGR)	**0.700**	1	0.002 ‡	**0.650**	1	0.019 ‡	0.483	8	0.535	0.600	2	0.036 ‡

Panel C Forecasting results based on adjusted MSFE

	1 month ahead (h=1)			3 months ahead (h=3)			6 months ahead (h=6)			12 months ahead (h=12)		
	AMSFE	Rnk	MCS p-value	AMSFE	Rnk	MCS p-value	AMSFE	Rnk	MCS p-value	AMSFE	Rnk	MCS p-value
Baseline	**0.418**	1	1.000 ***	0.982	7	0.480 ***	1.178	6	0.016	1.665	6	0.010
Baseline plus FSSI	0.461	2	0.601 ***	1.070	8	0.194 **	1.492	7	0.005	2.175	7	0.002
Medium (CKM)	0.882	7	0.135 **	0.703	4	0.846 ***	0.787	3	0.050 *	0.656	2	0.035
Medium-Financial (CKM)	0.665	5	0.323 ***	0.697	3	0.880 ***	**0.629**	1	1.000 ***	1.051	4	0.030
Large (CKM)	0.895	8	0.077 *	0.706	5	0.759 ***	0.785	2	0.050 *	0.740	3	0.032
Medium (BGR)	0.479	3	0.601 ***	0.656	2	0.880 ***	0.972	4	0.050 *	**0.380**	1	1.000 ***
Medium-Financial(BGR)	0.651	4	0.378 ***	0.720	6	0.880 ***	1.759	8	0.008	2.687	8	0.030
Large(BGR)	0.697	6	0.437 ***	**0.598**	1	1.000 ***	1.175	5	0.027	1.283	5	0.030

Notes: See Table 3

Table 8 Models' ranking synopsis for the credit variables (Loans and Lending rates)

	h=1	h=3	h=6	h=12	Ranking based on *average* performance across forecasting horizons
Baseline	1	4	7	6	5
Baseline plus FSSI	1	4	7	6	5
Medium (CKM)	3	4	3	2	2
Medium-Financial (CKM)	6	4	1	2	3
Large (CKM)	3	1	1	4	1
Medium (BGR)	6	8	4	1	7
Medium-Financial (BGR)	6	2	5	6	7
Large (BGR)	3	2	5	4	4

Notes: For the synopsis of the forecasting performance across evaluation metrics and credit variables, we consider the MCS results for the MSFE (Panel A) and AMSFE (Panel B) measures and the PT test (Panel B). A model that manages to succeed in most of the abovementioned tests across target variables ranks first. Green, yellow and orange colors indicate the models that rank first, second and third, respectively.

Table A.1 Variables used in baseline VARs

Short name	Bloomberg Ticker	Code	Description	Source
Loans		5*	Outstanting amount of total loans	Bank of Greece
Lend. Rates		2	Lending rates of total loans	Bank of Greece
Ind. Prod.	GKIPI Index	5*	Industrial Production Index	National Statistical Service of Greece
CPI	GKCPNEWL Index	5*	Consumer Price Index all items (2009=100)	National Statistical Service of Greece
EONIA	EONIA Index	2	Effective Overnight Index Average Eonia rate	Bloomberg

Notes: Transformation codes: 1 no transformation, 2 first difference, 3 second difference, 4 log, 5 first difference of logged variables, 6 second difference of logged variables, * Seasonally adjusted.

Table A.2 Additional variables used in VARs

Short name	Bloomberg Ticker	Code	Description	Source
FSSI	-	5	Financial Systemic Stress Index	Louzis and Vouldis (2013)
Retail Sales	RSSAGRI Index	5	Retail Sales Volume Greece SA Real (2009=100)	Eurostat
For. reserves	EUFRGRI Index	6	Foreign Official Reserves Greece NSA	Eurostat
M2	GRCNM2 Index	6*	Contribution to Euro Area Monetary Aggregates M2	Bank of Greece
Econ. Sentiment	EUESGR Index	5	Economic SentiMent Indicator Greece SA	European Commission
Business Condition	EUICGR Index	2	Manufacturing Confidence Greece Industrial Confidence	European Commission
Consumer confidence	EUCCGR Index	2	Consumer Confidence Indicator Greece	European Commission
Unempl. Rate (SA)	UMRTGR Index	2	Unemployment Greece SA	Eurostat
Buildings	GKCOTOT Index	1*	Total New Built Properties	National Statistical Service of Greece
PPI	PPTXGR Index	5*	PPI Greece Industry Ex Construction	Eurostat
Harmonized CPI	GKCPIUHL Index	5*	Harmonized CPI 2005=100 NSA	National Statistical Service o
M1	GRCNM1 Index	6*	Contribution to Euro Area Monetary Aggregates M1	Bank of Greece
Imports	GKTBIME Index	5*	Trade Balance Imports EUR Noimnal	Bank of Greece
Exports	GKTBEXE Index	5*	Trade Balance Exports EUR Nimonal	Bank of Greece
Imp. Prices	IMPPGR Index	5	Import Price Index Greece NSA	Eurostat
ASE	ASE Index	5	Athens Stock Exchange (ASE) stock index	Bloomberg
10 yr Bond	GGGB10Y Index	2	10 year Greek government bond yield	Bloomberg
Ex. Rate	BISNGRN Index	5	Nominal Effective Exchange Rate Narrow	Bloomberg

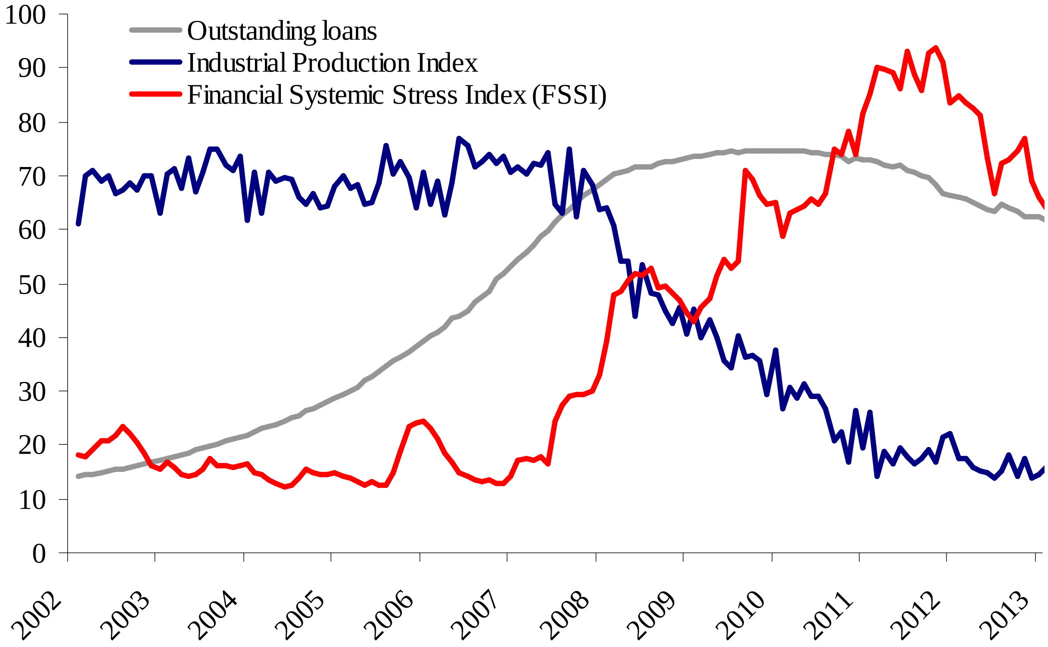
Notes: Transformation codes: 1 no transformation, 2 first difference, 3 second difference, 4 log, 5 first difference of logged variables, 6 second difference of logged variables, * Seasonally adjusted.

Table A.3 Additional financial variables used in VARs

Short name	Bloomberg Ticker	Code	Description	Source
Deposits	GDEPBBHH Index	6*	Greece Domestic Deposits Households and Businesses	Bank of Greece
Dep. Rates		2	Deposits interest rates	Bank of Greece
Inerest margins		2		
ASE eps	ASE Index, TRAIL_12M_EPS	2	ASE earnings per share	Bloomberg
ASE div yield	ASE Index, EQY_DVD_YLD_12M	2	ASE dividend yield	Bloomberg
Euribor 3m	eur003m index	2	3 month Euribor	Bloomberg
Euribor 6m	eur006m index	2	6 month Euribor	Bloomberg
OIS Eonia	OISEONIA Index	6	European Central Bank Eonia Overnight Interest Swap	
Euribor spread		2	3m EURIBOR - 3m German T-bill	Louzis and Vouldis (2013)
10 yr Spread	GGGB10Y Index, GDBR10 Index	2	10 year Greek govrn. bond yield - 10 year German govrn. bond yield	Bloomberg
CDS banks		2	Average of the 4 systemic Greek banks CDS spreads	Markit
Idios risk banks		2	Idiosyncratic risk of Greek banks	Louzis and Vouldis (2013)
Rcor		1	Realized correlation between ASE Index and 10 yr German Bond	Louzis and Vouldis (2013)
RV 10 yr bond		2	Realized volatility of 10 yr Greek bond	Louzis and Vouldis (2013)
RV ASE		4	Realized voplatility of ASE Index	Louzis and Vouldis (2013)
DAX	DAX Index	5	German DAX stock index	Bloomberg
Impl. Vol. DAX	V1X Index	2	DAX options implied volatility index	Bloomberg
SP500	SPX Index	5	US S&P 500 Index	Bloomberg
Imp. Vol. SP500	VIX Index	2	S&P 500 options implied volatility index	Bloomberg

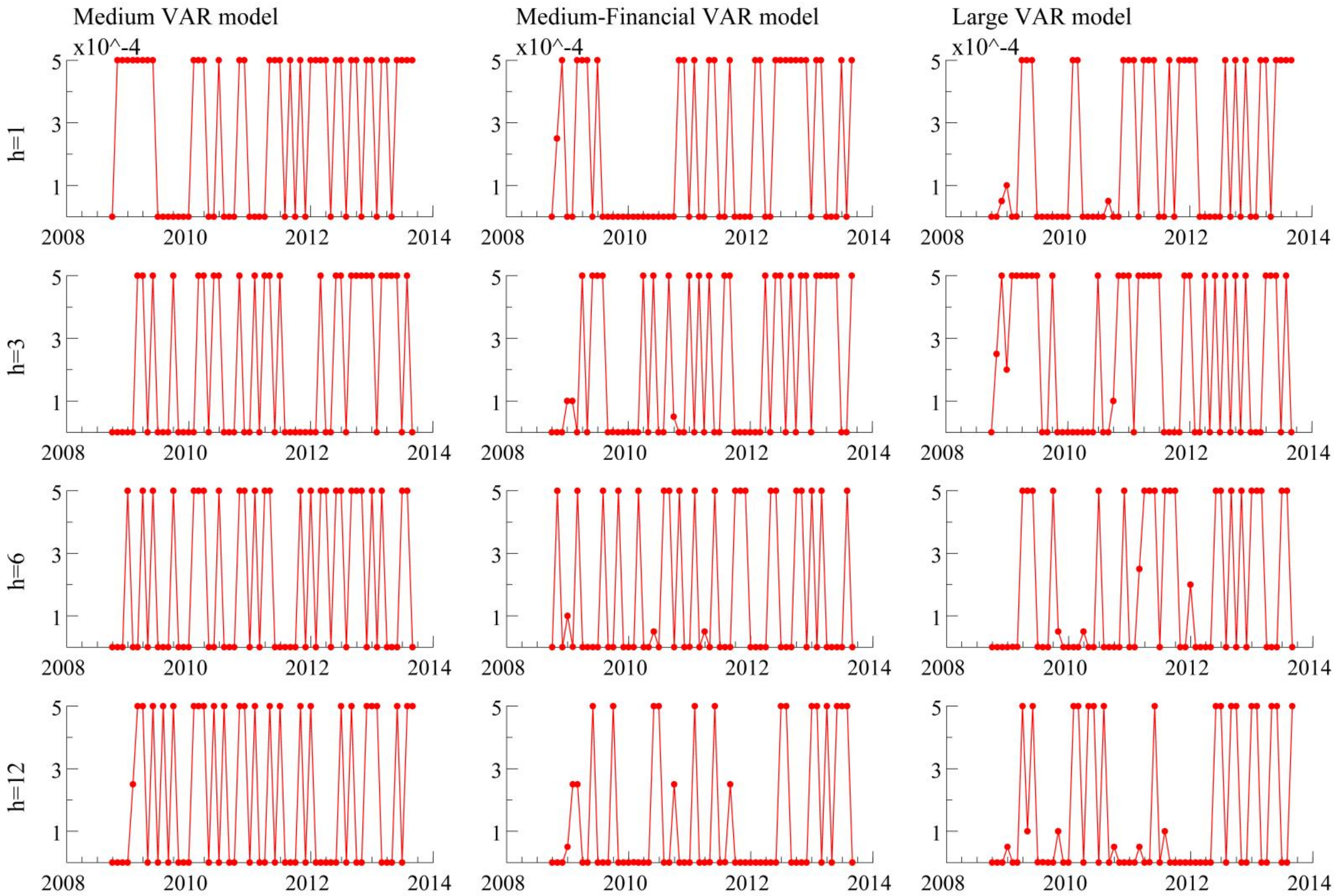
Notes: Transformation codes: 1 no transformation, 2 first difference, 3 second difference, 4 log, 5 first difference of logged variables, 6 second difference of logged variables, * Seasonally adjusted.

Fig. 1 Evolution of industrial production index, outstanding loans and financial systemic stress index



Notes: The variables have been deseasonalized (except for the FSSI), standardized and scaled from 0 to 100 using the logistic transformation. All variables are sampled at monthly frequency. For the construction of the FSSI see Louzis and Vouldis (2013).

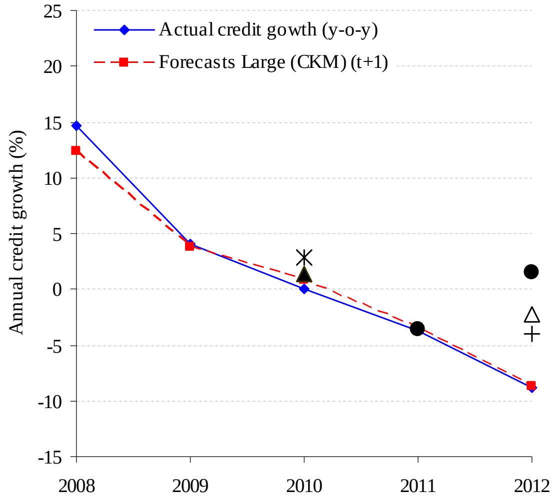
Fig. 2 Results for the shrinkage hyperparameter λ using the CKM method



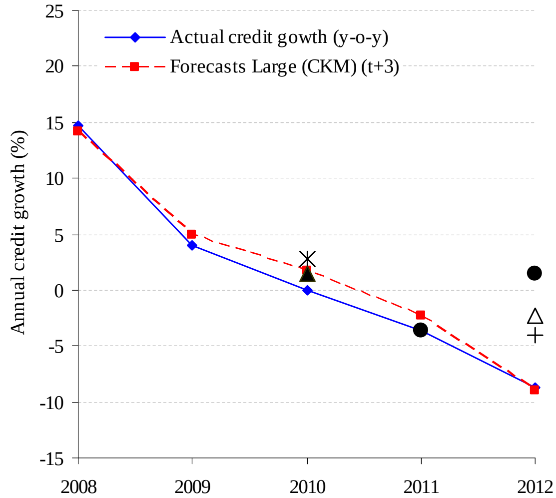
Notes: The CKM refers to the method proposed in Carriero et al. (2009)

Fig. 3 Model based and IMF based annual credit growth forecasts

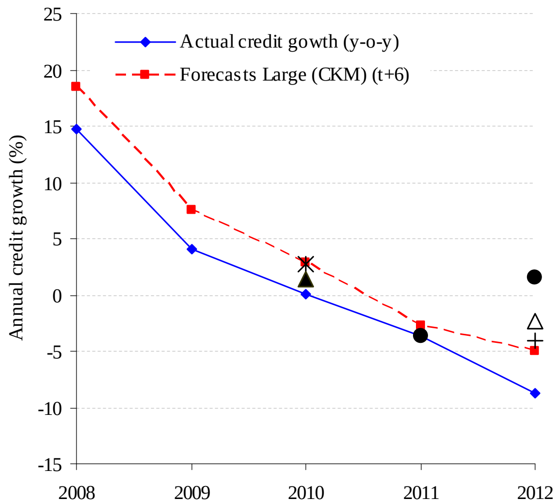
A. One month ahead forecasts



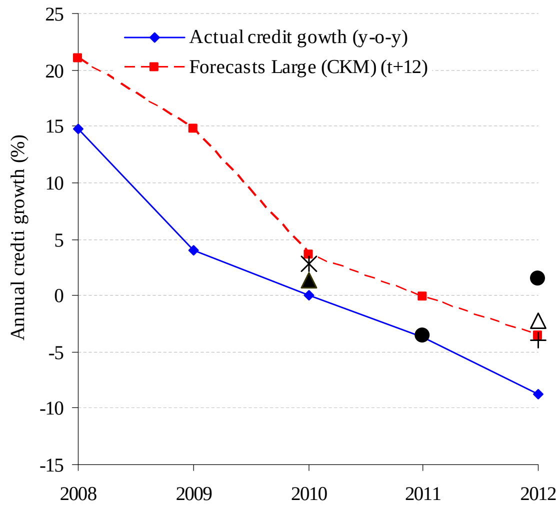
B. Three months ahead forecasts



C. Six months ahead forecasts



D. Twelve months ahead forecasts



Notes: The forecasts were produced using the *Large (CKM)* model. *Asterisk* denotes credit growth forecasts from the IMF country report No 10/286 – Sep. 2010, *filled triangle* denotes credit growth forecasts from the IMF country report No 10/372 - Dec 2010, *filled circle* denotes credit growth forecasts from the IMF country report No 11/75 - July 2011, *empty triangle* denotes credit growth forecasts from the IMF country report No 11/351 - Dec. 2011 and *cross* denotes credit growth forecasts from the IMF country report No 12/57 - Mar. 2012.

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