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Convergence in solvency and capital centralization: A B-VAR analysis for high-income and euro area countries

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Abstract

We apply a B-VAR technique to 28 high-income countries and 11 Euro area countries in 1999–2019 to analyze the causal relationships between centralization of capital measured in terms of network control and solvency conditions represented by the difference between GDP growth and interest rate. Results show a relationship that goes in two directions. First of all, divergent solvency conditions lead to an average increase in capital centralization and its greater convergence between countries. In turn, an average increase in capital centralization and its greater convergence produces a convergence of solvency conditions between countries. These outcomes are consistent for both groups of high-income countries and Euro area countries. Finally, in the group of high-income countries, we also note that an average deterioration in solvency conditions leads to a convergence of capital centralization between countries.

KEYWORDS

B-VAR models, centralization of capital, corporate ownership and control, divergence, network analysis, structural convergence

JEL CLASSIFICATION

C11, D85, E32, E5, G34

1 | INTRODUCTION

In Marx's view, the centralization of capital corresponds to the tendency to centralize capital control in a few's hands. Essentially, this phenomenon occurs due to liquidations, acquisitions, and control of the weaker capitals by the stronger ones. Marx speaks in this sense of the expropriation of the capitalist by the capitalist and evokes the famous allegory of Bruegel the Elder: the big fish eats the little fish. This tendency has always been a subject of great scientific interest (Leontief, 1938). It assumes relevance nowadays with current trends in corporate mergers, the concentration of share control, and rising market power (Mauro & Zhou, 2021).

Capital centralization, however, has also been a problematic theoretical and empirical issue, only rarely examined in depth. In recent years there have been some signs of openness of the mainstream literature to deal with updated interpretations of Marxian methodology (Blanchard & Brancaccio, 2019; Acemoglu & Brancaccio, 2021, commented in Brancaccio & De Cristofaro, 2022). However, the prevailing literature neglected or criticized the specific tendency towards capital centralization (Acemoglu & Robinson, 2015; De Grauwe & Camerman, 2002). Moreover, capital centralization has found few opportunities for further study even in the heterodox field due to some difficulties in the definition of the concept and its empirical verification (Sau, 1979). In the last few years, however, the situation has partly changed. Based on techniques borrowed from the theory of complex networks, some recent studies have elaborated measures of capital centralization, showing that global capital is highly centralized in the hands of a few top holders (Glattfelder & Battiston, 2009; Vitali et al., 2011). Brancaccio et al. (2018) also found that the fraction of "global big capitalists" controlling the global ownership network is less than 2% of total shareholders and further decreased between 2001 and 2016. However, although the literature on these issues is attracting attention, there is little empirical work on the dynamic relationships between capital centralization and macroeconomic trends, and none that wonders about the possible connections between solvency conditions and capital centralization in a multi-country setting. This paper aims to fill this gap.

In particular, we aim at analyzing the possible links between solvency conditions and capital centralization by evaluating whether and to what extent divergence or convergence in solvency across countries can interact with divergence or convergence in their different degrees of capital centralization. Specifically, we address the following research question: what are the relationships between capital centralization and solvency? How do these relationships play out across countries?

The first question relies on a new interpretation of the Marxian thesis of a tendency towards capital centralization. In its simpler and more vulgarized versions, the theory of centralization of capital focuses mainly on the ability of economies of scale to influence the capitalist struggle by favoring larger firms over smaller firms. This new interpretation does not deny the possible influence of economies of scale but focuses on another aspect of the phenomenon, which concerns the possible interdependencies between centralization of capital and solvency conditions in the economic system. The basic idea, in a nutshell, is twofold: on the one hand, economic policy can make solvency conditions more or less stringent, and thus can affect the pace of capital centralization, that is to say, the capacity of capital relatively stronger and more solvent to destroy or engulf weaker and insolvent capital; on the other hand, the centralization of capital changes the structure of economic and political power, and can therefore in turn affect economic policy decisions regarding solvency. In our analysis, the solvency conditions in the economic system have significant repercussions on the structure of the economy examined. These conditions verify whether the profits are on average sufficient to repay maturing loans and thus determine the average solvency of companies. It can be shown that, among other things, these conditions depend on the growth rate - which under certain assumptions contributes to determining the rate of profit - and on the interest rate, that is, variables also influenced by the

orientations of economic policy and in particular of the monetary policy. The so-called "central banker's solvency rule" is also derived from these conditions (Brancaccio, 2010; Brancaccio et al., 2020; Brancaccio & Fontana, 2013; Brancaccio & Suppa, 2012). By determining the solvency conditions of the economic system, economic policies can have an impact on the degree of centralization of capital: more stringent solvency conditions can fuel bankruptcies and favor liquidations, mergers, acquisitions, and controls of weak capital by the strongest capital, resulting in an acceleration of the centralization of capital in fewer and fewer hands (Brancaccio & Fontana, 2016). Finally, capital centralization can change the structure of social relations of production and related political power. In this way, it can influence economic policy lines, particularly the central banker's "solvency rule" (Brancaccio & Veronese Passarella, 2021). This paper provides further empirical validation of this theoretical literature.

Once we have analyzed the relationship between the solvency conditions of the economic system and the centralization of capital, we study if con(di)vergent dynamics in the conditions of solvency across countries are connected to similar dynamics of con(di)vergence in the degree of capital centralization. This focus is of foremost importance as it helps us to investigate if different solvency conditions can lead to homogeneity or heterogeneity in capital control structures; or to study if similar degrees of capital centralization are linked to convergent or divergent macroeconomic performances. More in general, we add to the literature on structural convergence (see among others Araujo, 2013; Botta, 2009; Fagerberg, 1995; Kaldor, 1972) studying how the dynamics of solvency in different countries impact capital control structures and vice-versa.

The starting point of this new line of research is a measure of share ownership networks calculated in terms of the so-called "network control" or "net control". Net control is obtained by using a graph traversal algorithm known as breadth search first (BFS). This algorithm navigates the ownership network of shares of listed companies and allows to select the fraction of the shareholders that own 80% of the control shares in the stock markets (Glattfelder & Battiston, 2009; Vitali et al., 2011). In subsequent works, net control was interpreted as a measure of capital centralization and then applied to a new database to elaborate the first empirical analysis on the global tendency towards centralization of capital over time. Results show empirical evidence of the tendency towards capital centralization: top holders who cumulatively control the 80% of the shares listed on the world stock exchanges are less than 2% of owners and this little percentage of "global big capitalists" further decreases between 2001 and 2016 (Brancaccio et al., 2018). Then, it was possible to investigate the dynamic relationships between capital centralization and macroeconomic trends. By adopting a Bayesian VAR (B-VAR) technique, new analyses were dedicated to the possible causal relationships between monetary policy, capital centralization and GDP from 2001 to 2016 in the United States and the Euro area. Findings suggest that a tightening monetary policy leads to a higher centralization of capital. In turn, a higher centralization of capital induces a reduction of GDP with respect to its trend (Brancaccio et al., 2019).

We build a bridge between the emerging studies in the field of network analysis and the standard econometric techniques to answer these research questions. Specifically, we first compute the measure of capital centralization at a country level by using a graph traversal algorithm known as breadth search first (BFS). This algorithm navigates the ownership network of shares of listed companies and allows to select the fraction of the shareholders that own 80% of the control shares in the stock markets (Glattfelder & Battiston, 2009; Vitali et al., 2011). This measure of share ownership networks known as "network control" or "net control", is a proxy of capital centralization (Brancaccio et al., 2018). Then, we examine the possible relationships between capital centralization in terms of network control and a standard measure of private and public debt sustainability expressed by the difference between GDP growth and interest rate, which is also considered as the solvency conditions of the economic system (Brancaccio, 2010; Brancaccio et al., 2020; Brancaccio & Fontana, 2013, 2016; Brancaccio

& Suppa, 2012). Finally, we analyze the relations between capital centralization and the solvency conditions in terms of international convergence or divergence calculated as standard deviation across countries. Focusing on high-income countries and Eurozone countries over 2 decades, we jointly investigate the possible interplay between convergent or divergent solvency dynamics expressed in terms of the difference between GDP growth and interest rate and convergent or divergent tendencies of capital centralization expressed in terms of network control.

Our empirical strategy is close to the method applied by Brancaccio et al. (2019) to study causal relationships between monetary policy, capital centralization, and GDP from 2001 to 2016 in the United States and the Euro area. However, our contribution differs from Brancaccio et al. (2019) along three main dimensions. First, we explore new relationships which have not been considered previously. Second, while in Brancaccio et al. (2019) international patterns are neglected, here we also focus on convergence and divergence across countries to study if similar schemes emerge. Finally, with respect to Brancaccio et al. (2019), we exploit a remarkable spatial specification of the database with 28 high-income countries and 11 Euro area countries, and an extension of the time frame that goes from 1999 to 2019. We employ yearly data as ownership relationship information are available - in a reliable way among different countries and legislation - only with a yearly frequency. The econometric analysis is carried out by using a B-VAR technique based on Minnesota prior. Since the dataset covers a limited period, this B-VAR specification proves to be the most appropriate for dynamic analysis (Impulse response functions (IRFs) and Forecast variance decomposition functions (FEVDs). It also fits the data better (lower RMSE and MAE in the model selection analysis) than VAR approaches and other B-VAR specifications.

As we shall see, our main findings can be summarized by the following two-way relationships between solvency and centralization. First of all, Divergent solvency conditions between countries lead to an average increase in capital centralization and its greater convergence between countries. Furthermore, an average increase in capital centralization and its convergence between countries generates a convergence of solvency conditions between countries. In summary, solvency divergence leads to higher and convergent capital centralization, which in turn produces solvency convergence. These results are consistent for both groups of high-income countries and Euro area countries. Finally, in the group of high-income countries we also note that an average deterioration in solvency can lead to a convergence of capital centralization between countries.

The article is organized as follows. In Section 2 we introduce the literature and the theoretical background behind the econometric analysis. In Sections 3 and 4 we present the method and data applied. In Sections 5 and 6 we comment on the results for high-income countries and Euro area countries, respectively. Section 7 provides robustness to the method adopted and to the results. Section 8 concludes.

2 | RELATED LITERATURE AND SCOPES OF THIS WORK

The econometrics of networks is a recent strand of research employing measures gathered with network analysis techniques in econometric models (Graham & de Paula, 2020). Networks econometrics has been applied to a broad range of economic issues such as systemic risk (Anufriev & Panchenko, 2015; Billio et al., 2012), price formation (Vignes & Etienne, 2011), carbon emission (Jiao et al., 2018), innovation (Maggioni et al., 2011; Wanzenböck et al., 2015), consumption choices (Richards et al., 2014), gender inequality (Walther et al., 2019).

However, in this literature, the econometric analysis of ownership networks and their possible relationships with macroeconomic variables is still neglected. A first attempt to link ownership networks

and macro-dynamics is the work by Brancaccio et al. (2019), who use a B-VAR model to provide first empirical evidence on the relationships between monetary policy, GDP and capital centralization calculated in terms of network control. Findings suggest that a tightening monetary policy increases network control, which results in a higher centralization of capital. A higher centralization of capital, in turn, leads to a reduction of GDP with respect to its trend. We build on the same B-VAR methodology to further investigate the relationships between capital centralization and macroeconomic dynamics. In particular, here we examine the possible links between centralization expressed in terms of network control and a measure of solvency condition in the economic system represented by the difference between the GDP growth rate and the interest rate.

What are the theoretical links between the variables examined in this analysis? A possible nexus goes back to a new interpretation of the Marxian thesis of a tendency towards capital centralization, which considers the possible interdependencies between this tendency, the solvency conditions in the economic system and the directions of economic policy. First, public and private debt sustainability can be expressed in terms of the difference between the GDP growth rate and the interest rate, which is a feature common to various strands of macroeconomic literature (Blanchard, 2019; D'Erasmo et al., 2016; Ghosh et al., 2013; Mauro & Zhou, 2021; Sylos Labini, 2003). Then, this notion of debt sustainability can be linked to a more specific condition of solvency, which is dependent on general policy lines, and in particular on monetary policy decisions summarized in the so-called "solvency rule" of the central banker (Brancaccio, 2010; Brancaccio et al., 2020; Brancaccio & Fontana, 2013; Brancaccio & Suppa, 2012). Finally, more stringent solvency conditions can fuel bankruptcies such as to favor liquidations, mergers, acquisitions and controls of weak capital by the strongest capital, resulting in an acceleration of the centralization of capital in fewer and fewer hands (Brancaccio & Fontana, 2016; on the relations between financial distress and mergers see also Shaut & Mili, 2011). Capital centralization, in turn, can change the structure of social relations of production and related political power, and in this way it can influence economic policy lines and in particular the "solvency rule" of the central banker (Brancaccio & Veronese Passarella, 2021).

Based on such theoretical premises, in this paper, we analyze the possible relationships between centralization of capital in terms of network control on one hand and solvency in terms of the difference between the GDP growth rate and the interest rate on the other, both between 28 high-income countries and between 11 Euro area countries, in the period 1999–2019. Once we have analyzed the relationship between the solvency conditions of the economic system and the centralization of capital, we study how this relationship plays out across countries. Specifically, we examine the possible relationships between these variables by looking at the average trends in net control and solvency and their convergence or divergence calculated in terms of standard deviations across countries.

This attention to convergence or divergence phenomena deserves further reflection, as its purpose is manifold. For example, one of our aims is to investigate if countries showing similar solvency conditions also have similar capital centralization degrees. On the other hand, we are also interested in studying if asymmetric solvency conditions are related to homogeneous or heterogeneous dynamics of capital centralization. Further, we ask if convergence or divergence in capital centralization are associated with similar or dissimilar macroeconomic performance. This focus on convergence and divergence across countries allows us to analyze the interplay between solvency and capital centralization dynamics.

Most of the literature on economic convergence relates to income and productivity convergence questions and has flourished due to the interrelatedness of these topics with neoclassical growth theory (Abramovitz, 1986; Barro, 1992). Here we deal with a different notion of convergence and refer to the literature on structural convergence. This is a multifaceted topic embracing issues on convergence and divergence in growth paths (Fagerberg, 1995), "cumulative causation" (Botta, 2009; Kaldor, 1972),

structural economic dynamics (Araujo, 2013), technological spillovers (Palan & Schmiedeberg, 2010), differences or similarities in corporate structures. This last line of research dedicated to divergence or convergence in ownership structures identifies two significant trends (Rasheed & Yoshikawa, 2012). Some authors have argued that convergence in the governance structure of corporations around the world towards the Anglo-American dispersed ownership model is inevitable (Goergen et al., 2005; Hansmann & Kraakman, 2004; Krafft et al., 2014). Others maintain that such convergence will not occur because of institutional path dependence (Bebchuk & Roe, 1999; Khanna et al., 2006; Matos & Faustino, 2012; O'Sullivan, 2000). A similar dichotomy is found in studies that have questioned the relationship between ownership structure and macroeconomic performance (for a wide review on the topic see Morck et al., 2005 and the literature therein). In line with standard corporate governance theory, several studies suggest a negative correlation between ownership concentration and output growth (Djankov et al., 2008; La Porta et al., 1998, 1999). On the other hand, some authors find that more concentrated ownership can speed up labor productivity (Claessens & Djankov, 1999) and growth (Gatti, 2009). Overall, though different in subject and results, the cited studies share two main features: they analyze ownership structure within firms and countries and separately analyze either the convergence of ownership structures or the macroeconomic impact of ownership concentration.

Inspired by this literature, in the following sections we analyze whether and to what extent divergence or convergence in solvency conditions across countries can interact with divergence or convergence in their different degrees of capital centralization.

3 | METHODOLOGY

Our work aims to determine the dynamic responses of the mean and standard deviation of capital centralization to mean and standard deviation of solvency condition shocks and vice versa using the impulse response and variance decomposition functions. In this framework, we opted for the econometric method of Bayesian VAR (B-VAR).

According to the literature on Panel Data and their limitations (Hill et al., 2020) the statistical behavior of these estimators can suffer for *low statistical power* when the dataset is of limited size (in our case 28 countries by 21 years, or 11 Euro area countries by 21 years) and when the variability of each regressor is not large enough during the observed period. Using a panel with fixed effects the coefficients have a large standard deviation that makes the model estimation prone to errors. Despite some techniques exists to address and improve on these concerns, we believe that the BVAR methods - that focus on the "shrinkage" of the standard errors of the estimated model parameters - have the potential to improve the estimation while keeping higher the statistical power leveraging on the "Bayesian methods".

The B-VAR approach helps overcome a potential limitation of our analysis consisting of a dataset with limited observations (1999–2019). In this case the application of the VAR methodology may lead to problems of identification, misspecification, overfitting due to high dimensionality and the poor forecasting (Auer, 2019; Canova, 2007; Doan et al., 1984; Kanngiesser et al., 2020; Litterman, 1986). Specifically, in a standard VAR model, we estimate many parameters even though some of them are scarcely significant. The B-VAR model, instead, by placing prior distributions as restrictions over these parameters (assuming that they are more likely to be close to zero than the coefficients on shorter lags) it shrinks the VAR model toward a more parsimonious model reducing parameter uncertainty while improving both forecast accuracy and sample fitting (Ca' Zorzi et al., 2015; Gimet et al., 2019).

By applying the Bayesian method to VAR models, we select the priors that better capture features of interest to the investigator (non-sample information) and mitigate the problem of VAR's overfitting. In contrast to the frequentist approach, where the process generating the data is random and the parameters are known, in the Bayesian methodology we do not need to make a priori assumptions about the data generating process (DGP) since the data are given and the parameter of interest are considered random and characterized by a probability distribution. In particular, if we assume that Y are the data available and θ are the parameters that we want to estimate by applying the Bayes' theorem the prior information $p\ (\theta)$ is formally combined with the information contained in the data and captured by the likelihood function $L(Y/\theta)$ of the model with the goal of producing a tractable posterior function that generally has the same density function of the prior. After looking at the data, this posterior contains what the researcher knows about the model parameters.

$$p\left(\frac{Y}{\theta}\right) \propto L\left(\frac{Y}{\theta}\right) * p(\theta) \tag{1}$$

We start from a VAR methodology that typically utilizes simultaneous equation modeling and several endogenous variables. In a general VAR model, each endogenous variable is explained by its lagged values and by the lagged values of all other endogenous variables:

$$Y_t = c + B_1 Y_{t-1} + B_2 Y_{t-2} + \ldots\ldots + B_q Y_{t-q} + u_t \tag{2}$$

More precisely, in the VAR process of order q that is the maximum lag, c is the vector of constant variables, Y_t is the vector of the endogenous variables (N), B are the coefficients of a $(N \times N)$ matrix, and u_t is a zero mean independent white noise process with non-singular time invariant variance-covariance matrix $E\left(u_t u_t'\right) = \psi$. Therefore, to estimate the VAR model, we can write the VAR (q) with a concise matrix notation:

$$Y = XB + U \tag{3}$$

Where:

(a) $Y_t = (y_1, \ldots\ldots\ldots\ldots, y_T)'$. The matrix dimension is $T \times N$ (number of observations $\times$ each dependent variable).

(b) $X = (x_1, \ldots\ldots\ldots\ldots, x_T)'$ with $X_t = \left(1, y_{t-1}', \ldots\ldots\ldots\ldots, y_{t-q}'\right)'$.The matrix dimension is $T \times k$ where $k = NQ + 1$ (number of observations $\times$ each lagged dependent variable).

(c) $B = \left(c, B_1 \ldots\ldots\ldots\ldots, B_q\right)'$. The matrix dimension is $k \times N$ (number of constant/autoregressive terms $\times$ each lagged dependent variable).

(d) $U = (u_1, \ldots\ldots\ldots\ldots, u_T)'$ collects the error terms. The dimension is $T \times N$ (number of error terms $\times$ each dependent variable).

The autoregressive representation presented above can be completed with the specification of a prior distribution of the coefficients. In setting the prior distribution we use the Litterman-Minnesota prior (Litterman, 1986) for its success in the dynamic analysis and for its superior precision in macroeconometric forecasting when the dataset is short. Specifically, in the Minnesota prior all equations are centered around a random walk process with drift such as:

$$y_t = c + y_{t-1} + u_t \tag{4}$$

which simplify the form of the matrix B shrinking the coefficients on the diagonal towards one and the remaining coefficients towards 0. In this way it is possible to reduce the risk of overfitting.

In the so-called Minnesota (Litterman) prior the beliefs of the investigator are specified as:

$$B \sim \left(\beta, \sum_{e}\right) \tag{5}$$

where β (the parameter of our interest) and the matrix of variance-covariance $\sum_e$ are functions of a small number of hyperparameters. In particular, this prior assumes that the values of β are all the same (hyperparameter μ) and are set close to zero, while the covariance prior is non-zero. When the macroeconomic series are persistent the value of μ is chosen close to the unity. In general, the variance-covariance matrix is assumed to be fixed, diagonal and known where all coefficients, except their own lags are equal to zero.

Hence, we assume that: a) there are no relationships between the coefficients of the various equations of the B-VAR model; b) the most recent lags provide more reliable information rather than the more distant ones; c) the lags of the other variables have less information than the lags of own variable.

If we replace $\sum_e$ with its estimate from the data V we obtain the prior distribution of B based on the Minnesota prior as a *priori* normal and conditional upon the variance-covariance matrix $\sum_e$:

$$p\left(B/\sum_{e}\right) \sim N(\beta, V) \tag{6}$$

Then, we can group the explanatory variables of each VAR equation into three blocks: 1) the own lags of the dependent variable; 2) the lags of the other dependent variables; 3) exogenous variables (Koop & Korobilis, 2010). Since the prior covariance matrix V is diagonal we do not specify all the elements of V but we select only the following scalars (Koop & Korobilis, 2010):

$$V_{ijj} = \begin{cases} \dfrac{\lambda_1}{r^2} \text{ for coefficients on own lag } r \text{ for } r = 1, \ldots\ldots, p \\ \dfrac{\lambda_2}{r^2} * \dfrac{\sigma_{ii}}{\sigma_{jj}} \text{ for coefficients on lag } r \text{ of variable } J \neq j \\ \lambda_3 * \sigma_{ii} \text{ for coefficients on exogenous variables} \end{cases} \tag{7}$$

Given a diagonal variance-covariance matrix we specify the prior covariance for β considering the three hyperparameters:

(a) λ_1 controls the relative importance of sample and prior information. If it is large the prior becomes uninformative (the likelihood would be relatively flat) and the posterior estimates collapse into an unrestricted VAR model. If it is small prior information dominates.
(b) λ_2 sets the relative importance of cross-variables lags (i.e. lagged variable i-th in j-th equation with $i \neq j$).
(c) λ_3 regulates the relative importance of exogenous variables (i.e. a constant; dummy variables).

Once the prior covariance is set, the mode and the mean of the posterior of β will show a normal distribution.

4 | DATA

The focus of our work is a B-VAR analysis on solvency conditions and capital centralization in 28 high-income countries and 11 Euro area countries between 1999 and 2019. The high-income countries list is formed by countries that represent the largest economies in terms of average GDP of the last five years (2016–2019) and have a ratio of total market capitalization over GDP larger than 20% (GDP indexed at the year 2010). Based on these criteria, we select 31 countries: United States, China, Japan, Germany, France, India, United Kingdom, Brazil, Italy, Canada, Russian Federation, Spain, Australia, Korea, Mexico, Turkey, Indonesia, Netherlands, Saudi Arabia, Switzerland, Poland, Belgium, Norway, Austria, South Africa, Thailand, Sweden, United Arab Emirates, Colombia, and Malaysia. Then we have to leave out United Arab Emirates, Saudi Arabia and Thailand for the lack of data on the long-term interest rate. So, the group of high-income countries examined here is comprises 28 countries. For the Eurozone, we have chosen the first 11 countries that jointly adopted the euro since 1999: Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain.

The dataset for both high-income countries and Euro area countries includes the following time series: 1) "network control" or "net control" (*nc*, hereafter); 2) logarithm of the nominal GDP transformed in the GDP growth rate making the first difference between the log GDP_t and the log GDP_{t-1} (*g*, hereafter); 3) nominal long-term interest rates with 10 years maturity (*i*, hereafter). The data of nominal GDP were extracted from the World Bank database. The nominal long-term interest rate with 10 years maturity and the net control are drawn from the Eikon database. All series of our study are annual data, except the ones regarding long-term interest rates that are monthly and have been transformed in annual observations by taking the arithmetic mean over 12 months. For both high-income countries and Euro area countries the data cover 1999–2019. We do not extend the sample before 1999 since the net control time series start from that year. The data just described allow us to measure the means and the standard deviations of solvency conditions and capital centralization (on the use of mean, variance, and standard deviation in the VAR literature see, among many others: Amisano & Giannini, 1997; Canova et al., 2012; Stock & Watson, 2005).

As mentioned above, the definition of solvency is derived from previous contributions on the subject. The solvency condition in the economic system verifies whether the profits are on average sufficient to repay maturing loans and thus determine the average solvency of companies. Under given assumptions, in macroeconomic equilibrium this condition depends on the growth rate - which contributes to determining the rate of profit - and on the interest rate (Brancaccio, 2010; Brancaccio et al., 2020; Brancaccio & Fontana, 2013, 2016; Brancaccio & Suppa, 2012). Then, as a proxy of solvency conditions at a country level here we use the difference between *g* and *i* that we insert in the B-VAR models as a unique aggregate variable *(g-i)*.[1] We compute the difference *(g-i)* per each country in each given year and then we calculate the mean of *(g-i)* of all countries per each year. Then, we create the "network control" or "net control" (*nc*) data, a measure of corporate control used in the ownership network literature (see Brancaccio et al., 2018, 2019; Glattfelder & Battiston, 2009; Vitali et al., 2011). This measure attributes direct and indirect control within and across corporations to each unit of our sample.[2] More precisely, the *nc* expresses a measure of ownership mediated by the network

[1]It should be noted that since we do not consider inflation or make assumptions about expectations in our empirical analysis, there is no distinction between solvency in real or nominal terms. Therefore, the use of the difference (*g-i*) in real or nominal terms is not decisive for our results. Future research can be devoted to further assumptions about expectations.

[2]The variable (*g-i*) plays the role of the y_t variable in the B-VAR model while *nc* is equivalent to the *x* variable of the Equation 3 (see Methodology).

trajectories that connect, in the shareholder network, a company or an individual to all its direct or indirect shareholding positions. We computed the *nc* variable using a graph traversal algorithm known as breadth search first (BFS) that sum all direct and indirect positions of a shareholder avoiding potential cycles and duplicates in the network paths (for more details see also Appendix). This technique navigates the network (where nodes are companies/investors, and links are ownership relationships) link by link, creating tree-like structures with the strict rule of avoiding counting links more than once. In this way, once the- BFS algorithm has explored the network, the net control part of the computation becomes the sum of the ownership contributions of every individual company/investor. The ownership relationships initiating on a company (in network terms, this starting node is known as "root node") develop to form a tree. Each link represents an ownership relationship. If the percentage value of this link is above a given threshold - usually 5% in the literature (Zingales, 1994, 1995) - this relationship is considered as "control", hence the term "net control". By considering only the links where the percentage is above the control threshold and summing up, we obtain the net control of each company/investor. Finally, the sum of the net control of each company can be grouped at the country level, creating a national measure for each country. Instead of using the absolute values of net control (that are expressed in USD and account for the entire market total amount of controlling ownership) we consider the fraction of the shareholders, over the total number, that own 80% of the overall net control. This level of market share has proven to be robust and can be eventually substituted using other lower/upper threshold levels (see supplementary for a detailed discussion). Finally, we have one ownership network per country and per year examined. We calculate the variable "net control" from the ownership network that we call *nc* in the paper.

The term *nc* can be considered a measure of capital control centralization. With respect to the previous version of the *nc* database (Brancaccio et al., 2018, 2019), the one used in this paper is much larger, counting a total of 5,062,314 nodes for both companies/investors that are exchanging 31,948,027 ownership positions in the period examined. Furthermore, the new database has a longer timespan (1999–2019) allowing to capture a better dynamic. It has no lower limit in terms of the market capitalization of the companies, which implies that the new database can also report smaller investments. For the scopes of this paper, we calculate the average net control *nc* among countries per each year examined.

Finally, we compute per each year the standard deviation of solvency as the distance of *(g-i)* of each country from the mean of all countries. In the same way, we calculate the standard deviation of capital centralization expressed by the *nc* variable. The standard deviations help to visualize whether significant differences exist among the countries in terms of dispersion. The more the observations are dispersed, the higher the variability and vice versa. Thus, a lower standard deviation signifies less variability while a higher standard deviation indicates more spread out of data. In this sense, our experiment is not far from the conventional sigma-convergence tests (Barro, 1992; see Matos & Faustino, 2012 for a specific sigma-convergence test on corporate structures). We shall define an increase in standard deviation as a phenomenon of divergence across countries while a decrease in standard deviation as a convergence phenomenon across countries. We examine the dynamic relations between our key variables (net control (*nc*) and solvency expressed in terms of the difference between the GDP growth rate and the interest rate *(g-i)*) using two main types of analysis: impulse response functions (IRFs) and forecast error variance decomposition functions (FEVDs). We use these functions for two reasons: to track the effects of a sudden change in the average and standard deviation of solvency *(g-i)* on the average and standard deviation of capital centralization *nc*, and to analyze the impact of changes in the average and standard deviation of capital centralization *nc* on the average and standard deviation of solvency *(g-i)*. When we refer to averages, we use the terms *(nc)* and *(g – i)*, while when we refer to standard deviations, we use the terms *STD (nc)* and *STD (g – i)*.

The B-VAR models are fitted with the lag length equal to 2 and selected by minimizing the Bayesian information criterion (BIC). The models are estimated using the standard Minnesota prior, whose tightness is chosen as follows: λ1 (prior information) is set to a small value since the prior beliefs are informative to the sample information. In this case the posterior mostly mirrors prior information. λ2 (cross variables lag) is assumed to be greater than zero since the information of cross variable lags is important while λ3 (exogenous variables) is set close to zero because the exogenous variables information is not relevant for our analysis. All the variables in the model are considered of a similar scale.

5 | IMPULSE RESPONSE AND FORECAST ERROR VARIANCE DECOMPOSITION FUNCTIONS IN HIGH-INCOME COUNTRIES

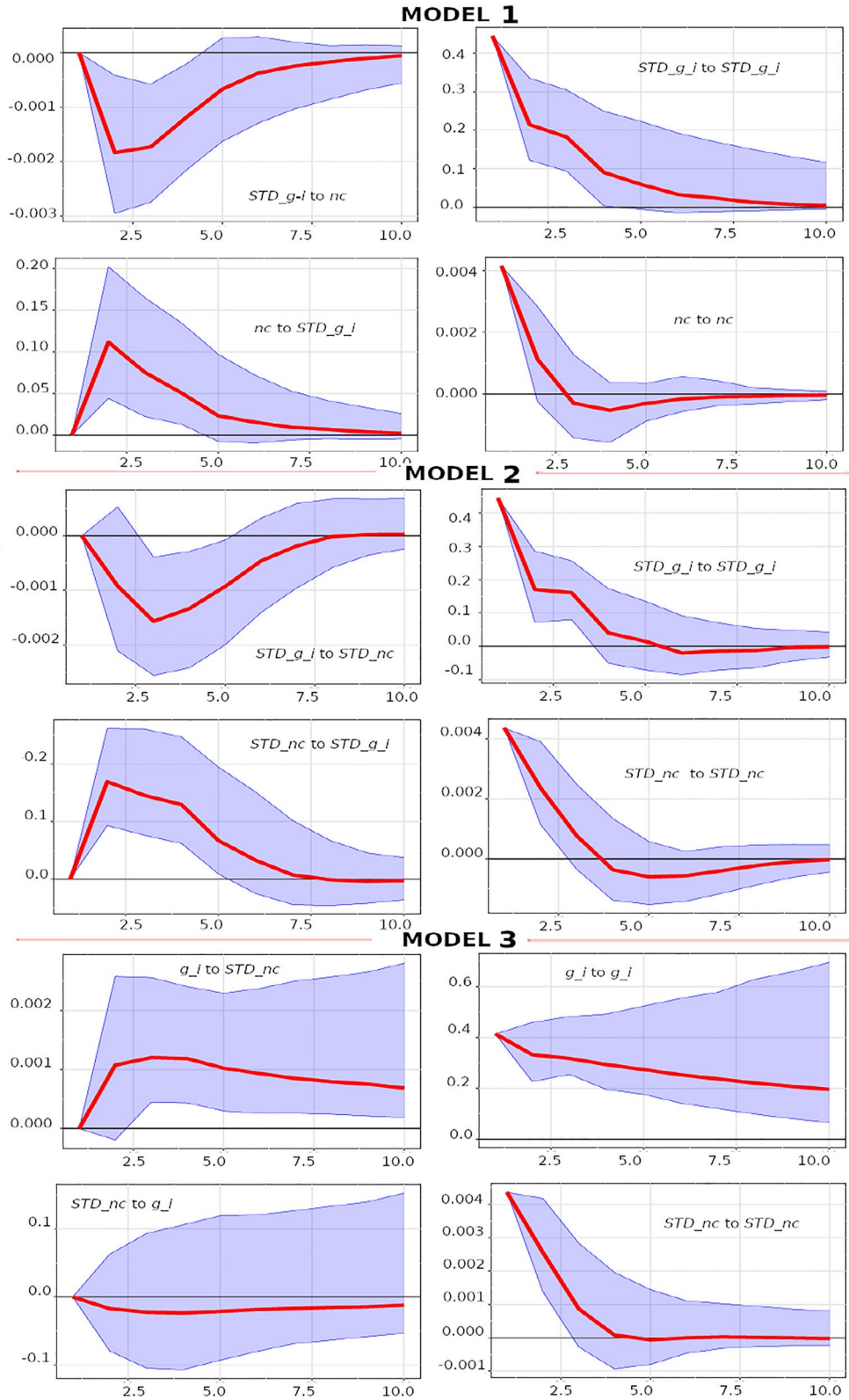
In this paragraph we specify four B-VAR models of the 28 high income countries relative to our key variables (net control (*nc*) and solvency expressed in terms of the difference between the GDP growth rate and the interest rate *(g-i)*) in the following way:

- Model 1: STD (g-i) versus (nc) and vice versa;
- Model 2: STD (g-i) versus STD (nc) and vice versa;
- Model 3: (g-i) versus STD (nc) and vice versa;
- Model 4: (g-i) versus (nc) and vice versa.

In Model 1 we analyze the relation between the standard deviation of g-i and the average of nc. In Model 2 we consider the standard deviation of both variables. In Model 3 we examine the relations between the average of (g-i) and the standard deviation of nc. Finally, in Model 4 we investigate the relations between (g-i) and nc, both expressed in average values.

Figure 1 plots the IRFs relative to the three B-VAR models specifications. In each impulse response functions graph the shaded regions indicate the posterior coverage intervals corresponding to the 95% of the credible Bayesian sets obtained through Gibbs sampling using 1000 iterations. We do not report the impulse response functions for the relation (g-i) versus nc of the Model 4 because they were not significant. The detailed findings are included in the Appendix.

Here we describe the response of a variable to a shock from another variable for the bivariate B-VAR models Model 1, Model 2, Model 3 in 10 years until this effect dissipated. For the three B-VAR models we investigate the presence of statistically significant relationships and the relative impact between the variables. As illustrated in Figure 1, in Model 1 (STD (g-i) versus (nc)) we find a significant two-way relation between STD (g-i) and (nc). Specifically, a STD (g-i) shock (+10%) reduces (nc) of 0.02% after 2.5 years and the effect of the shock becomes not significant after 5 years (first row, first column, Figure 1, Model 1). On the other hand, STD (g-i) reacts positively to (nc) and the effect of the shock is felt for about 3 years (from 1.5 to 5 years) with a peak around 10% after 2.5 years (second row, first column-Model 1). In the Model 2 (STD (g-i) versus STD (nc)), too, we find a significant bi-directional relation between STD (g-i) and STD (nc). In detail, STD (g-i) negatively impacts on STD (nc). This effect, however, is significant only in the period between 2.5 and 5 years (first row, first column-Model 2). Meanwhile, STD (g-i) responds positively to a shock on STD (nc) and this effect remains significant over a longer period (1–6 years) (second row, first column-Model 2). Finally, in Model 3 ((g-i) versus STD (nc)) a shock on (g-i) leads to a one-way persistent in time increase of STD nc (by 0.01% after 3 years) (first row, first column-Model 3). In all these cases, the solvency response to a capital centralization shock is greater than the centralization response to a solvency shock.



To better understand the relative importance of each variable in affecting other variables we compute the forecast error variance decomposition functions (FEVDs) for all bivariate B-VAR models (Model 1, Model 2, Model 3) for the same time horizon of 10 years (Figure 2). The FEVD shows which portion of the forecast error variance in predicting a variable is due to the shock in another variable. The fitted B-VAR model relative to Model 1 shows a contribution of STD (g-i) around 40% to the variance of (nc) (first row, first column-Model 1). A minor contribution of about 10% is observed in the opposite direction, from (nc) to STD (g-i) (second row, first column- Model 1). In Model 2, STD (g-i) accounts for about 30% of STD (nc) forecast error variance after 10 years (first row, first column-Model 2). A similar contribution of about 30% is found from STD (nc) versus STD (g-i) (second row, first column-Model 2). Finally, in Model 3 (g-i) most of the variance of STD (nc) is due to (g-i) shocks (first row, first column-Model 3). The findings of forecast error decomposition functions confirm the robustness of the impulse response functions analysis.

6 | IMPULSE RESPONSE AND FORECAST ERROR VARIANCE DECOMPOSITION FUNCTIONS IN EURO AREA COUNTRIES

The same analysis conducted on the high-income countries is replicated on Euro area countries. We discuss here the results. We specify B-VAR (2) models with a constant consisting of these two key-variables (nc and g-i). Again, we set the priors $\lambda 1$ to a small value, $\lambda 2$ larger than zero and $\lambda 3$ close to zero. We report only the impulse response functions relative to Model 1 and 2 excluding Model 3 and 4 in which they were not significant. The IRFs and FEVDs results of Models 3 and 4 are shown in the Appendix.

The impulse response functions plotted in Figure 3 reveal that a unit shock on STD (g-i) results in a decline in (nc) of approximately 0.01% after 4 years and this effect becomes insignificant after 5 years (Model 1-left panel-first row, second column). The effect of (nc) on STD (g-i) is positive with a lag peak response of 1.5% after 3 years but lasting less than 5 years (Model 1- left panel-second row, first column). We also observe that the STD (nc) response turns significantly negative to STD (g-i) shock only in the period between 2.5 and 7.5 years (Model 2-left panel-second row, first column). We find a positive and more persistent STD (g-i) response to STD (nc) shock and this effect remains significant during up to 5 years (Model 2-left panel-first row, second column). As in the high-income countries group, in the Euro area solvency is more reactive to capital centralization shocks concerning centralization responses to solvency shocks.

In order to investigate how relevant is each shock in explaining the variation of each of the variables involved in the B-VAR models, in Figure 3 we also consider the forecast error variance decomposition functions (FEVDs) within the same time horizon of 10 years. The variance decomposition shows a significant contribution of around 10% of STD (g-i) to the variance of (nc) (Model 1-right panel-first row, second column). We note a weaker influence of about 2.5% in the opposite direction from (nc) to STD (g-i) (Model 1-right panel-second row, first column). Finally, STD (g-i) is significantly explained by STD (nc) shocks and vice versa (Model 2-right panel).

Apart from Model 3 that in the Euro area becomes not significant, the results from the impulse response and forecast decomposition analysis for the Euro area confirm those obtained by Models 1 and 2 for the high-income countries group.

FIGURE 1 B-VAR impulse response functions with 95% credible intervals (10-year horizon) – high-income countries

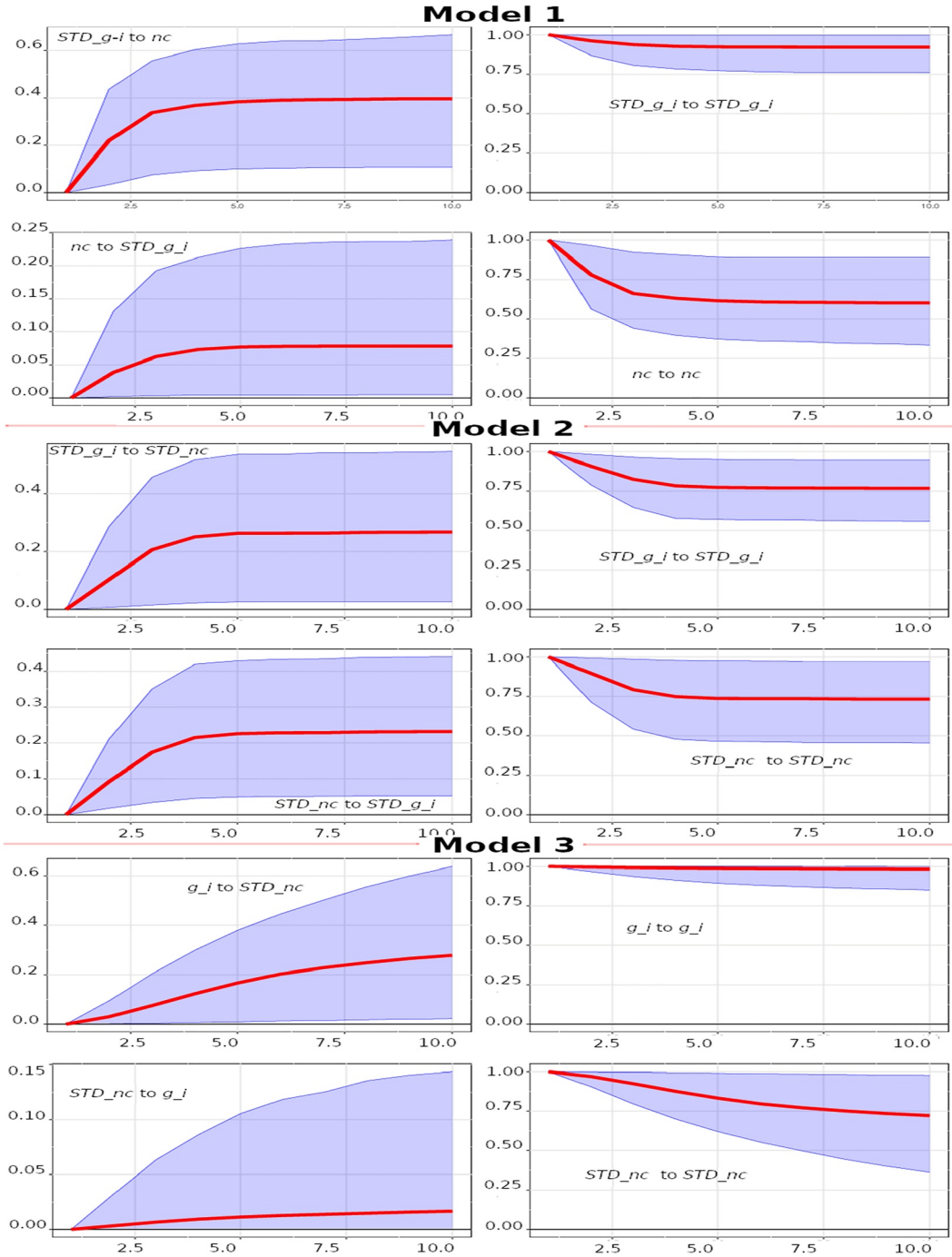


FIGURE 2 B-VAR forecast error variance decomposition functions with 95% credible intervals (10-year horizon) – high-income countries

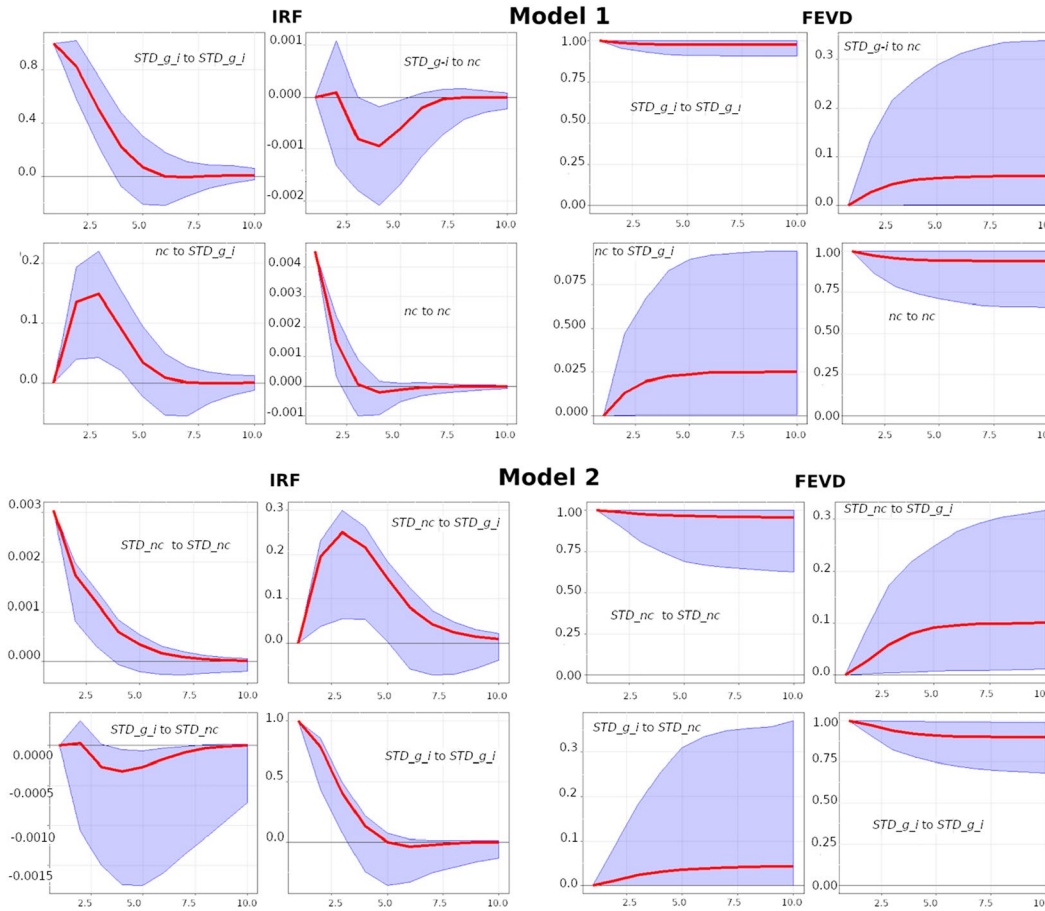


FIGURE 3 B-VAR impulse response functions and forecast error variance decomposition functions with 95% credible intervals (10-year horizon) – Euro area

7 | MODEL SELECTION ASSESSMENT

To ascertain the performance of the B-VAR models based on the Minnesota prior we compare our benchmark in both high-income countries and Euro area countries with respectively unrestricted VAR models and B-VAR models based on the Normal-inverse-Wishart prior. We consider the Normal Inverse Wishart prior since it overcomes the two main weaknesses of the Litterman prior: the posterior independence between equations and the fixed, and the diagonal residual variance-covariance matrix.

Regarding model selection assessments, since our sample is short, we dropped the last 2 years that we used to construct out of sample forecasts. Then, we forecast these last two observations and compare them with the actual values in the sample using the following criteria based on modified RMSE and modified MAE [2] a pena:

1)
$$\text{RMSE} = \sqrt{\frac{\sum_i^n \left(y_i - \overline{y_i}\right)^2}{n-k}} \tag{3}$$

2)
$$\text{MAE} = \frac{\sum_i^n |\, y_i - \overline{y_i}|}{n-k} \tag{4}$$

where y_i are the time series data and $\overline{y_i}$ the forecast values of the time series y_i. The Mean Absolute Error or Mean Absolute Deviation (MAE or MAD) is the mean of the absolute errors, and it measures how much the forecast is biased in terms of the deviation of the series in absolute terms (deviation of y_i to $\overline{y_i}$). This measure is one of the most commonly used for analyzing the quality of different forecasts. The Root Mean Squared Error (RMSE) computes the forecast "error" as the difference between forecasted and corresponding observed values each one squared and then averaged over the entire sample. Finally, the square root of the average is taken.

We prefer to use both measures to compute the point forecasts (2 years ahead) and to diagnose the variation in the errors in our models. The reasons are that RMSE is more sensitive to large deviations from the actual time series values giving greater importance to the highest errors (outliers) that become much larger as they are squared; MAE, instead, avoids the problem of negative and positive forecasts but sometimes it is difficult to separate a large error from a small one. For the two measures above, the smaller the value, the better the model's fit. Therefore, the model with the minimum RMSE and MAE result are the selected model. The findings in Tables 1 and 2 respectively referred to

TABLE 1 VAR versus B-VAR for high-income countries

Model 1	**Variable**	**RMSE**	**MAE**
STD (g-i) versus **nc**			
Standard VAR	STD (g-i)	0.422	0.418
	(nc)	0.026	0.028
Minnesota prior	STD (g-i)	0.157	0.101
	(nc)	0.011	0.012
Normal-Wishart prior	STD (g-i)	0.409	0.115
	(nc)	0.013	0.016
Model 2	**Variable**	**RMSE**	**MAE**
STD (g-i) versus **STD**			
Standard VAR	STD (g-i)	0.295	0.264
	STD (nc)	0.153	0.256
Minnesota prior	STD (g-i)	0.215	0.211
	STD(nc)	0.024	0.062
Normal-Wishart prior	STD (g-i)	0.253	0.225
	STD(nc)	0.023	0.065
Model 3	**Variable**	**RMSE**	**MAE**
(g-i) versus **SD(nc)**			
Standard VAR	(g-i)	0.851	0.874
	STD (nc)	0.069	0.067
Minnesota prior	(g-i)	0.771	0.742
	STD(nc)	0.055	0.050
Normal-Wishart prior	(g-i)	0.825	0.792
	STD(nc)	0.065	0.062

TABLE 2 VAR versus B-VAR for Euro area countries

Model 1	Variable	RMSE	MAE
STD (g-i) versus **nc**			
Standard VAR	STD (g-i)	0.326	0.317
	(nc)	0.066	0.060
Minnesota prior	STD (g-i)	0.259	0.304
	(nc)	0.027	0.021
Normal-Wishart prior	STD (g-i)	0.303	0.306
	(nc)	0.041	0.046
Model 2	**Variable**	**RMSE**	**MAE**
STD (g-i) versus **STD (nc)**			
Standard VAR	STD (g-i)	0.689	0.657
	STD (nc)	0.014	0.015
Minnesota prior	STD (g-i)	0.565	0.541
	STD(nc)	0.010	0.012
Normal-Wishart prior	STD (g-i)	0.578	0.577
	STD(nc)	0.011	0.012

high-income countries and Euro area countries show that, the RMSE and MAE values for the whole B-VAR models based on Minnesota prior are the lowest. This means that B-VAR models based on Minnesota prior are more appropriate to fit the model (lower RMSE and MAE) with respect to VAR approaches or other B-VAR specifications when, as in our case, the dataset is short.

8 | CONCLUDING REMARKS

This work analyzes the possible relationships between average levels and divergent or convergent trends expressed in terms of higher or lower standard deviation across countries of two key variables: the degree of centralization of capital represented by net control and solvency represented by the difference between the GDP growth rate and the interest rate. The geographical areas considered are 28 high-income countries selected based on GDP and market capitalization and the first 11 countries joined the Euro area. The period spans from 1999 to 2019. Given the short length of our sample, we apply Bayesian VAR (B-VAR) models based on Minnesota prior. Since the dataset covers a limited period, this technique has proven to be the most appropriate to fit the data than VAR approaches and other B-VAR specifications.

The main results of our analysis are the following. Divergent solvency conditions across countries lead to an average increase in capital centralization and its greater convergence across countries. In turn, an average increase in capital centralization and its convergence across countries generates a convergence of solvency conditions across countries. That is, solvency divergence produces higher and convergent capital centralization, which in turn directs toward solvency convergence. These results are consistent for both high-income and Euro area countries groups. Finally, in the group of high-income countries, we also note that an average deterioration in solvency indicates a convergence of capital centralization between countries. It is also interesting to note that for both high-income countries and the Euro area by analyzing both the average and the standard deviation of the variables,

the impact of capital centralization on solvency is more significant than the impact of solvency on capital centralization.

These empirical results are still preliminary. However, they could find some first hint of explanation in the following considerations. On the one hand, a divergence in the solvency conditions of the different countries could lead to a gap between the financial positions of the respective national capitals and this could determine an average increase and a convergence of capitalist centralization processes, that is, liquidation, acquisition and control of relatively weak capitals by stronger capitals. On the other hand, an average increase and the convergence of capital centralization across countries could induce a convergence in the macroeconomic performances and the related policy lines, explaining the convergence in the solvency conditions. In other words, the evidence that diverging solvency creates converging capital centralization and that the latter in turn creates converging solvency, seems to indicate a trend towards greater international economic homogeneity in the ownership and control structures, in the connected processes of capital centralization and in the relative conditions of solvency among the countries examined.

This phenomenology of "convergence" is a far cry from the homonymous and optimistic concept typical of the mainstream literature on economic growth. Instead, the empirical results described here seem to provide some elements suggesting a peculiar declination of the Marxian "historical trajectories" of capitalism (Dumenil & Levy, 2003). In particular, our evidence seems to give support to an interpretation of the tendency towards capital centralization, which takes into account the possible interdependencies between this tendency, the solvency conditions in the economic system and the related economic policy lines (Brancaccio, 2010; Brancaccio et al., 2020; Brancaccio & Fontana, 2013, 2016; Brancaccio & Suppa, 2012; Brancaccio & Veronese Passarella, 2021).

We could say, in a nutshell, that a tendency seems to emerge from divergence towards convergence in the structures of solvency and ownership control of national capitalisms. We would be tempted to affirm that divergence tends towards convergence, as if a sort of "law of one price" also operated on the structure of the centralization of capital and the relative conditions of solvency of the various nations. However, this cannot be the place to assess whether and to what extent this convergence is an unstoppable phenomenon or is rather destined to suffer sudden repercussions, perhaps precisely as a result of the transformations it could induce in the structure of political power and institutions. Whether and to what extent this international convergence in the concentration of economic power can have more general repercussions on the "resilience of liberal capitalism", "its democratic institutions" and even peace between nations remains an open question that will merit further investigation (Acemoglu & Brancaccio, 2021; Aspromourgos, 2015; Brancaccio & De Cristofaro, 2022).

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APPENDIX

A1 | Robustness of the market shareholder level

In this paragraph we show, how the variation of the market global shareholder level from 70% to 90% does not change the net control behaviour (all the curves remain mostly parallel). In Figure A1 we present the case of the Eurozone, the countries forming the European currency followed as an aggregate an identical behaviour if we consider different levels of total market share from 70% to

FIGURE A1 The Eurozone net control at different market share levels

90%. In other words, the net control series computed at the level of a minimum ownership equal to 5% shows the same behaviour with different total market share levels. In Figure A2 we replicate the same computation for the 28 largest economies of the World getting similar results. In conclusion we can affirm that the robustness of the data makes our choice of the 80% reliable and consistent.

A2 | The BFS algorithm

Breadth–first search (BFS) is a network traversal algorithm that explores nodes in the order of their distance from the source node (root node), where distance is the minimum length of a path from the source vertex to each node. An example is show in Figure A3 where it is evident that exploration is per level from the root node. Main advantages of this method are:

1. It finds the shortest path between two nodes, with path length measured by the total number of edges. This expresses the ownership control through the shortest path, over all possible indirect combinations
2. Minimum Spanning Tree for an unweighted graph. It founds the subset of links that in an undirected and weighted graph connects all the links together, without any cycles and with the minimum possible total link weight. In other words the spanning tree is a technique to cover the network with the minimum number of links avoiding cycles and minimizing the total weight. This technique finds the most direct and the easiest paths for the ownership relations.

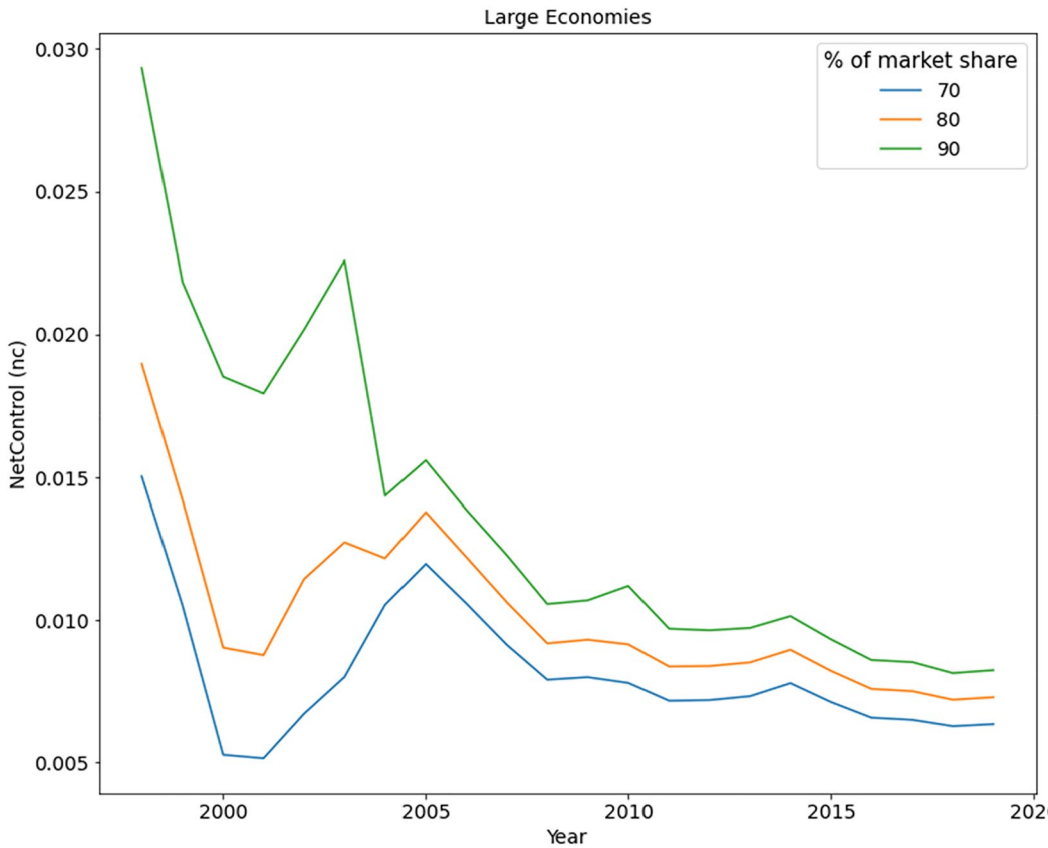

FIGURE A2 The 28 largest economies net control at different market share levels

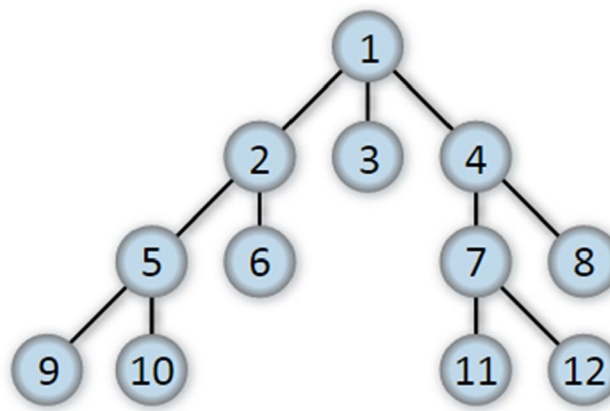

FIGURE A3 The BFS algorithm explores the network building a minimum spanning tree, avoiding cycles and minimizing the total weight of the network. For the ownership it expresses the control and the power with the most direct relationship and path structure

A3 | Robustness of the mean/median for the *nc* and *g-i* data

Our hypothesis is that we can aggregate the country data using a yearly series (yearly average for each country) without loosing generality while reducing the variability. We used a simple measure to analyze the relative differences (%) between the mean and the median (in absolute value (abs)) for each country (Tables A1 and A2):

TABLE A1 High income countries relative differences (%) and coefficient variation (CV) for nc and g-i

Country	% diff (*g-i*)	CV (*g-i*)	%diff (*nc*)	CV (*nc*)
Australia	20.68	0.66	23.72	0.36
Austria	15.25	0.62	4.30	0.15
Belgium	23.23	0.58	0.17	0.20
Brazil	0.24	0.26	6.00	0.21
Canada	4.43	0.47	19.78	0.56
China	11.07	0.36	34.14	0.69
Colombia	11.07	0.36	13.04	0.23
France	15.60	0.59	2.82	0.10
Germany	22.10	0.71	7.36	0.22
India	11.07	0.36	27.49	0.48
Indonesia	9.25	0.25	19.53	0.35
Italy	11.87	0.36	0.51	0.14
Japan	18.71	0.67	9.01	0.16
Korea, Rep.	12.75	0.43	6.20	0.19
Malaysia	11.07	0.36	38.44	0.44
Mexico	1.15	0.20	5.87	0.22
Netherlands	19.24	0.65	3.66	0.11
Norway	4.08	0.48	6.34	0.28
Poland	5.16	0.42	0.87	0.11
South Africa	13.94	0.45	21.08	0.47
Spain	6.72	0.23	0.27	0.12
Sweden	12.10	0.64	1.12	0.23
Switzerland	25.07	0.86	4.00	0.26
Turkey	8.68	0.23	8.83	0.30
United Kingdom	7.24	0.49	16.84	0.31
United States	6.87	0.40	5.42	0.23
AVERAGE	***11.87***	***0.47***	***11.03***	***0.27***

Note: *g-i* is the difference between GDP growth rate (*g*) and nominal long-term interest rates with 10 years maturity (*i*) that we used as a proxy of solvency conditions.

nc is the net control that we used to measure capital centralization.

%diff for both variables (*g-i* and *nc*) is defined as how much in % the median of (*g-i* or *nc*) is different from the mean of (*g-i* or *nc*): in other words %diff (*g-i* or *nc*) = 100*absolute value (median − mean)/mean.

CV for both variables (*g-i* and *nc*) is computed as standard deviation/(absolute value [mean]) and measures the level of dispersion around the mean.

CV (*g-i*) is the coefficient variation of *g-i*.

CV (*nc*) is the coefficient variation of the *nc*.

TABLE A2 EU countries relative differences (%) and coefficient variation (CV) for nc and g-i

Country	% diff (nc)	CV (nc)	% diff (g-i)	CV (g-i)
Austria	8.60	0.37	12.41	0.58
Belgium	0.35	0.51	19.95	0.54
Finland	71.10	1.09	14.40	0.60
France	5.65	0.26	12.92	0.54
Germany	14.72	0.54	24.18	0.67
Ireland	4.56	0.53	2.90	0.59
Italy	1.02	0.35	5.97	0.33
Luxembourg	2.22	0.44	9.41	0.72
Netherlands	7.32	0.28	16.51	0.60
Portugal	9.69	0.27	6.49	0.51
Spain	0.53	0.30	10.64	0.42
AVERAGE	***11.43***	***0.45***	***12.34***	***0.56***

Note: *g-i* is the difference between GDP growth rate (*g*) and nominal long-term interest rates with 10 years maturity (*i*) that we used as a proxy of solvency conditions.

nc is the net control that we used to measure capital centralization.

%diff for both variables (*g-i* and *nc*) is defined as how much in % the median of (*g-i* or *nc*) is different from the mean of (*g-i* or *nc*): in other words %diff (*g-i* or *nc*) = 100*absolute value (median − mean)/mean.

CV for both variables (*g-i* and *nc*) is computed as standard deviation/(absolute value [mean]) and measures the level of dispersion around the mean.

CV (*g-i*) is the coefficient variation of *g-i*.

CV (*nc*) is the coefficient variation of the *nc*.

R = abs(mean – median)/mean

According to the results, it is clear that mean and median of the *g-i* for the 28 high income countries differs for no more than 25% (Switzerland) with a computed average of 11.87%. Also for *nc* this gap is at most 38.4% (Malaysia) and in average 11.3%. These discrepancies (for *nc* and *g-i*) are not so large to justify the usage of robust measures (median in this case) with respect to the average. Finally, the low average level of the coefficient of variation (CV = standard deviation/(abs(mean))) suggests that there is not a real necessity to study the differences across countries for both *g-i* (CV = 0.47) and *nc* (CV = 0.27) (Table A1). Same findings we obtain in the case of the Euro area countries in which mean and median diverge of a small value respectively for *nc (11.4)* and *g-i (12.34)*. Similar results we find also for the CV(*g-i*) equal to 0.56 and CV(*nc*) equal to 0.45 (Table A2).

A4 | Impulse response and forecast error variance decomposition functions in high-income countries-Model 4

In the Model 4 we investigated the relations between (*g-i*) and *nc*, both expressed in average values for high income countries. As we can see the relationships from *g-i* to *nc* (first row-second column) and vice versa (second row-first column) of the impulse response functions are not significant (Figure A4). The same results are confirmed by the forecast error variance decomposition functions (Figure A5, first row, second column; second row, first column).

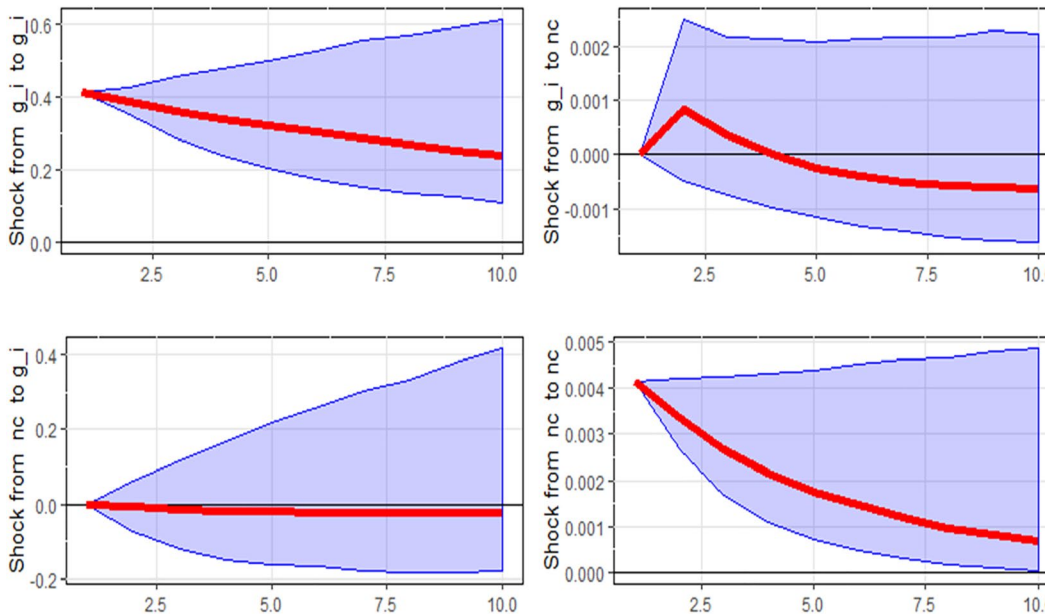

FIGURE A4 B-VAR impulse response functions with 95% credible intervals (10 years-horizon)-high income countries

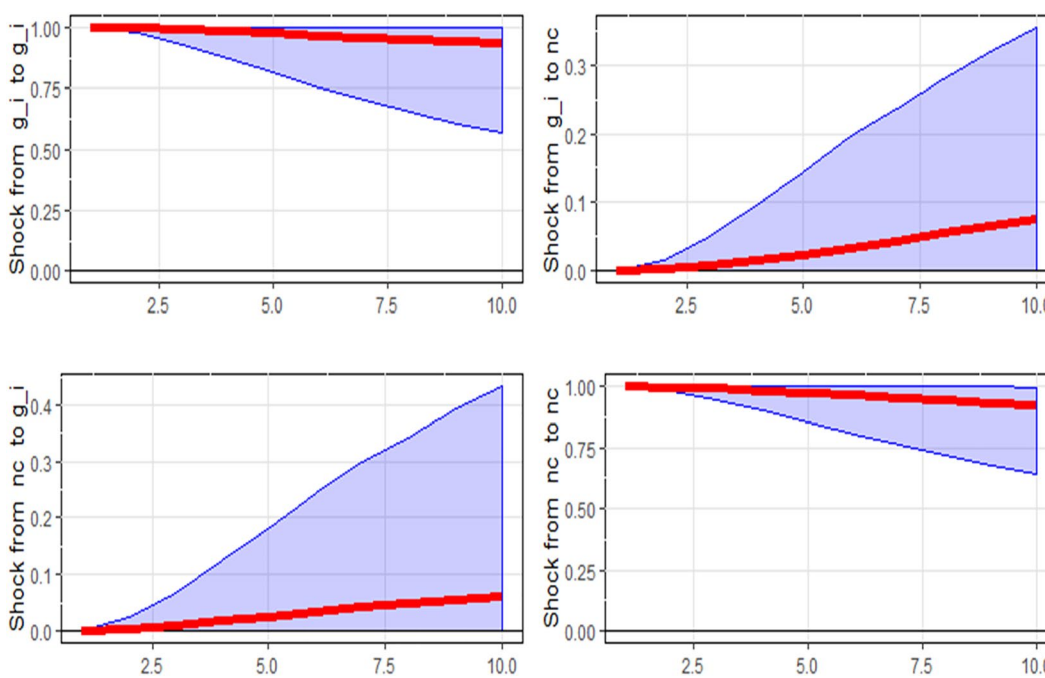

FIGURE A5 B-VAR forecast error decomposition functions with 95% credible intervals (10 years-horizon)-high income countries

A5 | Impulse response and forecast error variance decomposition functions in Euro area countries-Model 3,4

In this section we report the plots of the Euro area countries of the impulse response functions and forecast error variance decomposition functions relative to the Model 3 ((*g-i*) versus STD (*nc*) and vice versa-Figures A6 and A7) and Model 4 ((*g-i*) versus (*nc*) and vice versa-Figures A8 and A9) that we excluded to the manuscript because they were not significant ((Figure A6, Model 3-first row-second column; second row-first column); Figure A7, Model 3-first row-second column; second row-first column); Figure A8, Model 4-first row-second column; second row-first column); Figure A9, Model 4-first row-second column; second row-first column).

A6 | Impulse response and forecast error variance decomposition functions in high-income countries (Results in Tables)

In this section we show in Tables A3–A5 the results of the impulse response functions (IRF) which were significant for high income countries relative to the Model 1(STD (g-i) versus (nc) and vice versa), Model 2 (STD (g-i) versus STD (nc) and vice versa) and Model 3 ((g-i) versus STD (nc) and vice versa). We also report in table form the outcomes for the Model 1-2-3 of forecast error variance decomposition functions (FEVD) (Tables A6–A8).

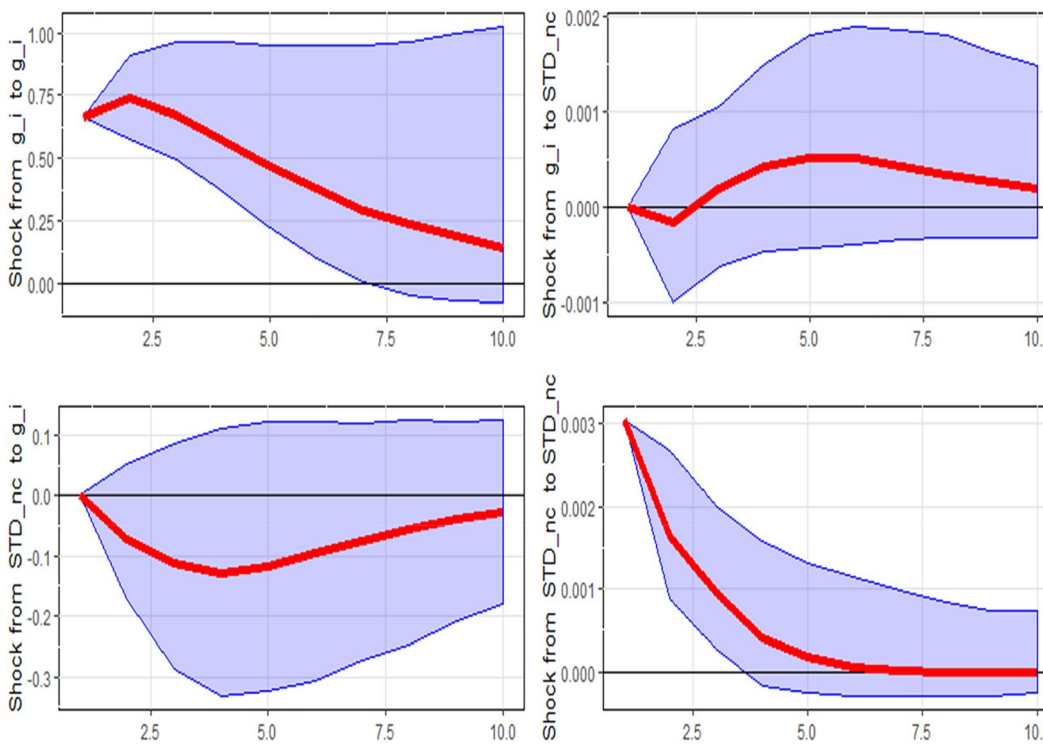

FIGURE A6 B-VAR impulse response functions with 95% credible intervals (10 years-horizon)- Euro Area countries (Model 3)

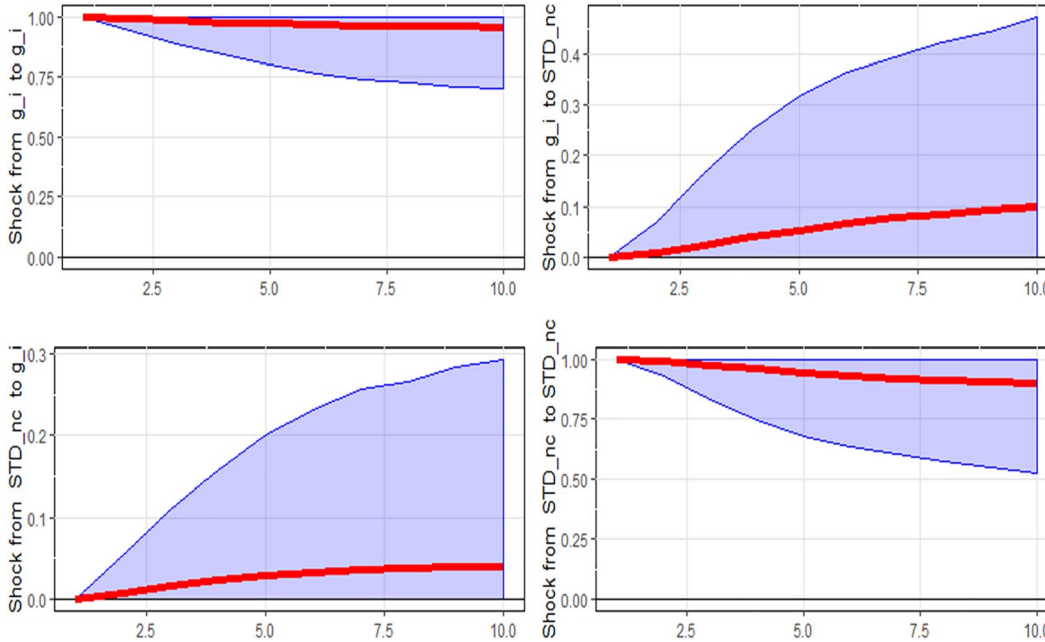

FIGURE A7 B-VAR forecast error decomposition functions with 95% credible intervals (10 years-horizon)- Euro Area countries (Model 3)

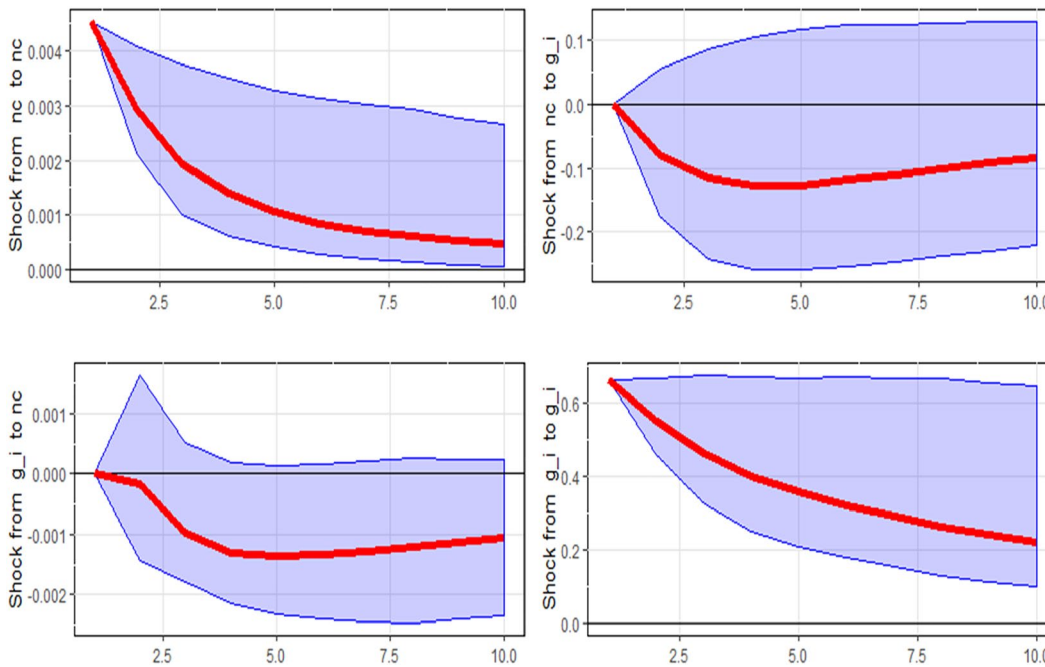

FIGURE A8 B-VAR impulse response functions with 95% credible intervals (10 years-horizon)- Euro Area countries (Model 4)

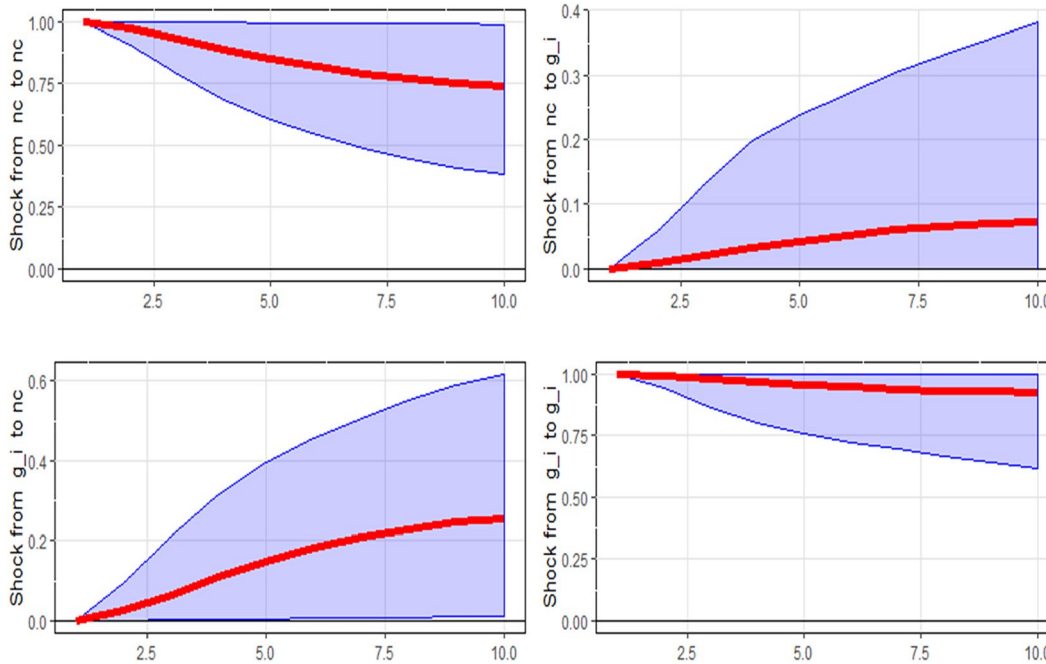

FIGURE A9 B-VAR forecast error decomposition functions with 95% credible intervals (10 years-horizon)- Euro Area countries (Model 4)

TABLE A3 B-VAR impulse response functions with 95% credible intervals (10-year horizon)– Model 1

	nc	STD (g-i)
IRF-nc (horizon in years)		
0	0.004	0
2	0.001	0.1
3	−0.001	0.05
6	0	0.03
10	0	0
IRF-STD(g-i) (horizon in years)		
0	0	0.4
2	−0.0015	0.2
3	−0.002	0.15
6	−0.001	0.05
10	0	0

A7 | Impulse response and forecast error variance decomposition functions in Euro area countries (Results in Tables)

In this paragraph we summarize in a table form the findings relative to the Euro area countries respectively of the significant impulse response functions (IRF-Table A9 (Model 1(STD (g-i) versus (nc) and vice versa), Table A10 (Model 2 (STD (g-i) versus STD (nc) and vice versa)) and the forecast error variance decomposition functions relative to the Model 1, 2 (FEVD- Tables A11 and A12).

TABLE A4 B-VAR impulse response functions with 95% credible intervals (10-year horizon) – Model 2

	STD (nc)	STD (g-i)
IRF-STD(nc) (horizon in years)		
0	0.004	0
2	0.002	0.15
3	0.001	0.12
6	−0.001	0.05
10	0	0
IRF-STD(g-i) (horizon in years)		
0	0	0.4
2	−0.001	0.3
3	−0.0015	0.2
6	−0.005	−0.1
10	0	0

TABLE A5 B-VAR impulse response functions with 95% credible intervals (10-year horizon)– Model 3

	STD(nc)	g-i
IRF-STD(nc) (horizon in years)		
0	0.004	−0.1
2	0.0025	−0.1
3	0.005	−0.1
6	0	−0.01
10	0	−0.01
IRF g-i (horizon in years)		
0	0	0.4
2	0.01	0.3
3	0.015	0.25
6	0.05	0.23
10	0.03	0.2

TABLE A6 B-VAR forecast error variance decomposition functions with 95% credible intervals (10-year horizon) – Model 1

	nc	STD (g-i)
FEVD-nc (horizon in years)		
0	1	0
2	0.75	0.05
3	0.6	0.07
6	0.6	0.07
10	0.6	0.07
FEVD-STD (g-i) (horizon in years)		
0	0	1
2	0.2	0.9
3	0.3	0.8
6	0.4	0.8
10	0.4	0.8

TABLE A7 B-VAR forecast error variance decomposition functions with 95% credible intervals (10-year horizon) – Model 2

	STD(nc)	STD (g-i)
FEVD-STD(nc) (horizon in years)		
0	1	0
2	0.9	0.1
3	0.75	0.15
6	0.75	0.25
10	0.75	0.25
FEVD-STD(g-i) (horizon in years)		
0	0	1
2	0.1	0.9
3	0.25	0.8
6	0.3	0.75
10	0.3	0.75

TABLE A8 B-VAR forecast error variance decomposition functions with 95% credible intervals (10-year horizon) – Model 3

	STD(nc)	g-i
FEVD-STD(nc) (horizon in years)		
0	1	0
2	0.9	0.01
3	0.8	0.02
6	0.75	0.03
10	0.75	0.03
FEVD- g-i (horizon in years)		
0	0	1
2	0.1	0.9
3	0.15	0.85
6	0.20	0.8
10	0.25	0.8

TABLE A9 B-VAR impulse response functions with 95% credible intervals (10-year horizon)– Model 1

	nc	STD (g-i)
IRF-nc (horizon in years)		
0	0.004	0
2	0.003	0.15
3	0	0.017
6	−0.001	0.02
10	0	0
IRF-STD(g-i) (horizon in years)		
0	0	0.9
2	0.001	0.8
3	−0.001	0.4
6	0	0
10	0	0

TABLE A10 B-VAR impulse response functions with 95% credible intervals (10-year horizon)– Model 2

	STD (nc)	STD (g-i)
IRF-STD(nc) (horizon in years)		
0	0.003	0
2	0.002	0.1
3	0.001	0.25
6	0	0.05
10	0	0
IRF-STD(g-i) (horizon in years)		
0	0	1
2	0	0.8
3	−0.0005	0.4
6	−0.0001	−0.1
10	0	0

TABLE A11 B-VAR forecast error variance decomposition functions with 95% credible intervals (10-year horizon) – Model 1

	nc	STD (g-i)
FEVD-nc (horizon in years)		
0	1	0
2	0.9	0.01
3	0.9	0.02
6	0.9	0.025
10	0.9	0.025
FEVD-STD (g-i) (horizon in years)		
0	0	1
2	0.01	0.9
3	0.02	0.8
6	0.1	0.8
10	0.1	0.8

TABLE A12 B-VAR forecast error variance decomposition functions with 95% credible intervals (10-year horizon) – Model 2

	STD(nc)	STD (g-i)
FEVD-STD(nc) (horizon in years)		
0	1	0
2	0.9	0.01
3	0.8	0.05
6	0.8	0.1
10	0.8	0.1
FEVD-STD(g-i) (horizon in years)		
0	0	1
2	0.01	0.8
3	0.02	0.8
6	0.03	0.8
10	0.03	0.8