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Monetary Policy, Crisis and Capital Centralization in Corporate Ownership and Control Networks: a B-Var Analysis

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Abstract

Based on a connection between network analysis and B-VAR models, this paper provides a first empirical evidence of the relationships between capital centralization expressed in terms of network control on one hand and monetary policy guidelines and business cycles on the other. Our findings suggest that a tightening monetary policy leads to a decrease in the fraction of top shareholders of network control which results in a higher centralization of capital; and that a higher centralization of capital, in turn, leads to a reduction of GDP with respect to its trend. These relations are confirmed both for the United States and the Euro Area.

Keywords: network analysis, ownership and control networks, centralization of capital, monetary policy, business cycle, financial crisis, B-VAR models

JEL Classification: C11, D85, E32, E5, G34

1. Introduction

Before and after the great financial crisis started in 2007, important changes occurred in the degree of capital centralization expressed in terms of "network control", i.e. ownership concentration of corporate control shares in the world. While in the first years of the century the fraction of top holders of capital control shares gradually increased, near the crisis it showed a sudden reduction and then continued to decline also in the following years with a consequent increase of global capital centralization (Brancaccio et al. 2018; see also Vitali et al. 2011, Glattfelder and Battiston 2019). This new empirical evidence revives attention to the old "law of tendency" towards capital centralization, firstly described by Marx (Marx, 1867|1976|1981, Vol. I, Ch. 25, 32; Vol. III, Ch. 27) and then analysed by some of his successors (Hilferding 1910; Sweezy 1942; Baran and Sweezy 1966; Mandel 1975; Sau, 1979; Weeks, 1979; Shaik 1991; Desai, 2002) or scholars of others lines of thought (Schumpeter 1942; Elliott, 1980). In this regard, it is important to assess whether the trends of capital centralization are related to the financial crisis and the economic policy guidelines. In particular, it may be interesting to check two possible causal relations: whether there are interactions between capital centralization and the tendency towards economic depression (Hilferding, 1910; Magdoff and Sweezy, 1987; Lazonick, 1992; Crotty, 1993; Sweezy, 1994; Dore, 2008; Foster et al., 2011) and whether there are elements supporting the thesis of a possible impact of monetary policy on the solvency conditions in the economic system and the related centralization of capital (Brancaccio and Fontana 2013, 2016; see also Radcliffe Report 1959; Kaldor 1985; Aikman et al. 2016).

In order to test these relations empirically, it is necessary to build a bridge between the emerging studies in the field of network analysis and the traditional macroeconomic research on business cycles and monetary policy. In this sense we propose here two analyses: the first one is dedicated to the possible effects of the interest rate policy by the Federal Reserve and by the European Central Bank on capital centralization expressed in terms of network control, i.e. ownership concentration of corporate control shares in the US and the Euro Area respectively, with reference to the period 2001-2016; and the second one is focused on the possible causal relations between the trends of centralization of capital and the deviations of GDP from its trend in the same period and in the same two economic areas. For these scopes we integrate network analysis and Bayesian VAR econometric techniques in an original way. With the help of these tools, although preliminarily, we provide a first empirical evidence of the relationships between monetary policy guidelines, the structure of ownership and control networks and the tendency of GDP towards recession. As we shall see, our findings suggest that a tightening monetary policy leads to an increase in the ownership concentration of corporate control shares which results in a higher centralization of capital; and that a higher centralization of capital, in turn, causes a reduction of GDP with respect to its trend. These relations are confirmed for both the United States and the Euro Area.

The remainder of this paper is organized as follows. In Section 2 we present a short review of the literature on the relations between network analysis on one hand and business cycle and monetary policy on the other. In Section 3, we define the concept of capital centralization in terms of net control and provide empirical evidences about World, U.S. and Euro Area. In Section 4 we introduce the Bayesian VAR methodology and we explain why it may fit well with the scopes of this study. In Section 5 and 6 we show the results of the impulse response functions based on B-VAR models (Minnesota prior specification) relative on one hand to the possible relations between corporate network control and monetary policy and, on the other hand to the links between network control and economic crisis. In Section 7 we compare VAR and B-VAR analyses based on different priors (i.e. Normal-inverse-Wishart prior) in terms of forecast performance. Section 8 concludes.

2. Network analysis, business cycle and monetary policy: a short review

Economic networks are webs where nodes represent economic agents – individuals, firms, consumers, organizations, industries, countries, etc. – and links depict market interactions. Economic network analysis applies general network science models (Caldarelli, 2007; Newman, 2010) to economic analysis (Schweitzer et al., 2009; see also: Economidies, 1996; Goyal, 2007; Jackson, 2008; Bramoullé et al., 2016), with more and more frequent uses in many different fields, especially after the crisis (Chinazzi and Fagiolo, 2013; Thiemann et al., 2017). One of the most promising implementations of network analysis is the study of capital ownership and control structures (Corrado and Zollo, 2006; Carroll, 2007; Vitali et al., 2011; Heemskerk and Takes, 2016; Glattfelder and Battiston, 2019; van Lidth de Jeude et al., 2019). A recent result in this field can be considered the first empirical evidence of a Marxian tendency towards global centralization of capital expressed in terms of "network control", i.e. ownership global concentration of corporate control shares between 2001 and 2016: this analysis reveals that the fraction of top holders holding cumulatively the 80 percent of the total network control is within the range between 1 percent and 2 percent; furthermore, while in the first years of the century the fraction of top holders of network control gradually increased, near the crisis it showed a sudden reduction and then continued to decline also in the following years with a consequent increase of global capital centralization of more than 20% (Brancaccio et al., 2018).

This latter result raises two important questions. First, to what extent is the trend of centralization of capital connected to the phenomenon of the economic crisis? Secondly, in what terms can centralization be influenced by economic policy guidelines and in particular by monetary policy decisions? These are two typical themes in the heterodox literature on capital centralization. As regards the first theme, the studies on the possible nexus between centralization of capital and economic crisis have often focused on the role played by the credit system. According to Marx (1867|1981), the development of the credit system boosts capital centralization inducing a separation between ownership and control and, in this way, it brings about instability, overproduction and economic downturns. Building on this intuition, Hilferding (1910) stressed the role played by credit, the stock exchange and the centralization of capital in causing economic crises. In particular, ownership and control fragmentation fosters instability due to, among other things, a difficult re-proportioning between sectors (see also Mandel, 1975; Magdoff and Sweezy, 1983; Sweezy, 1994; Foster et al., 2011). As regards the second theme, a more recent literature has focused on a possible link between capital centralization and monetary policy decisions:central bankers could pursue the aim of adjusting interest rates in order to manage the solvency conditions in the economic system and the related rhytms of liquidations, mergers and centralization of capital (Brancaccio and Fontana 2013; Brancaccio et al. 2015). These themes have been mainly studied from a theoretical perspective and they have rarely been addressed from a strictly empirical point of view, especially with reference to the links between macroeconomic dynamics and capital centralization. To deepen the empirical exam of these links it is necessary to put together network analysis and macroeconomics in order to assess the possible interactions between network control on one hand and business cycles, crises and monetary policies on the other.

Although in very general terms, in the academic literature it is already possible to find some early attempts at building bridges between network analysis and studies on aggregate fluctuations and economic policies.

As regards the application of network analysis to aggregate fluctuations, there are studies dedicated to business cycles (Acemoglu et al., 2012, 2016, 2017; Carvalho, 2014; Carvalho et al., 2016; Di Giovanni et al., 2018; Oberfield, 2018), cascade failures (Gai et al., 2011; Delli Gatti et al., 2010; Battiston et al., 2012a,b; Battiston, Puliga, et al. 2012; Markose et al., 2012; Elliott et al., 2014; Acemoglu et al., 2015a,b) and economic downturns (Sheng, 2010; Acemoglu et al., 2013; Fagiolo, 2016; Heemskerk et al., 2016). This growing literature, which has boomed after the last international financial crisis, emphasized the relevance of input-output production linkages and financial connections to explain the interplay between the real and financial sides of the economy and shocks propagation.

With respect to the relations between networks and economic policies, network analysis techniques are well suited to explore the direct and indirect effects of policy interventions (Haldane, 2014), as they represent a nonpareil informative tool for the policymaker dealing with macro-prudential regulation (Haldane, 2009; Farmer et al., 2012; Battiston et al., 2016; Gaffeo and Molinari, 2016), trade policy (Gala et al., 2018; Giammetti et al., 2019; Giammetti, 2019), climate policy (Balint et al., 2017; Vega and Mandel, 2018), fiscal policy (Briganti et al., 2018). Furthermore, with respect to the specific field of monetary policy, the Bank of England's chief economist calls for an understanding of the complex international monetary network dynamics as a pre-requisite for effective management of monetary policies (Haldane 2014). Among the contributions that have followed this suggestion, Pasten et al. (2018) develop a multi-sector model to study the quantitative importance of input-output linkages and their interaction for the real effects of monetary policy shocks. Empirically, they find that the size and interconnectedness of a sector and the interaction with frequencies of price adjustment matter for the real effects of monetary policy. Input-output linkages matter also in the model developed by Ghassibe (2018), whose main result is that production networks substantially contribute to monetary non-neutrality and their presence accounts for 20-45 percent of the effect of monetary policy shocks on US consumption. These estimates about the relevance of production networks in the transmission of monetary policy to macroeconomic aggregate are somewhat lower than Ozdagli and Weber (2017) findings, which study the response of stock prices to monetary policy shocks and attribute 50 to 85 percent to production network effects. Other contributions in this field have focused on the interplay between monetary policy, financial networks and stability. In compliance with the main findings of this literature, central bank liquidity supply usually enlarges the volume of the interbank market and increases systemic risk: in particular, expansionary monetary policy seem to make banks more resilient to shocks, at least in the short run (Georg, 2013), but liquidity provision might be detrimental to financial stability in the sense that it encourages risk-taking behaviour and results in a more interconnected financial system, in which shocks are more easily propagated (Bluhm et al., 2014). Finally, with regards to the transmission of monetary policy shocks, Silva et al. (2018) develop a model in which central bank policy rates affect – either directly or indirectly – individual firms and banks, and find that monetary policy can have linear or nonlinear implications for financial stability, depending on network relationship patterns. Multilayer networks have been also used to evaluate the impact of unconventional monetary policies on macroeconomic aggregates. For example, Perillo and Battiston (2018) map the multilayer macro-network of financial exposures among institutional sectors in Europe to shed light on the implications of ECB quantitative easing in terms of stimulation of the real economy: they find that the resources provided to the banking system through quantitative easing have been transmitted mainly to the financial sector.

In this study, we propose a further connection between network analysis and studies on macroeconomic fluctuations and economic policy. We intend to verify whether the recent evidences on the increase in centralization of capital in terms of network control (Brancaccio et al. 2018) have causal relations with the fluctuations of the GDP around its trend and with monetary policy guidelines in the USA and in the Euro Area between 2001 and 2016. More specifically, we intend to check whether it is possible to find empirical evidences of the theses according to which: 1) monetary policies can have an impact on the solvency conditions in the economic system and the related centralization of capital (Brancaccio and Fontana 2013, 2016; see also Radcliffe Report 1959; Kaldor 1985; Aikman et al. 2016); and 2) capital centralization, in turn, can cause economic depression (Hilferding, 1910; Magdoff and Sweezy, 1987; Lazonick, 1992; Crotty, 1993; Sweezy, 1994; Dore, 2008; Foster et al., 2011). For these scopes, as we shall see in the following sections, we propose an original application of B-VAR analysis on policy interest rates, network control and GDP fluctuations around its trend for USA and Euro Area in the period 2001-2016, before and after the so-called great financial crisis.

3. Capital centralization in terms of net control: World, USA and Euro Area

The prevailing literature on corporate governance usually investigates the ownership and control structures by looking at the concentration of ownership within corporations (Berle and Means, 1932; Granovetter, 1995; La Porta et al., 1998, 1999; Djankov et al., 2008; Wang and Szirmai, 2008; Gatti, 2009; Wang, 2009; see also the essays contained in Dosi et al., 1998). Here we build on the literature on ownership and control networks (Corrado and Zollo, 2006; Carroll, 2007; Vitali et al., 2011; Heemskerk and Takes, 2016; Brancaccio et al., 2018; Glattfelder and Battiston, 2019; van Lidth de Jeude et al., 2019) and focus on the so-called “network control” or “net-control”. This is a measure of control within and across corporations which is defined by “the value of control gained from the intrinsic value reached by all direct and indirect paths or the value of control given by the network value of directly controlled companies” where “the network value of an economic actor is given by its intrinsic value plus the value gained from network” (Vitali et al. 2011). The basis of net-control is an algorithm known as BFS (Breaths First Search) that explores the neighbourhood of a node avoiding the multiple counting of a link during the exploration. Net-control can be calculated by accumulating the total economic value contained in the ownership relationship with the BFS algorithm, removing the contribution for the node itself - i.e. its own total capital - and imposing a minimum ownership threshold (for example of 5%, that is considered a first share of control in literature: Zingales, 1994, 1995). In a previous study we applied this definition of capital centralization in terms of net-control to the Thomson Reuters Eikon database of stock market shares and proposed a first analysis of the global evolution of capital centralization from 2001 to 2016: we found that the fraction of the top holders cumulatively holding the 80 percent of the global economic value of the companies examined does never exceed 2 percent; we also noticed that the centralization of capital increases during the period examined and assumes a more regular and general character since the financial crisis started in 2007, with a growth of more than 20 percent. (Brancaccio et al. 2018).

In this study, we consider again the Eikon database of stock markets in order to propose a first calculation of the net-control no more at the global level but at the level of single nations or economic areas, with specific reference to United States and Euro Area 12 (the first twelve countries to join the euro). The aim is to examine the possible relationships between centralization of capital, economic policy guidelines and the business cycle in those specific areas examined. With respect to the previous study there is a slight difference here. In order to determine net-control at the national rather than global level we had to take into account the possibility of having foreign links when a company from a given country can control another company in the same country passing by the control of a foreign company. To address this problem we use a bootstrap technique, randomly allowing for a small percentage of foreign links during the BFS exploration of the neighbourhood. By using the statistical Monte Carlo technique, we compute the national level of the net control as the sum of the net-control relationships company by company at a national level allowing the exploration, in a set of experiments, of k% random foreign links. In practical terms, for each tree of ownership that starts from a company we explore the contribution of foreign links by fixing a probability of k% = 10 percent to have foreign links in each run (randomly chosen). The result is a random exploration of the net-control of each country contaminated by a 10 percent of foreign net-control. The exploration with this Monte Carlo procedure allows the creation of the confidence intervals which allows to calculate national measures of total net-control.

Then, for each economic area examined we can calculate the percentage of “top holders of net control” (*thnc*), which corresponds to the fraction of companies owning the 80 percent of the net-control: when this percentage goes up then the capital centralization decreases and vice versa. In Figure 1 are reported the paths of the fraction of top holders for the entire World, United States and Euro Area 12 between 2001 and 2016.

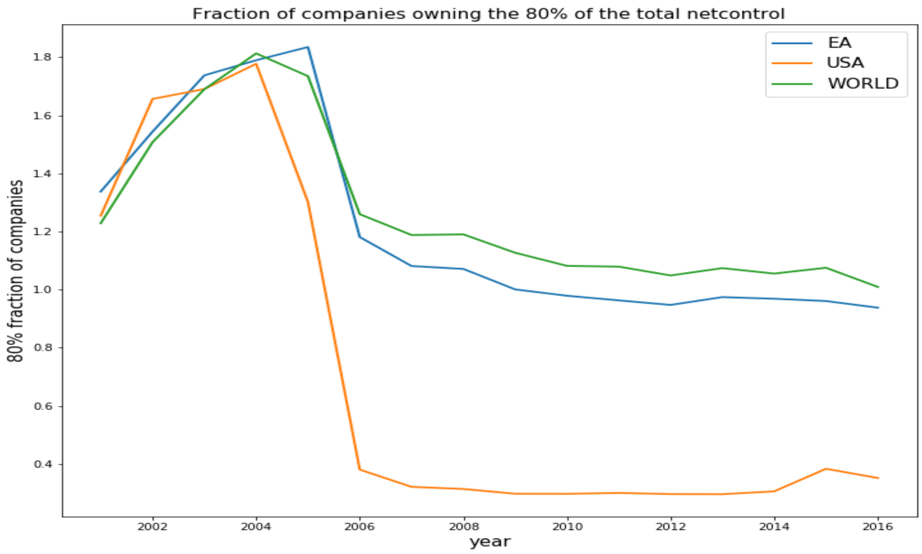

Figure 1: Top holders of net control (thnc): fraction of companies owning the 80% of the net-control in EMU12, USA, World (2001-2016). When this fraction decreases, capital centralization increases and vice versa.

As we can see, capital centralization had a drastic change immediately before the international financial crisis: after increasing in the first years of the century, the percentage of the companies owning 80 percent of the total net-control falls down since 2006 in all the three economic areas examined, which means that capital centralization first declines and then rises. While in the United States the increase in capital centralization is more pronounced, in the EA it is more in line with the worldwide path. In the next sections, we shall apply Bayesian VAR models (B-VAR) in order to check whether this measure of capital centralization is causally related with economic crisis and monetary policy.

4. A Bayesian VAR model

Although VAR models are still widely used in the field of macroeconomics studies, they present several problems. First, they fail in terms of dynamic analysis when the dataset is short, sample information is weak or the number of parameters is large (the "overfitting problem"). Moreover, VAR models are not parsimonious: they contain too many parameters and then tend to be bad in forecasting. Finally, the VAR approach suffers from the loss of degree of freedom when the lag length increases and becomes too large; in this case we have large standard errors and then unstable point estimates. These problems are particularly relevant in our context, where due to the lack of data we cannot extend our calculation of capital centralization beyond the period 2001-2016.

In recent years, Bayesian techniques applied to VAR models (B-VAR models) have been introduced in several fields - especially macroeconomics and finance - providing valid solutions to VAR deficiencies (Litterman 1981, 1986; Sims 1982; Doan et al. 1984; Stock and Watson 2001; Canova 2007; Banbura et al. 2010; Auer 2014).

The reasons why B-VAR models may be more effective than VAR models in forecasting and macro dynamic analysis is that instead of deleting longer lags they impose the restrictions (priors) on the model coefficients assuming that they are more likely closer to zero with respect to the coefficients of the shorter lags (Litterman 1981, 1986; Doan et al. 1984). In this case, it is possible to reduce the estimation error because there are smaller bias on the estimated parameters.

A big advantage of the Bayesian approach is to mitigate the problem of overfitting by introducing prior distributions. In a classical estimation framework based on a frequentist VAR approach, it is difficult to incorporate non-sample information into the estimation. By using Bayes' theorem, our knowledge about the parameters of the model observed from the data (the beliefs of the investigator) is easily incorporated into the Bayesian framework. In essence, the analysis of VAR models using a Bayesian framework needs to know in advance the distributional properties of the estimates of the parameters.

Let us assume that the parameters of interest that we want to estimate are collected in θ and Y denotes the available data that we use for the purpose of the estimation of these parameters. Then, with the help of the Bayes theorem, we have:

$$p(\theta|Y)=\frac{p(Y|\theta)*p(\theta)}{p(Y)} \tag{1}$$

in which p is a probability distribution and $p(\theta|Y)$ is a posterior distribution that characterises the knowledge about the parameters of the model conditional to the data. In the numerator, we have the joint distribution of the data and the parameters factorised into a product of the conditional distribution of the data given the parameters, and of the marginal distribution of parameters.

The likelihood function is defined as the conditional distribution of the data given the parameters of the model. It explains the differences between the frequentist and Bayesian methodology. In the frequentist approach, the process generating data is reflected into the model. If we know the process and its parameters θ, then we can randomly generate data from their distribution. In the frequentist view, the available data Y, are a single random realization of the process generating data. However, the parameters of the models themselves are non-random, although their actual values are unknown. From a Bayesian perspective, instead, the observed data are given and not random, while the parameters are considered random and thus are characterised by a probability distribution. It is this last consideration that leads us to the possibility of introducing a prior distribution of the parameters p(θ).

An alternative formulation of the Bayes theorem derives the posterior distribution as the product of the likelihood function $L(Y|\theta)$ and of the prior $p(\theta)$:

$$p(\theta|Y) \propto L(Y|\theta)p(\theta) \tag{2}$$

Our goal is estimating the moments of the parameters' posterior distributions that we can interpret as the location (mean) and dispersion (variance) of each parameter.

In order to do this we review two of the most popular priors that we used in the analysis related specifically to VAR coefficients: the Litterman-Minnesota prior (Litterman 1986) and the Normal Inverse Wishart prior. We start from the VAR (*p*) model:

$$Y_t = c + B_1 Y_{t-1} + B_2 Y_{t-2} + \ldots\ldots + B_p Y_{t-p} + u_t \tag{3}$$

Where *p* is the maximum lag order, *c* is a vector of constants, Y_t is a vector of the *N* endogenous variables included in the model, B are the *N*x*N* square matrices of the parameters and $u_t$is the white noise error term with a covariance matrix $E(u_t u_t^{'})=\psi$.

Rewriting the VAR equation (1) as a system of multivariate regressions, we have:

$$Y = XB + U \tag{4}$$

The matrices Y, X, B and U are defined as follow:

- $Y_t = (y_1, \ldots\ldots\ldots, y_T)^{'}$ stacks the observations (T) on each dependent variables (N). The matrix dimension is *TxN*
- $X = (x_1, \ldots\ldots\ldots, x_T)^{'}$ with $X_t = \left(1, y_{t-1}^{'}, \ldots\ldots\ldots, y_{t-p}^{'}\right)^{'}$ collects the observations on each lagged dependent variable. The matrix dimension is *Txk* where k=Np+1
- $B = \left(c, B_1 \ldots\ldots\ldots, B_p\right)^{'}$ collects the intercept term and the autoregressive terms. The matrix dimension is *kx N*
- $U = (u_1, \ldots\ldots\ldots, u_T)^{'}$ collects the error terms. The dimension is *TxN*

To apply the Bayesian inference in VAR estimation we specify the prior distribution of the parameters.

We use the Litterman/Minnesota prior (Litterman 1981, 1986) where the coefficients of the matrix B are random and are assumed to be *a priori* independent and normally distributed. The investigator can specify his/her beliefs on the value of B as following:

$$B \sim N\,(\beta_0, \Sigma) \tag{5}$$

where the vector β_0 is the prior mean and the matrix Σ is a dispersion measure, that accounts for the uncertainty about the prior beliefs.

In the Minnesota prior all the equations are "centred" around a random walk with drift similar to:

$$Y_t = c + Y_{t-1} + u_t \tag{6}$$

This representation of the data excludes cross-correlation among variables since each variable at time t depends only on a constant, its own first lag with coefficient equal to one, and a stochastic disturbance u_t. This choice simplifies the form of the matrix B that keeps non null only the coefficients on the diagonal.

Another relevant featureof the Litterman/Minnesota prior is that it does not require to set the prior distribution for the variance-covariance matrix ∑ since it is assumed to be fixed and known before sampling begins. Finally, the Litterman/Minnesota prior sets the $\psi = \sum$ matrix to be diagonal (∑=diag $(\sigma_1^2, \ldots \ldots \ldots \ldots \ldots \sigma_n^2)$) further simplifying the estimation of the model, as it is assumed that the errors are independent for each equation. Specifically, each equation of the VAR model can be estimated one by one. Finally, by assuming that all coefficients except their own lags terms are equal to zero, and setting the prior means (β_0) of B close to zero ensures the shrinkage of the VAR coefficients towards zero and reduces the risk of overfitting. In some particular cases β_0 is close to one reflecting the belief that all variables are characterized by high persistence.

Replacing ∑ with its estimate V_0 from the data, the prior distribution of B under the Minnesota prior is *a priori* normal and conditional upon the variance-covariance matrix ∑:

$$p(B|\sum) \sim N(\beta_0, V_0) \tag{7}$$

We can divide the explanatory variables in each equation of the VAR model into three groups: a) the own lags of the dependent variable; b) the lags of the other dependent variables; c) exogenous variables (Koop and Korobilis 2010). In Koop and Korobilis (2010) V_0 is the prior covariance matrix and since it is diagonal they simplifies further avoiding the choice of fully specifying all the elements of V_0 by selecting only the following scalars:

$$V_{ijj} = \begin{cases} \frac{\lambda_1}{r^2} \quad for\ coefficients\ on\ own\ lag\ \ r\ for\ r = 1, .., p \\ \frac{\lambda_2}{r^2} * \frac{\sigma_{ii}}{\sigma_{jj}} \quad for\ coefficients\ on\ lag\ r\ of\ variable\ j \neq j\ for\ r = 1, \ldots, p \\ \lambda_3 * \sigma_{ii} \quad for\ coefficients\ on\ exogenous\ variables \end{cases} \tag{8}$$

a) λ_1 controls the overall tightness of the prior distribution around the random walk or white noise. It governs the relative importance of the prior information with respect to the information contained in the sample. Setting λ_1 to a small value implies that the prior information dominates the sample information. On the other hand, if $\lambda_1 \to \infty$, the prior becomes non-informative and the posterior estimates converge to the unrestricted VAR coefficients.
b) λ_2 controls the standard deviation of the prior on lags of variables other than the dependent variable. If λ_2 is equal to one there is no restriction between lags of the dependent variable and other variables.
c) λ_3 reflects if the prior is informative for the exogenous variables (i.e a constant).

A great advantage of the Minnesota prior is that it leads to a simple posterior inference involving only the Normal distribution. Once set the prior covariance, the posterior of β will also be normal. Although the Litterman/Minnesota is actively used for its success in forecasting, it ignores any correlation among the residuals of different variables that is important in the case of structural analysis. An alternative prior is the Normal Inverse Wishart prior that retains the principles of the Minnesota prior but it relaxes the assumption of a fixed and diagonal variance-covariance matrix of the error terms.

Starting from the system of multivariate regressions shown in the equation (2) the Normal Inverted Wishart prior is specified conditionally to the knowledge of $\sum$:

$$B|\sum \sim N(\beta_0, \sum \otimes V_0) \text{ and } \sum^{-1} \sim W(S_0^{-1}, v_0) \quad (9)$$

The prior parameters β_0, V_0, S_0 (identity matrix), and v_0 (degrees of freedom parameter) are prior hyperparameters chosen by the researcher.

In the following sections, among other things, we shall also compare B-VAR with respect to VAR models in order to describe the relevant advantages that can come from the application of Bayesian methods to the subject considered in this work.

5. Monetary Policy and Capital Centralization: Impulse Response Functions

In this section, we apply impulse response functions based on different B-VAR models in order to investigate on the possible existence of a causal relationship between capital centralization and monetary policy. The sample time span 2001-2016 for both the Euro Area 12 and the United States is determined by the availability of data needed to construct the net control measure.

The data of nominal interest rate and inflation are extracted for the United States from the Federal Reserve Economic Data (FRED) database, while for the Euro Area they are drawn from the Eurostat database and the ECB statistical data warehouse. The variable "top holders of net-control" is defined with the acronymous *thnc*: it is computed from Eikon ownership data summing up the net-control per company and computing the fraction of companies owning the 80 percent of the stock market in each nation or economic area considered. With the threshold of 5 percent for each ownership relationship, the *thnc* variable represents an inverse measure of the centralization of capital control: the higher the *thnc* the lower the centralization. All examined data are annual (federal funds interest rate data are monthly but we transformed this series in annual).

Our variables of interest are the following: the already described fraction of top holders of net control (*thnc*); the U.S. federal funds rate (*FUNDS*); the European main refinancing rate (*REFI*); the price inflation calculated for the United States as the annual rate of change of the implicit price deflator (*pi*) with index 2012=100; the price inflation for the Euro Area calculated considering the annual rate of change of harmonized consumer price index (*hcpi*) with index 2010=100. We respectively compute the real federal funds rate (*rFUNDS*) as *FUNDS* minus *pi* and the real refinancing rate (*rREFI*) as *REFI* minus *hcpi*.

In order to analyse the dynamic relation between the fraction of top holders of net control and the real interest rate we use the impulse response functions based on Bayesian VAR models. We estimate for the United States and for the Euro Area two different B-VAR models with two lags selected according to the Schwartz Bayesian criterion. We specify the first model called the "USA model", with a constant, *rFUNDS* and *thnc*. We also add as exogenous variable a dummy *dum* to capture the specific effects of the financial crisis: we assume the value of 1 in the year 2007-2008 and zero otherwise. The second model called the "EA model" is specified in the same way of the USA model except for *rFUNDS* that is replaced by *rREFI*.

We use for both the B-VAR models the Litterman-Minnesota prior specification for two reasons: firstly, the Litterman/Minnesota prior works well with series in levels used in our analysis. Moreover, using the variables in levels we can obtain short run and long run information through the impulse response functions. Finally, the Litterman/Minnesota prior has the advantage to lead to a normal posterior inference because it is based on a normal distribution. Thus, the B-VAR model with this prior specification will tend to shrink the estimated coefficients of the VAR model towards the prior mean and away from the OLS estimates giving prediction gains with respect to a VAR model. We estimate the two B-VAR models with diagonal VAR estimates and Litterman/ Minnesota prior specification of the hyperparameters. Specifically, we select the four scalar hyperparameters as follow: a) we set λ_1(prior information) to a small value since the prior information dominates the sample information; $b)\lambda_2$(cross variables lags) and λ_3(exogenous variables) are set greater than zero since the information of the exogenous variables is important in our analysis.

Figures 2 and 3 display the impulse response functions respectively for the United States and for the Euro Area 12. The variables ordering (ORDER I) is respectively for the USA model: *rFUNDS* vs *thnc*; and for the EA model: *rREFI* vs *thnc*.

The plots show the region delimited by the 95 percent credible intervals, obtained through Gibbs sampling using 1000 iterations. We display the effect (one standard deviation) of a variable to the other variables for each B-VAR model until this effect becomes negligible (10 years). If there is a reaction of one variable to an impulse in the other variable, then we can say that the latter is causal of the former.

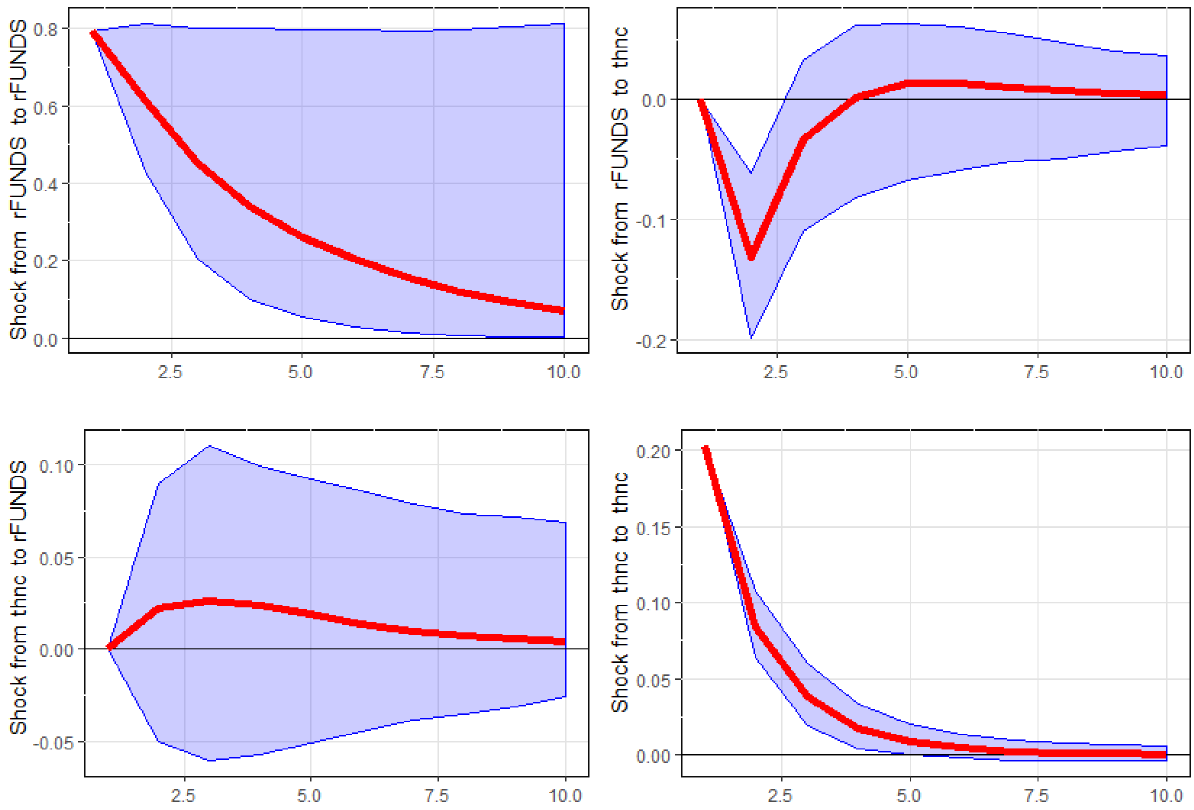

Figure 2: Impulse response functions with 95% credible intervals of *rFUNDS* vs *thnc* for USA Model

Regarding the United States examined in Figure 2, the second column of the first row shows that *thnc* declines in response to a *rFUNDS* shock. It means that a contractionary monetary policy is followed by a significant increase of capital centralization that reaches a level of 13 percent after 2.4 years and then becomes insignificant in the long term. In turn, the impact of *thnc* shocks on *rFUNDS* is poor and not significant (second row, first column). These results are significant at the 95 percent confidence level.

The impulse response functions of the EA model displayed in Figure 3 confirm the results for the USA model. In particular, it is confirmed an insignificant causal dependence of *rREFI* to *thnc* (second row, first column). Moreover, in response to a tightening policy (one standard deviation of *rREFI* shock), after 2.4 years the centralization (*thnc*) decreases by of 5 percent (first row, second column). Also in this case this is a significant evidence, although less pronounced than for the USA. For both models over time, all variables should gradually return to their steady state level. Moreover, in order to examine if the ordering of the variables changes the results of the impulse response functions, we computed the impulse response functions with the following variables ordering (ORDER II): a) *thnc* vs *rFUNDS* (USA model); b) *thnc* vs *rREFI* (EA model). The results show that the ordering of the variables is irrelevant (impulse response functions are available upon request).

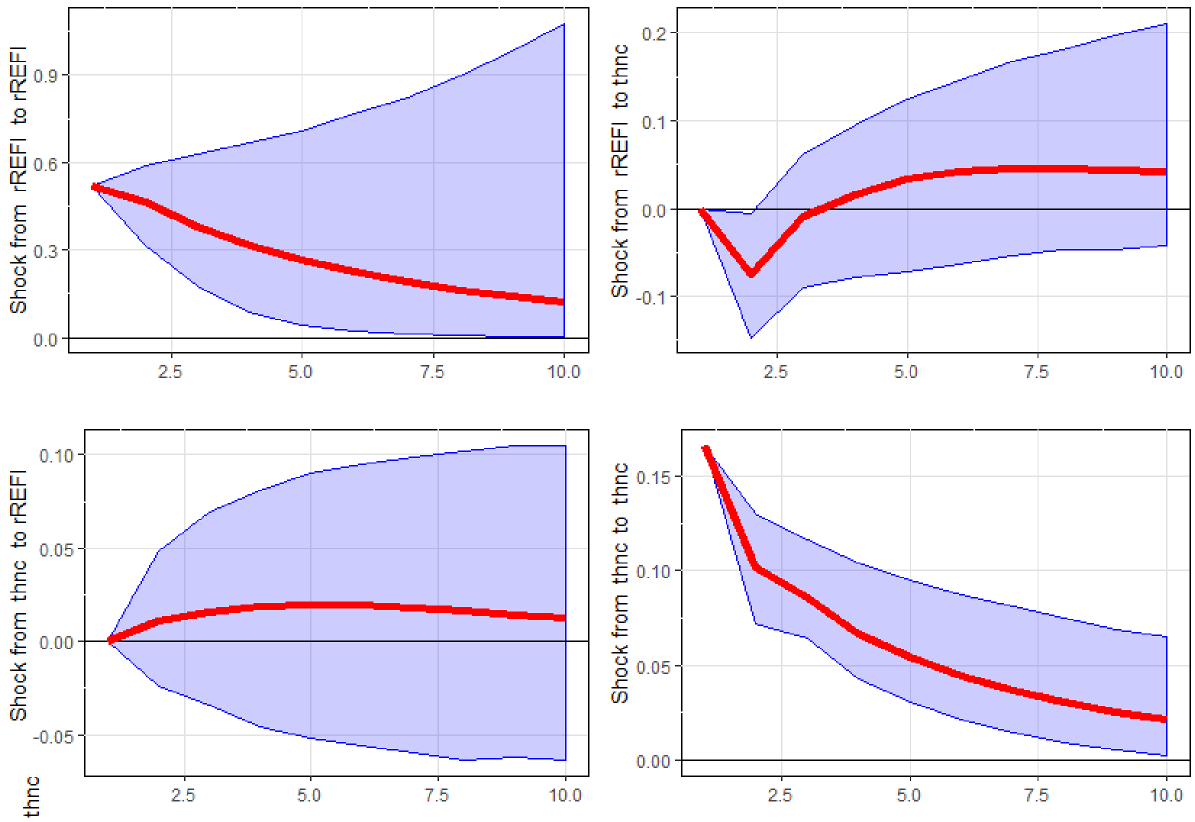

Figure 3: Impulse response functions with 95% credible intervals of *rREFI* vs *thnc* for EA Model

Finally, very similar results - available upon request – are obtained as a robustness check if in the USA model we use the discount interest rate, LIBOR interest rate or treasury bill interest rate instead of the Federal Funds interest rate, and if we use the Consumer Price index based on 2010 year or the GDP deflator with index 2015=100 instead of the GDP deflator with index 2012=100. The same goes for the EA model if we replace the refinancing interest rate with the EONIA interest rate, the Euribor interest rate and the discount interest rate and if we substitute the Harmonized price index based on 2010 year with the GDP deflator based on year 2005 or based on year 2010.

These findings suggest that restrictive monetary policies statistically cause an increase in capital centralization while expansionary policies cause a decrease in capital centralization. This relation is confirmed for both USA and Euro Area, with a stronger effect in the first case with respect to the second one.

6. Capital Centralization, Business Cycle and Crisis: Impulse Response Functions

In this section we analyse the relation between crisis and capital centralization through the impulse response functions based again on two different B-VAR models: the USA model and the EA model. The dataset contains the following macro-variables: the usual fraction of top holders of net control (*thnc*) and the deviation of nominal GDP from its trend (*gdp_dev*). The sample spans from the year 2001 to the year 2016 and it is determined, also in this case, by the data availability necessary to build the net control measure. The data of the nominal GDP (*gdp*) are obtained for the United States from the Federal Reserve Economic Data (FRED) database and for the EA12 are drawn from the Eurostat database. The fraction of top holders of net control *thnc* is calculated in the same way of the previous section. We apply the logarithms to the nominal GDP in order to reduce the dimensional effects and to minimize the linearity and the normality requirements. In accordance with Woodford (2012) we compute the deviation *gdp_dev* of nominal GDP from its trend by assuming that the target levels of the nominal GDP correspond to its log-linear trend obtained by applying the OLS method on a portion of the data sample in the years 2001 to 2008 when the Great Recession (IMF 2012) started (on this point see also Brancaccio et al. 2015).

Following the Bayesian VAR analysis, we estimate two B-VAR models with two lags selected according to the Schwartz Bayesian criterion. All models are specified by considering the net control (*thnc*), the nominal GDP deviation (*gdp_dev*) and a constant. The four hyperparameters of the Minnesota prior covariance matrix are set in the same way of the Section 5.

The Figures 4 and 5 respectively report the B-VAR impulse response functions for the USA model (variables ordering *thnc* vs *gdp_dev* USA) and the EA model (variables ordering *thnc* vs *gdp_dev* EA). In both cases, we see a significant response of *gdp_dev* to *thnc* in the short-run and in the long-run. Specifically, looking at the USA model in Figure 4, we notice that *gdp_dev* increases in response to a positive *thnc* shock and *gdp_dev* decreases as a consequence of a negative *thnc* shock. In other words, a reduction in the fraction of the top holders of net control and a consequent increase in capital centralization, leads to a significant worsening of the business cycle and maybe to a possible recession. Each increase of 1.0 percent in *thnc* has an impact on *gdp_dev* of 1.5 percent after 6.3 years before getting less significant. On the contrary, the impact of the *gdp_dev* shock on *thnc* is not significant (second row, first column). Figure 5 that describes the EA model shows analogous results. A reduction of the fraction of the top holders of net control and a consequent increase in capital centralization provokes a worsening in the business cycle. In this case, the impact on *gdp_dev* of a change of 1.0 percent in *thnc* has a peak of 2.3 percent after 6.3 years (Figure 5-first row, second column). On the contrary, the effect of *gdp_dev* on *thnc* is not significant (Figure 5 second row, first column). It is also interesting to notice that the impact of *thnc* on *gdp_dev* is stronger in the EA model with respect to the USA model. Also in this case a change in the ordering of the variables (*gdp_dev* vs *thnc*) has no effect on the impulse response functions (impulse response functions available upon request).

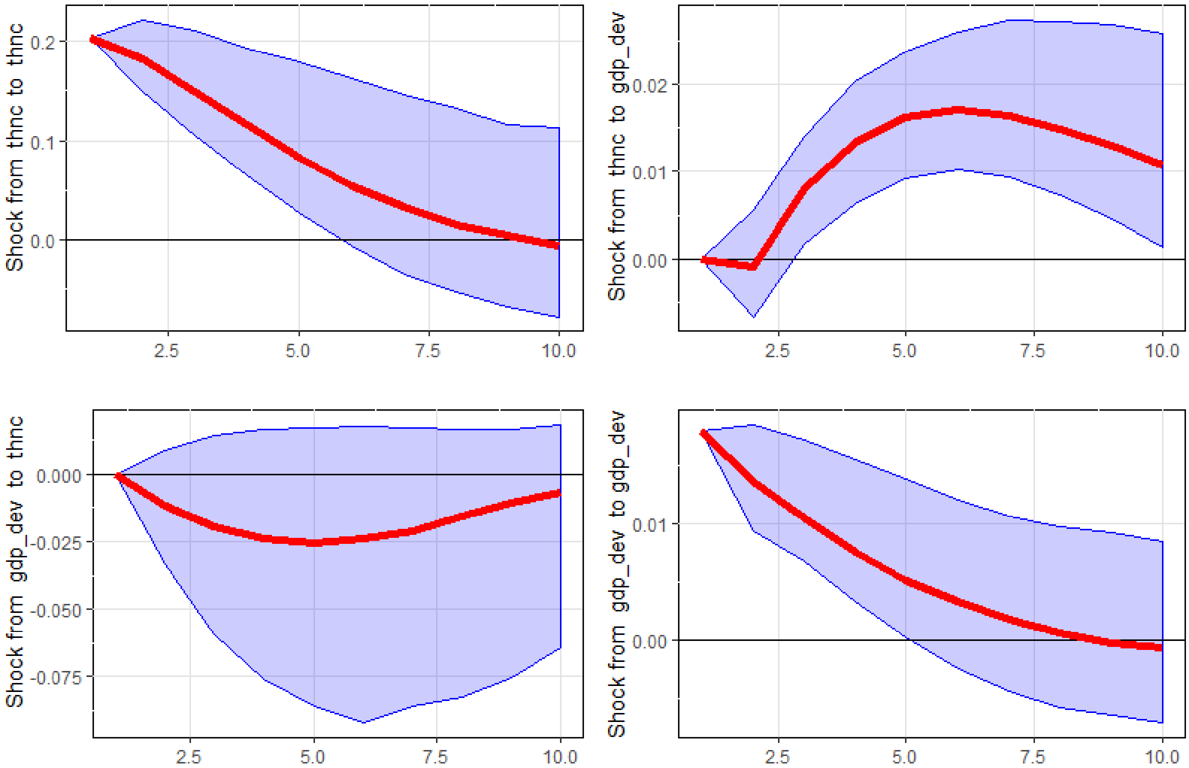

Figure 4 : B-VAR Impulse response functions with 95% credible intervals of *gdp_dev* vs *thnc* for the USA Model.

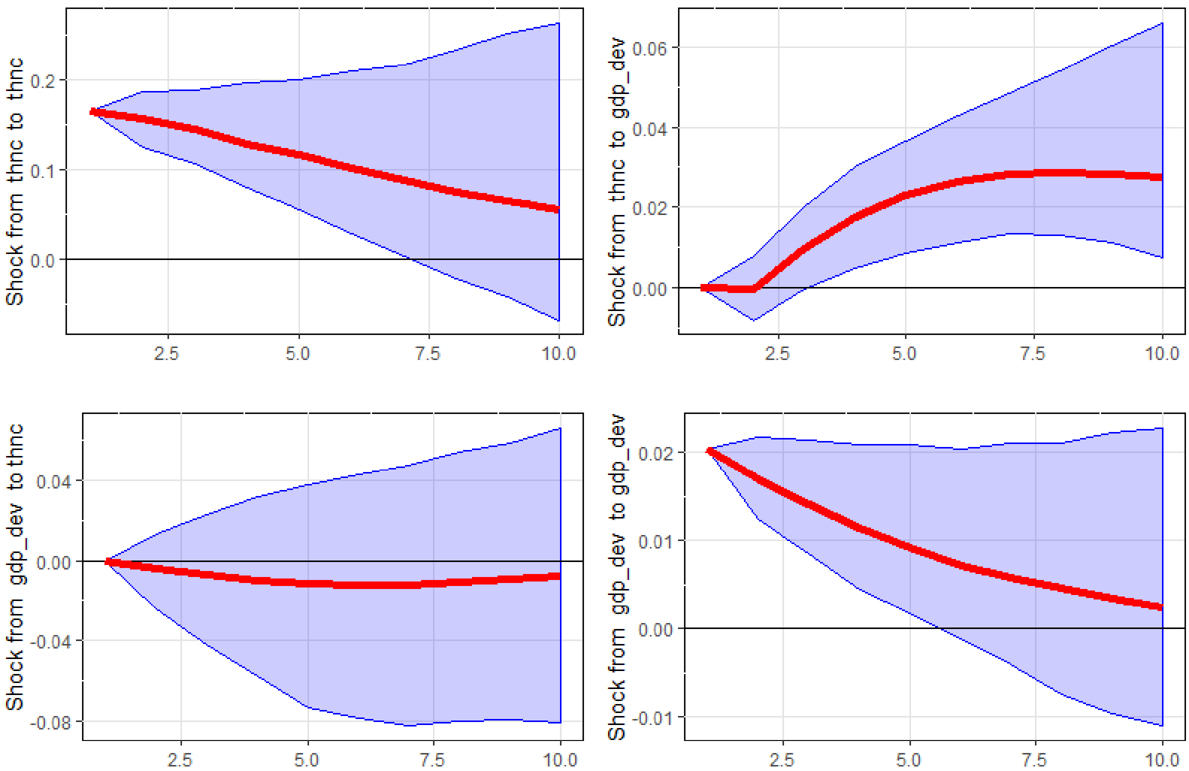

Figure 5: B-VAR Impulse response functions with 95% credible intervals of *gdp_dev* vs *thnc* for the EA Model.

Very similar results are found in both models if we adopt alternative measures of GDP trend or compute *gdp_dev* by replacing the nominal GDP with a nominal GDP in purchasing power parity (PPP), a real GDP in PPP, or a real GDP based respectively on the years 2010 and 2012 for the USA model, on the years 2010 and 2005 for the EA model. These findings give further support to the robustness of the analysis.

7. VAR versus B-VAR: Forecast Evaluation

In this work, we have chosen B-VAR models for our analysis. In order to validate our choice, we compare for the United States and for the Euro Area the forecast performance of an unrestricted VAR model on one hand and B-VAR models on the other which are based respectively on the Minnesota prior and on the Normal-inverse-Wishart prior.

To assess the forecast accuracy of BVAR model we do not use all of the observations but we drop the last two and use them for comparison. Those two points sample, known as holdout sample, are used to construct out-of sample forecasts. The 14th and 15th observations are forecasted from the fitted model and compared with the actual values that are in the holdout sample using RMSE and MAE (computed only on those two last values). Leaving out two values we can establish how good is the forecast on unseen data (the test data). As the our sample is short we selected only two points for the forecasting evaluation. The RMSE and MAE can be defined as follow:

1. The Root Mean Square Error (RMSE) is given as RMSE $= \sqrt{\frac{\sum_i^n (y_i - \bar{y}_i)}{n}}$ where y_i is the time series data and $\bar{y}_i$is the forecast value of y.
2. The Mean Absolute Error (MAE) is defined as $MAE = \frac{\sum_i^n | y_i - \bar{y}_i |}{n}$. This criterion measures the deviation from the series in absolute terms, and it provides a measure on how much the forecast is biased.

While RMSE gives more relevance to the larger deviations from true values (as it computes the square of the deviations), MAE is less sensitive to large deviations and conversely it is more able to capture small deviations from the true value. In order to assess the goodness of fit of the models we used both measures. A good forecast performance corresponds to a small value of both RMSE and MAE.

First, we focus on the relationship between monetary policy and capital centralization by considering the nexus between the real interest rates (*rFUNDS* and *rREFI*) and the fraction of top holders of the net control (*thnc*). The analysis shows relevant gains by using Bayesian methods: the poor performance of the VAR model with respect to the B-VAR models confirms that the informative priors significantly improved the forecasts of our models.

Analogous results come from the analysis of the relationship between capital centralization and business cycle, by examining the nexus between the fraction of the top holders of net control (*thnc*) and the deviation of nominal GDP from its trend (*gdp_dev*). The findings show that also in this case the B-VAR models based on Minnesota prior fit better than a VAR model and a B-VAR model based on the Normal-inverse-Wishart prior. Overall, the Minnesota prior information improves the forecast accuracy of the B-VAR models outperforming the other specifications.[1]

8. Conclusions

The aim of this paper was to assess whether there are relationships between capital centralization expressed in terms of fraction of top holders of network control on one hand and monetary policy guidelines and business cycles on the other. The analysis considers the United States and the Euro Area over the period 2001-2016.

The innovative features of this study are the following. First, the analysis complements the literature on the causes and implications of ownership concentration (Berle and Means, 1932; Granovetter, 1995; La Porta et al., 1998, 1999; Djankov et al., 2008; Wang and Szirmai, 2008; Gatti, 2009; Wang, 2009). Typically, these studies aim to provide evidence on the macroeconomic consequences of alternative models of governance by looking at the concentration of ownership only within corporations. Instead, as in Brancaccio et al. (2018), in this paper we adopt a network-based measure of capital centralization which considers corporate links within and across corporations and includes direct and indirect ownership and control relations. Furthermore, with respect to previous studies here we innovate by proposing a measure of capital centralization not only at a global level but also at a national or single economic area level. Finally, this study proposes an original integration of network analysis techniques and Bayesian VAR econometric tools. The preference for the Bayesian methods relies on the fact that they are particularly well suited in handling time series even when are short as in our study; they are an a-theoretically grounded way to impose judgmental information and a priori beliefs in the model; they improve the dynamical analysis and the forecast performance when the VAR is unstable by reducing the bias and the standard errors. Further, the use of the impulse response functions allows us to obtain long-run information investigating the dynamic relationship between the variables of interest on a longer time horizon of ten years after the initial time span of 15 years, for a total of 25 years. This feature is of foremost importance in a study aiming to analyze economic tendencies. Clearly, the hope is to further develop the analysis in the future over more extensive available datasets..

The results of the analysis support the thesis that monetary policy has an impact on capital centralization but not vice versa, and that capital centralization influences the business cycle

[1] Results published in the final version of this paper, forthcoming in *Structural Change and Economic Dynamics*.

but not vice versa. In particular, an increase in the interest rates leads to a reduction of the fraction of the top holders of the net control and a consequent increase in capital centralization, and an increase in capital centralization causes a reduction of the nominal GDP with respect to its trend and a possible economic recession. More specifically: a one percent increase in the policy interest rate brings about a reduction in the fraction of top shareholders of net control of about 13 percent in the US and of 5 percent in the Euro Area; and a one percent decrease in the fraction of top shareholders leads to a 1.5 percent contraction of the nominal GDP deviation from its trend in the Euro Area, and a 2.3 percent contraction in the United States. These results seem to give empirical support to the theses according to which monetary policy can have an impact on the centralization of capital (Brancaccio and Fontana 2013, 2016; Brancaccio, Califano, Lopreite, Moneta 2019; see also Radcliffe Report 1959; Kaldor 1985; Aikman et al. 2016) and capital centralization, in turn, can cause economic recession (Hilferding, 1910; Magdoff and Sweezy, 1987; Lazonick, 1992; Crotty, 1993; Sweezy, 1994; Dore, 2008; Foster et al., 2011).

This study does not contemplate all the possible determinants of the centralization processes nor all the economic implications of centralization. Our results, however, leave the door open to future research. A promising field of further investigation could be a study of the relationship between our specific measure of capital centralisation and innovation measures. The prevailing studies tend to estimate ownership concentration within corporations (Dosi, 1990; Carlin and Mayer, 2003; Brossard et al., 2013; Belloc et al., 2016). Future analyses could be dedicated to the study of the nexus between innovation and our computation of capital centralisation expressed in terms of direct and indirect network control. In this sense, future research may explore in a new theoretical guise the nexus between the Marxian “law of tendency” towards capital centralization (Marx 1867; Hilferding, 1910; Lenin, 1917; Baran and Sweezy, 1966; Sau, 1979) and the Schumpeterian themes on industrial evolution and technical change (Nelson and Winter, 1982; Dosi et al., 2008; Mazzucato, 2013), shedding further light on the possible interactions between these two lines of research.

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