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What drives business cycle synchronization? BMA results from the European Union

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ABSTRACT

The last twenty years have brought a bulk of inconsistent results on the determinants of business cycle synchronization (BCS). Researchers have usually focused their attention on a limited set of possible determinants, not accounting for model uncertainty. For these reasons, Bayesian Model Averaging has been applied in this paper to the dataset with 43 potential determinants of BCS for the EU. There is strong evidence to claim that migration, exchange rate variability, similarity of production structures, TFP shocks, similarity in exchange rate policy, intra-industry trade, risk sharing, and capital mobility are robust determinants of BCS. Some well-established determinants such as bilateral trade, monetary policy similarity, gravity variables, and participation in a monetary union and free trade area have turned out to be fragile. The structure of trade is more important for BCS than its magnitude, as intra-industry trade and structural similarity are taking explanatory power away from the bilateral trade.

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1. Introduction

Since the publication of the seminal work of Frankel and Rose (1998), research into the determinants of business cycle synchronization (BCS) has been overflowing economic literature. The interest was fuelled by the fact that BCS can be treated as one of the major criteria of optimum currency areas (OCA), and the OCA literature is full of potential candidates for determinants. At the same time, the emergence of the Eurozone created the need for better guidance about the pace of integration and potential costs and benefits of currency unification. The knowledge about the determinants of BCS can improve the ability of the EU institutions as well as governmental bodies in designing policies aimed at improvement of the effectiveness of the common monetary policy conduct.

The last twenty years have brought a bulk of inconsistent or conflicting results. Researchers have usually focused their attention on a limited set of possible determinants of BCS. Consequently, variables that were classified as significant in one research turned out to be not significant in others. The present paper brings all of this research together and checks which out of the long list of potential incentives are robust determinants of

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business cycle synchronization. In order to achieve this goal, Bayesian model averaging (BMA) along with jointness measures have been employed to a rather homogenous dataset covering 26 European Union countries over the period between 1999 and 2011. The analysis with BMA should enable the listing of correct drivers of BCS among its 43 potential determinants.

The paper is structured as follows. A literature review is presented in section 2. Measures of the BCS and its determinants as well as shows the BMA framework are described in section 3. Estimation results along with vast robustness checks are presented in section 4. Section 5 concludes.

2. Literature review

Research into the determinants of BCS spans over the last 20 years, and it has brought about a bulk of inconsistent or even conflicting results. It starts with the seminal work of Frankel and Rose (1998), who report that bilateral trade influence on BCS is positive and significant. The result is confirmed by some authors (e.g. Alimi, 2015; Calderón, Chong, & Stein, 2007; Duval, Cheng, Hwa Oh, Saraf, & Seneviratne, 2014), some demonstrate the fragility of the impact of trade on business cycle synchronization (e.g. Crosby, 2003; Rana, Cheng, & Wai-Mun, 2012; Shin & Wang, 2003), while others show that the significance of trade relies upon specification of the used model (Lee, 2010). Gruben, Koo, and Millis (2002) demonstrate the role of intra-industry trade as a business cycle transmission channel and argue that it takes explanatory power away from total trade. The significance of intra-industry trade in the determination of BCS is corroborated by Fidrmuc (2004) and Duval et al. (2014).

Another strain of the literature presents research into the impact of structural similarity on business cycle synchronization. On the one hand, there are papers that show a positive and significant impact of structural similarity (Azali & Lee, 2010; Beck, 2013a; Kalemli-Ozcan, Sørensen, & Yosha, 2001; Siedschlag, 2010), while others show that it depends on the other variables included in the model (Baxter & Kouparitsas, 2005; Inklaar, Jong-A-Pin, & de Haan, 2008; Kalemli-Ozcan, Papaioannou, & Peydró, 2013). While empirical results are ambiguous, the theory is straightforward and predicts a positive relationship between similarity of production structures and BCS.

The same cannot be said about the impact of capital mobility or financial integration on the synchronization of business cycles. International real business cycle literature predicts a negative impact on BCS (Backus, Kehoe, & Kydland, 1992), while arguments based on shock spillovers (Kose, Otrok, & Prasad, 2012; Kose, Otrok, & Whiteman, 2003) point to a positive influence. Empirical results are similarly ambiguous. Otto, Voss, and Willard (2001) and Imbs (2004, 2006) show a positive impact, Cerqueira and Martins (2009), Kalemli-Ozcan et al. (2013), and Monnet and Puy (2016) a negative one, while Nguyen (2007), Akın (2012) and Dées and Zorell (2012) report not significant results. Herrero and Ruiz (2008), Antonakakis and Tondl (2014), and Jansen and Stokman (2014) show a positive influence of FDI flows on BCS, while Lee (2010) finds it significant only in some model specifications.

Similarly to financial integration, the impact of macroeconomic policy coordination on output correlations is uncertain in both theory and empirics. On theoretical grounds, a similar fiscal and monetary policy can lead to higher business cycle synchronization in the presence of symmetric shocks, while a lower one in the presence of asymmetric

ones. Rana (2008), Pentecôte, Poutineau, and Rondeau (2013) and Duval et al. (2014) show that fiscal policy similarity has an impact on BCS, while Böwer and Guillemineau (2006), Nguyen (2007) and Shin and Wang (2003) find no such relationship. Monetary policy similarity has a significant impact on output comovement in works of some authors (Beck, 2013b; Chang, Kim, Tomaljanovich, & Ying, 2013; Clark & van Wincoop, 2001; Duval et al., 2014), while it is fragile in others (Böwer & Guillemineau, 2006; Pentecôte et al., 2013).

Another strain of literature considers the impact of the exchange rate regime on the correlation of business cycles. Exchange rate variability has a significant impact on BCS in some of the research studies (Chang et al., 2013; Duval et al., 2014; Inklaar et al., 2008; Pentecôte et al., 2013); in others, it depends on the model specification (Akın, 2012; Otto et al., 2001), or is insignificant (Crosby, 2003; Herrero & Ruiz, 2008). The impact of monetary integration on the correlation of business cycles is positive and significant in most of the research (Beck, 2013b; Fidrmuc, 2004; Rose, 2011), yet the variable representing the currency union turns out to be fragile in some papers (Baxter & Kouparitsas, 2005; Böwer & Guillemineau, 2006).

BCS literature is linked to the OCA theory (Kenen, 1969; McKinnon, 1963; Mundell, 1961). Two of the OCA criteria,[1] namely wage elasticity and labour force mobility, have not been adequately investigated thus far. Exceptions are papers by Sachs and Schleer (2013), who analyze the similarity of labour market institutions and structural reforms, and by Böwer and Guillemineau (2006), who research differences in labour protection. Still, the former team finds the examined variables robust, while the latter finds them fragile. Another main criterion of the Optimum Currency Areas, namely labour force mobility, has still been left unexplored up to this day.

Baxter and Kouparitsas (2005) examine the role of differences in factor endowments for business cycle correlations. They analyze differences in years of schooling, capital per worker, and arable land, yet they find all these variables fragile. Some authors also explore the role of macroeconomic factors, but these investigations are mostly limited to inflation (Beck, 2014; Chang et al., 2013; Herrero & Ruiz, 2008), technological shocks (Crosby, 2003), and GDP volatility (Kose et al., 2003). Still, other macroeconomic variables remain uninvestigated in the business cycle synchronization literature. Finally, gravity variables, *ergo* real GDP product, geographical distance, common border, and common language, are significant in some studies (Baxter & Kouparitsas, 2005; Clark & van Wincoop, 2001) while fragile in others (Beck, 2014; Crosby, 2003).

The brief literature review presented above unequivocally demonstrates the scale of ambiguity over the determinants of BCS in both theory and empirics. Consequently, the present paper aims at the assessment of the robustness of all the determinants examined up to date and even at extension of this list. So far, there have been five attempts at achieving this goal: Baxter and Kouparitsas (2005), Böwer and Guillemineau (2006), Nguyen (2007), Sachs and Schleer (2013) and Beck (2013a). All of them use somewhat limited sets of potential determinants of BCS, and outdated methodologies: the former two the Extreme Bound Analysis (Leamer, 1983), whereas the latter three its extension proposed by Sala-i-Martin (1997).

For this reason, this paper attempts to achieve that by applying BMA to determine which out of 43 variables are robust determinants of BCS. Moreover, jointness measures available within the BMA framework enable the analysis of relationships between them. Additionally, in order to account for possible endogeneity and to explore the dynamic

dimension of the data, Moral-Benito BMA approach has been utilized to deepen the analysis of the determinants of business cycle synchronization.

3. Methodology

Subsection 3.1 presents all variables used in the estimation with the sources of data, while subsection 3.2 presents the BMA framework along with jointness measures.

3.1. Data and measurement

The analysis covers 26 European Union countries, namely: Austria, Belgium, Bulgaria, Cyprus, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxemburg, the Netherlands, Poland, Portugal, Romania, the Slovak Republic, Slovenia, Spain, Sweden, and the United Kingdom. All variables are in a bilateral form: for 26 countries, it amounts to 325 country pairs. The time span of the research covers the period between 1999 and 2011.

3.1.1. Cross-sectional data setting

A dependent variable is a measure of business cycle synchronization. In order to build the measure of BCS, the seasonally adjusted time series of real GDP from Eurostat covering the period from the first quarter of 1997 to the first quarter of 2014 are tested for the presence of trend with ADF and KPSS test. Based on the results, the data is adjusted for drift for all the countries, except for Poland, where the time trend was extracted from the time series. Secondly, Christiano and Fitzgerald (2003) filter is applied to the transformed data, where the cyclical component is defined as the part of time series with a frequency between 1.5 and 8 years.[2] Finally, the correlation coefficient of cyclical components of GDP for the period between the first quarter of 1999 and the fourth quarter of 2011 is the used measure of BCS. This measure of BCS is most commonly used in the applied work aforementioned in the literature review; thus, it enables a comparison of the present results with the previous research. All the variables below are expressed in real terms unless it is stated otherwise.

Explanatory variables can be divided into four groups. The first group contains variables related to the theory of optimum currency areas. The first one is bilateral trade. In the paper, two measures of bilateral trade are utilized. The first is the sum of imports and exports from country *i* to country *j* divided by the sum of their GDPs (the measure is the average value for the entire period: 1999–2011, the same is applicable to measures 1 through 7):

$$TRADE1_{ij} = \frac{1}{T}\sum_{t=1}^{T}\frac{IMPORT_{ijt} + EXPORT_{ijt}}{GDP_{it} + GDP_{jt}}, \tag{1}$$

and the second is the sum of imports and exports from country *i* to country *j* divided by the sum of their total trades:

$$TRADE2_{ij} = \frac{1}{T}\sum_{t=1}^{T}\frac{IMPORT_{ijt} + EXPORT_{ijt}}{TOTAL\ TRADE_{it} + TOTAL\ TRADE_{jt}}. \tag{2}$$

Data about $TRADE1_{ij}$ and $TRADE2_{ij}$ comes from IMF Directions of Trade and World Bank (WB).

The second variable based on the OCA theory is intra-industry trade. Here, two measures are also used. The first is the ratio of intra-industry trade to total trade in intermediate goods:

$$IIT_{ij} = \frac{1}{T}\sum_{t=1}^{T}\frac{INTRA\_INDUSTRY\ TRADE_{ijt}}{TOTAL\ TRADE_{ijt}}, \tag{3}$$

and the second is the above-mentioned ratio multiplied by bilateral trade of two countries expressed as the share of the sum of their GDPs:

$$IITT_{ij} = \frac{1}{T}\sum_{t=1}^{T}\frac{INTRA\_INDUSTRY\ TRADE_{ijt}}{TOTAL\ TRADE_{ijt}} * TRADE1_{ijt}. \tag{4}$$

Data about IIT_{ij} and $IITT_{ij}$ is annual and comes from World Input-Output Database (WIOD).

Another variable measures the similarity of production structures between two countries. It is the value of bilateral Krugman specialization index (1991) for sectoral value added under the division of the economy into 35 sectors:

$$KSI_{ij} = \frac{1}{T}\sum_{t=1}^{T}\sum_{l=1}^{L}|v_{lit} - v_{ljt}|, \tag{5}$$

where v_{lit} denotes the share of the value added of sector l in total value added for country i at time t, and L is a total number of sectors. This variable takes values from 0 to 2, where 0 represents an identical production structure in both countries. Data for KSI_{ij} is annual and was taken from WIOD.

The next variable is a proxy for fiscal policy similarity and is calculated as the absolute value of the difference in budget balances (expressed as shares of GDP) between two countries:

$$FISCAL_{ij} = \frac{1}{T}\sum_{t=1}^{T}|BUDGET\ BALANCE_{it} - BUDGET\ BALANCE_{jt}|. \tag{6}$$

Data for $FISCAL_{ij}$ is annual and was taken from the Eurostat database.

The proxy for monetary policy is computed as the absolute value of the difference of real interest rates between two countries:

$$MONET_{ij} = \frac{1}{T}\sum_{t=1}^{T}|REAL\ INTEREST\ RATE_{it} - REAL\ INTEREST\ RATE_{jt}|. \tag{7}$$

Data for $MONET_{ij}$ is annual and was taken from the AMECO database.

In order to capture the impact of exchange rate variability on BCS coefficient of variation of the bilateral nominal exchange rate for the 1999–2011 period is calculated using data from AMECO:

$$EXCHANGE_{ij} = \frac{STANDARD\ DEVIATION(NOMINAL\ EXCHANGE\ RATE_{ij})}{MEAN(NOMINAL\ EXCHANGE\ RATE_{ij})}. \tag{8}$$

In order to capture the effects of exchange rate policy, variable $RESERV_{ij}$ is computed as a correlation coefficient of currency reserves position of central banks for each pair of

countries over the 1999–2011 period. Data for $RESERV_{ij}$ was taken from WB. Variable MU_{ij} captures the impact of participation in a monetary union. It is constructed for the 1999–2011 period in the following way: firstly, value 1 is assigned for each year when both countries were members of the monetary union, and 0 otherwise. Then, the mean value for the entire period is calculated. The variable expressing participation in free trade area – EU_{ij} – is calculated in the same fashion, with value 1 assigned to years when both countries were members of the European Union.

The measures of capital mobility are based on Feldstein and Horioka's (1980) equation modified for time series data and were estimated for each country *i*:

$$\frac{I_{it}}{Y_{it}} = \alpha_i + \beta_i \frac{S_{it}}{Y_{it}} + \varepsilon_{it}, \tag{9}$$

where $\frac{I_{it}}{Y_{it}}$ is investments share of GDP, and $\frac{S_{it}}{Y_{it}}$ is savings share of GDP. α_i and β_i are parameters estimated with OLS for each country using annual data for the 1999–2011 period. Data used in estimation comes from IMF World Economic Outlook (WEO). Coefficients β_i are then utilized in order to calculate the following two measures of difference in capital mobility between country *i* and *j*:

$$CAPFLOW_{ij} = |\beta_i - \beta_j|, \tag{10}$$

and

$$MOBILITY_{ij} = |\beta_i * R_i^2| - |\beta_j * R_j^2|, \tag{11}$$

where R_i^2 denotes the coefficient of determination for model *i*. The former measure captures differences in directions of flows, while the latter differences in the degree of capital mobility. The last measure associated with capital mobility is based on the absolute value of the difference of FDI flows (expressed as a percentage of GDP) between country *i* and *j*. The data used is annual, it covers the period between 1999 and 2011, and the measure is the mean value for the entire period:

$$FDI_{ij} = \frac{1}{T}\sum_{t=1}^{T} |FDI_{it} - FDI_{jt}|. \tag{12}$$

Data for FDI_{ij}, was taken from the UNCTAD database.

Another measure associated with the OCA theory is a proxy for risk sharing calculated as follows:

$$RISK_{ij} = cor(Cgrowth_i, Cgrowth_j) - cor(GDPgrowth_i, GDPgrowth_j), \tag{13}$$

where *cor()* denotes correlation coefficient, $Cgrowth_i$, $Cgrowth_j$ time series of consumption growth, and $GDPgrowth_i$, $GDPgrowth_j$ times series of real GDP growth in country *i* and *j* respectively. All time series are annual, covering the 1999–2011 period, and were taken from PTW.

To assess the difference in wage elasticity, the following equation was estimated with OLS for the 1999–2011 period for each country using data from AMECO and PWT:

$$\ln(REAL\ WAGE)_{it} = \alpha_i + \beta_i \ln(EMPLOYMENT)_{it} + \ln(time) + \varepsilon_{it}. \tag{14}$$

The measure is defined as follows:

$$RWELASTIC_{ij} = |\beta_i - \beta_j|. \tag{15}$$

The final variable from the OCA group measures the differences in net migrations between countries. It is computed as the absolute value of the difference in net migration per one thousand inhabitants. The data is annual, and the measure is the mean value for the 1999–2011 period:

$$MIGR_{ij} = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{NET\ MIGRATION_{it}}{1000 * POPULATION_{it}} - \frac{NET\ MIGRATION_{jt}}{1000 * POPULATION_{it}}\right|. \tag{16}$$

Data for $MIGR_{ij}$ comes form Eurostat and Penn World Table (PWT) (Feenstra, Inklaar, & Timmer, 2015).

The next group of variables contains those which could be described as associated with macroeconomic indicators. In order to assess the impact of technological shocks, variable TFP_{ij} was calculated as the correlation coefficient of growth rates of total factor productivity between the two countries. TFP_{ij} was calculated for the 1999–2011 period using annual data from PWT. The next variable measures differences between the degrees of openness between the two economies, and is calculated as follows:

$$OPEN_{ij} = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{IMPORT_{it} + EXPORT_{it}}{GDP_{it}} - \frac{IMPORT_{jt} + EXPORT_{jt}}{GDP_{jt}}\right|, \tag{17}$$

over the 1999–2011 period using annual data from PWT. The third variable from this group captures real GDP *per capita* distance. It is calculated with annual data from PWT as follows:

$$RGDPpc_{ij} = \frac{1}{T}\sum_{t=1}^{T}\left|\ln\left(\frac{REAL\ GDP\ per\ capita_{it}}{REAL\ GDP\ per\ capita_{jt}}\right)\right|. \tag{18}$$

Variable $AGROWTH_{ij}$ is calculated as an absolute value of the difference between mean GDP growth rates over the 1999–2011 period between two countries. Data for this variable is annual and comes from PWT. $INFVAR_{ij}$ is computed as an absolute value of a difference between standard deviations of inflation rates in two countries over the 1999–2011 period. Data for $INFVAR_{ij}$ was taken from IMF WEO. The last variable from this group – GOV_{ij} – is calculated as an absolute value of the difference of government shares of GDP between two countries averaged over the 1999–2011 period. The data for this measure comes from PWT.

The third group of measures is differences in factor endowments. Each of them is calculated as the absolute value of a difference in a given factor endowment averaged over the 1999–2011 period. Data from PWT was taken for $EMPDIFF_{ij}$ – employment, $HUMAN_{ij}$ – human capital index (Barro & Lee, 2013), $CAPDIFF_{ij}$ – capital, and $CPWDIFF_{ij}$ – capital per worker. From WB, comes data for $ARABLE_{ij}$ – arable land, $LAND_{ij}$ – land, $URBAN_{ij}$ – urban population, $EPCpc_{ij}$ – electricity consumption per capita, and $OILpc_{ij}$ – oil usage per capita. Data from PWT and WB was taken for $ARABLEpw_{ij}$ – arable land per worker and $URBANshare_{ij}$ – the share of the urban population.

The last group is composed of gravity variables. The first two are the products of real GDPs and populations of two countries averaged over the 1999–2011 period denoted as

$RGDPPROD_{ij}$ and $POPPROD_{ij}$ respectively. $RGDPDIFF_{ij}$ and $POPDIFF_{ij}$ denote the absolute value of the differences in real GDP and population respectively averaged over 1999–2011 period. Data for all the four above-mentioned variables comes from PWT. $DGEO_{ij}$ is the geographical distance between the capital cities of the two countries. B_{ij} is a binary variable that takes the value of 1 if two countries share a common border, and 0 otherwise. L_{ij} is a binary variable taking the value of 1 if two countries share at least one official language, MA_{ij} is a binary variable taking the value of 1 if both countries have access to the ocean or the sea, MB_{ij} is a binary variable taking the value of 1 if both countries share only a marine border, $TRANS_{ij}$ is a binary variable taking the value of 1 if both countries are transition countries, and $OLDUE_{ij}$ is a binary variable taking the value of 1 if both countries were members of the EU before 2004. That brings the total to 43 explanatory variables.

3.1.2. Panel data setting

The first two measures of business cycle synchronization in the panel data approach are constructed using Christiano and Fitzgerald (2003) and Baxter and King (1999) filtered seasonally adjusted time series of real GDP from Eurostat, covering the period from the first quarter of 1995 to the first quarter of 2018. Time series of the cyclical component are divided by trend component in order to obtain deviations of real GDP from the trend. Secondly, the correlation coefficient is calculated for each consecutive three-year period from 2000 to 2011 (variable *CFy* and *BKy* for Christiano-Fitzgerald and Baxter-King filter respectively), and for the 1997–1999 period[3] to obtain the lagged values of the variables (*CFylag* and *BKylag*). To assure robustness of the results, two more BCS measures are calculated. The cyclical component is extracted from time series of real GDP growth rates using with Christiano-Fitzgerald and Baxter-King filter. Correlation coefficients of these cyclical components give the last two BCS measures, denoted *CFdlny* and *BKdlny*, as well as lagged values *CFdlnylag* and *BKdlnylag*.

In the panel data setting, ten different determinants of BCS are examined. The first is the ratio of intra-industry trade to total trade in intermediate goods (*IITp*). It is calculated in the same way as in (3), but this time, three-year averages are calculated for the four consecutive periods between 2000 and 2011. Similarly, the measure of structural similarity (*KSIp*) is constructed analogically to (5), fiscal policy similarity (*FISCALp*) analogically to (6), and migration flows (*MIGRp*) analogically to (16) but with the use of three-year averages. The variable capturing the impact of exchange rate volatility on business cycle synchronization (*EXCHANGEp*) is calculated similarly as in (8). This time, monthly data on exchange rates from IMF International Financial Statistics is used, and the coefficient of variation is calculated over the three-year periods.

The variable capturing the effects of exchange rate policy is calculated as an absolute value of the difference between growth rates of currency reserves position (*RPgr*) of central banks for each pair of countries averaged over the four consecutive three-year periods between 2000 and 2011:

$$RESERVp = \frac{1}{3}\sum_{t}^{3} |(RPgr_{it} - RPgr_{jt}|. \tag{19}$$

Another potential determinant of BCS is the extent of capital mobility. The variable representing this determinant is calculated as an absolute value of the difference between

capital flows between two countries averaged over three years:

$$CAPFLOWp = \frac{1}{3}\sum_{t}^{3}\left|\left(\frac{I_{it}}{Y_{it}} - \frac{S_{it}}{Y_{it}}\right) - \left(\frac{I_{jt}}{Y_{jt}} - \frac{S_{jt}}{Y_{jt}}\right)\right|. \tag{20}$$

The impact of technological shocks is captured by the absolute value of the difference in total factor productivity growth rate (*TFPgr*) averaged over a three years:

$$TFPp = \frac{1}{3}\sum_{t}^{3}|(TFPgr_{it} - TFPgr_{jt}|. \tag{21}$$

The extent of risk sharing is measured as follows:

$$RISKp = \frac{1}{3}\sum_{t}^{3}|(Cgrowth_{it} - GDPgrowth_{it}) - (Cgrowth_{jt} - GDPgrowth_{jt})|, \tag{22}$$

with notation analogical to equation (13).

The last examined determinant of business cycle synchronization is the difference in the wage elasticity between two countries, calculated as follows:

$$RWELASTICp = \frac{1}{3}\sum_{t}^{3}\left|\left(\frac{\Delta RW_{it}}{\Delta E_{it}}:\frac{RW_{it}}{E_{it}}\right) - \left(\frac{\Delta RW_{jt}}{\Delta E_{jt}}:\frac{RW_{jt}}{E_{jt}}\right)\right| \tag{23}$$

where *RW* denotes real wage and *E* denotes employment.

3.2. Bayesian model averaging and jointness measures

3.2.1. Cross-sectional data setting

In order to screen the above-mentioned set of variables for robust determinants of BCS, Bayesian model averaging is applied along with jointness measures to recognize the nature of the relationships between the analyzed regressors. At the first stage of the analysis, BMA is applied to cross-sectional data described in subsection 3.1.1. BMA assumes the following general form of the model:

$$y_j = \alpha_j + X_j\beta_j + \varepsilon_j \tag{24}$$

where $j = 1, 2, \ldots, m$ denotes the number of the model, y_j is a vector ($n \times 1$) of the values of the dependent variable, α_j is a vector of intercepts, β_j is a vector ($K \times 1$) of unknown parameters, X_j is a matrix ($n \times K$) of explanatory variables, whereas ε_j is a vector of residuals which are assumed to be normally distributed and conditionally homoscedastic, $\varepsilon \sim N(0, \sigma^2 I)$. n denotes the number of observations (325), and K is a total number of regressors (43). Moreover, each model M_j has a binary vector ascribed to it: $\varphi = (\varphi_1, \varphi_2, \ldots, \varphi_K)$, where zero signifies that a given regressor does not appear in the model, while 1 means that a given variable is in the model.

In the case of 43 regressors, the model space consists of $2^{43} = 8796093022208$ possible specifications. In order to reduce model space, MC^3 (Markov Chain Monte Carlo Model Composition), a sampler based on Metropolis-Hestings algorithm, is used (Madigan, York, & Allard, 1995). The convergence of the chain is assessed by the correlation

coefficient between the analytical and MC^3 posterior model probabilities for the best 10000 models (*Cor PMP*).

For the space of all models, unconditional posterior distribution of coefficient β is given by:

$$P(\beta|y) = \sum_{j=1}^{2^K} P(\beta|M_j, y) * P(M_j|y), \tag{25}$$

where: $P(\beta|M_j, y)$ is the conditional distribution of coefficient β for a given model M_j, and $P(M_j|y)$ is the posterior probability of the model. Using the Bayes' theorem, the posterior probability of the model (PMP – Posterior Model Probability) $P(M_j|y)$ can be rendered as:

$$PMP = p(M_j|y) = \frac{l(y|M_j) * p(M_j)}{p(y)} = \frac{l(y|M_j) * P(M_j)}{\sum_{j=1}^{2^K} l(y|M_j) * P(M_j)}. \tag{26}$$

PMP is proportional to the product of $l(y|M_j)$ – model specific marginal likelihood – and $P(M_j)$ – model specific prior probability. Because $p(y) = \sum_{j=1}^{2^K} l(y|M_j) * P(M_j)$, model weights can be treated as probabilities.

Applying BMA requires specification of the prior model structure. The value of the coefficient β is characterized by a normal distribution with zero mean and variance $\sigma^2 V_j$, hence:

$$P(\beta|\sigma^2, M_j) \sim N(0, \sigma^2 V_j). \tag{27}$$

It is assumed that the prior variance matrix V_j is proportional to the covariance in the sample:

$$V_j = (gX_j'X_j)^{-1}, \tag{28}$$

where g is the proportionality coefficient. The g prior was put forward by Zellner (1986) and is widely used in BMA applications. Fernández, Ley, and Steel (2001) proposed the so-called 'benchmark prior':

$$g = \frac{1}{\max(n, k^2)}, \tag{29}$$

where $\frac{1}{n}$ is known as *UIP* – unit information prior (Kass & Wasserman, 1995), whereas $\frac{1}{k^2}$ is convergent to *RIC* – risk inflation criterion (Foster & George, 1994).

In order to specify prior model probability, non-informative priors are utilized. For the binomial model prior (Ley & Steel, 2009; Sala-i-Martin, Doppelhofer, & Miller, 2004):

$$P(M_j) \propto \left(\frac{EMS}{K}\right)^{k_j} * \left(1 - \frac{EMS}{K}\right)^{K-k_j}, \tag{30}$$

where *EMS* denotes expected model size, while k_j is the number of covariates in a given model. When $EMS = \frac{K}{2}$, it turns into a uniform model prior ($P(M_j) \propto 1$) – priors on all the

models are equal to $\frac{1}{2^K}$. Binomial-beta model prior is given by (Ley & Steel, 2009):

$$P(M_j) \propto \Gamma(1 + k_j) * \Gamma\left(\frac{K - EMS}{EMS} + K - k_j\right). \tag{31}$$

When $EMS = \frac{K}{2}$ probability of each model size is equal $\left(= \frac{1}{K+1}\right)$.

Using the PMPs in the role of weights allows for the calculation of unconditional posterior mean and standard deviation of the coefficient β_i. Posterior mean (PM) of the coefficient β_i, independently of the space of the models, is given by:

$$PM = E(\beta_i|y) = \sum_{j=1}^{2^K} P(M_j|y) * \hat{\beta}_{ij}, \tag{32}$$

where $\hat{\beta}_{ij} = E(\beta_i|y, M_j)$ is the value of the coefficient β_i estimated with OLS for the model M_j. The posterior standard deviation (PSD) is equal to:

$$PSD = \sqrt{\sum_{j=1}^{2^K} P(M_j|y) * V(\beta_j|y, M_j) + \sum_{j=1}^{2^K} P(M_j|y) * [\hat{\beta}_{ij} - E(\beta_i|y, M_j)]^2}, \tag{33}$$

where $V(\beta_j|y, M_j)$ denotes the conditional variance of the parameter for the model M_j.

The probability of including the variable in the model – posterior inclusion probability (PIP) – is calculated as:

$$PIP = P(x_i|y) = \sum_{j=1}^{2^K} 1(\varphi_i = 1|y, M_j) * P(M_j|y), \tag{34}$$

where $\varphi_i = 1$ signifies including the variable x_i in the model.

The posterior probability of a positive sign of the coefficient in the model, $P(+)$ is calculated in the following way:

$$P(+) = P[\text{sign}(x_i)|y] = \begin{cases} \sum_{j=1}^{2^K} P(M_j|y) * CDF(t_{ij}|M_j), & \text{if } \text{sign}[E(\beta_i|y)] = 1 \\ 1 - \sum_{j=1}^{2^K} P(M_j|y) * CDF(t_{ij}|M_j), & \text{if } \text{sign}[E(\beta_i|y)] = -1 \end{cases} \tag{35}$$

where CDF denotes cumulative distribution function, while $t_{ij} \equiv (\hat{\beta}_i/\widehat{SD}_i|M_j)$.

Within BMA, it is possible to assess the nature of the relationships between regressors using jointness measures. Doppelhofer and Weeks (2009) define their jointness measure as:

$$J_{Dw(ih)} = \ln\left[\frac{P(i \cap h|y)}{P(i \cap \bar{h}|y)} * \frac{P(\bar{i} \cap \bar{h}|y)}{P(\bar{i} \cap h|y)}\right] = \ln\left[\frac{P(i|h, y)}{P(\bar{i}|h, y)} * \frac{P(\bar{i}|\bar{h}, y)}{P(i|\bar{h}, y)}\right], \tag{36}$$

where i and h represent two regressors in the model. Ley and Steel (2007) measure of jointness is calculated as:

$$J_{LS(ih)} = \ln\left[\frac{P(i \cap h|y)}{P(i \cap \bar{h}|y) + P(\bar{i} \cap h|y)}\right] = \ln\left[\frac{P(i \cap h|y)}{P(i|y) + P(h|y) - 2P(i \cap h|y)}\right] \tag{37}$$

For both jointness measures (J), the same critical values can be applied. When $J > 2$, two variables are referred to as strong complements, $2 > J > 1$ as significant complements, $1 > J > -1$ as unrelated, $-1 > J > -2$ as significant substitutes, while $-2 > J$ signifies strong substitutes.[4]

3.2.2. Panel data setting

In the second stage of the analysis, Moral-Benito (2016) econometric framework is used to account for possible endogeneity between business cycle synchronization and its determinants in the dynamic panel setting. The approach outlined below allows to deal with both model uncertainty and reverse causality by means of the likelihood function for dynamic panel models with weakly exogenous regressors and fixed effects. In a panel setting, the baseline regression can be expressed as follows:

$$y_{it} = \alpha y_{it-1} + x_{it}\beta + \eta_i + \zeta_t + \upsilon_{it} \quad (i = 1, \ldots, N; t = 1, \ldots, T) \tag{38}$$

where y_{it} is a BCS measure between country pair i at time t, x_{it} is a vector of potential BCS determinants, β is a parameter vector, η_i is a country-pair specific fixed effect, ζ_t is period specific shock and υ_{it} is a shock to BCS. The assumption of weak exogeneity can be formalized as:

$$\mathrm{E}(\upsilon_{it}|y_t^{t-1}, x_i^t, \eta_i) = 0 \quad (i = 1, \ldots, N; t = 1, \ldots, T) \tag{39}$$

where $y_t^{t-1} = (y_{i0}, \ldots, y_{it-1})'$ and $x_t^t = (x_{i0}, \ldots, x_{it})'$. Accordingly, weak exogeneity implies that the current values of the regressors, lagged dependent variable, and fixed effects are uncorrelated with the current shocks, while they are all allowed to be correlated with each other at the same time.

To derive a likelihood function within the outlined setting, Moral-Benito (2013) augmented equation (38) with reduced-form equations capturing the unrestricted feedback process is utilized:

$$x_{it} = \gamma_{t0}y_{i0} + \ldots + \gamma_{t,t-1}y_{i,t-1} + \Lambda_{t1}x_{i0} + \ldots + \Lambda_{t,t-1}x_{it-1} + c_t\eta_i + \vartheta_{it} \tag{40}$$

where $t = 2, \ldots, T$; c_t is the $k \times 1$ vector of parameters. For $h < t$, γ_{th} is a $k \times 1$ vector $(y_{th}^1, \ldots, y_{th}^k)'$ $h = 0, \ldots, T-1$; Λ_{th} is a $k \times k$ matrix of parameters, and ϑ_{it} is a $k \times 1$ vector of prediction errors. The mean vector and the covariance matrix of the joint distribution of the initial observations and the individual effects η_i are unrestricted:

$$y_{i0} = c_0\eta_i + \upsilon_{it} \tag{41}$$

$$x_{i1} = \gamma_{10}y_{i0} + c_1\eta_i + \vartheta_{it} \tag{42}$$

where c_0 is a scalar, and c_1 and γ_{10} are $k \times 1$ vectors. Given the model setup in equations (38) and (40–42), the natural logarithm of the likelihood function under Gaussian errors can be expressed as:

$$\log f(data|\theta) \propto \frac{N}{2}\log\det(B^{-1}D\Sigma D'^{B'^{-1}}) - \frac{1}{2}\sum_{i=1}^{N}\left\{R'_i(B^{-1}D\Sigma D'^{B'^{-1}})^{-1}R_i\right\} \tag{43}$$

where $R_i = (y_{i0}, x'_{i1}, y_{i1}, \ldots, x'_{iT}, y_{iT})'$ is a vector of observable variables, $\Sigma = \mathrm{diag}\{\sigma_\eta^2, \sigma_{v_0}^2, \Sigma_{\vartheta_1}, \sigma_{v_1}^2, \ldots, \Sigma_{\vartheta_T}, \sigma_{v_T}^2\}$ is the block-diagonal variance-covariance

matrix of $U_i = (\eta_i,\ \upsilon_{i0},\ \vartheta'_{i0}, \upsilon_{i1},\ \ldots,\ \vartheta'_{iT}, \upsilon_{iT})$. B is a matrix of coefficients given by:

$$B = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & \ldots & 0 & 0 & 0 \\ -\gamma_{10} & I_0 & 0 & 0 & 0 & \ldots & 0 & 0 & 0 \\ -\alpha & -\beta' & 1 & 0 & 0 & \ldots & 0 & 0 & 0 \\ -\gamma_{20} & -\Lambda_{21} & -\gamma_{21} & I_k & 0 & \ldots & 0 & 0 & 0 \\ 0 & 0 & -\alpha & -\beta' & 1 & \ldots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & 0 & 0 & 0 \\ -\gamma_{T0} & -\Lambda_{T1} & -\gamma_{T1} & -\Lambda_{T2} & -\gamma_{T2} & \ldots & -\gamma_{T,t-1} & I_k & 0 \\ 0 & 0 & 0 & 0 & 0 & \ldots & -\alpha & -\beta' & 1 \end{bmatrix} \tag{44}$$

and D is a matrix of coefficients given by:

$$D = \begin{bmatrix} \begin{bmatrix} c_0 & c'_1 & 1 & c'_2 & 1 & \cdots & c'_T & 1 \end{bmatrix} \\ I_{T(k+1)} \end{bmatrix}. \tag{45}$$

Summarizing, the approach proposed by Moral-Benito (2013, 2016) enables dealing with both model uncertainty and endogeneity in the dynamic panel setting. Unfortunately, due to the complex nature of the likelihood function given in equation (43) and unavailability of the MC^3 sampler, the method is able to deal with a far lower number of potential regressors in comparison with a conventional BMA approach. Consequently, Moral-Benito method was applied to a subset of variables classified as robust determinants of business cycle synchronization in the cross-sectional analysis. To improve the convergence, all the variables used in panel data estimations are standardized.

Except for the likelihood function, the averaging of the system of simultaneous equations, and the presence of the lagged term, the Moral-Benito approach is applied in the same way as BMA described in subsection 3.1.1. Accordingly, the robustness of the determinants of BCS is evaluated using the same posterior statistics, namely PIP, PM, and PSD. Both uniform and binomial-beta model priors are used in the application of BMA. UIP has been chosen for the g prior, as advised by Moral-Benito (2012).

4. BMA results

4.1. Cross-sectional data setting

Under 43 regressors and 325 observations, 'benchmark prior' (Fernández et al., 2001) dictates the use of *RIC* for g prior. Eicher, Papageorgiou, and Raftery (2011) recommend the use of a uniform model prior combined with *UIP* g prior. Ley and Steel (2009) warn that a uniform model prior puts too much prior probability mass on average size models and urges the use of a binomial-beta model prior. All the mentioned guidance was taken into consideration in the preparation of the main results. Vast robustness checks of changes in the prior structure are discussed later in the text. The results of the application of BMA under *UIP* and *RIC* as well as uniform and binomial-beta (with *EMS* = 21.5) priors are depicted in Tables 1 and 2.

For all four prior combinations, eight variables are classified as robust determinants of business cycle synchronization. Differences in migration flows are positively associated with BCS, which gives support to the notion that labour mobility can serve as an

Table 1. BMA statistics under *UIP* g prior and *EMS* = 21.5.

Model prior	Uniform				Binomial-beta			
Variable	PIP	PM	PSD	*P*(+)	PIP	PM	PSD	*P*(+)
MIGR	**1.000**	**0.026**	**0.004**	**1.000**	**1.000**	**0.026**	**0.004**	**1.000**
KSI	**1.000**	**−0.775**	**0.179**	**0.000**	**1.000**	**−0.781**	**0.159**	**0.000**
EXCHANGE	**1.000**	**−1.247**	**0.180**	**0.000**	**1.000**	**−1.257**	**0.159**	**0.000**
TFP	**0.998**	**0.267**	**0.063**	**1.000**	**0.997**	**0.268**	**0.063**	**1.000**
RESERV	**0.983**	**0.104**	**0.031**	**1.000**	**0.992**	**0.116**	**0.030**	**1.000**
IIT	**0.930**	**0.629**	**0.264**	**1.000**	**0.952**	**0.674**	**0.241**	**1.000**
RISK	**0.895**	**−0.160**	**0.077**	**0.000**	**0.841**	**−0.157**	**0.085**	**0.000**
MOBILITY	**0.825**	**0.112**	**0.065**	**1.000**	**0.762**	**0.107**	**0.070**	**1.000**
FISCAL	**0.639**	**−0.013**	**0.012**	**0.000**	0.339	−0.007	0.011	0.000
RWELASTIC	**0.625**	**−0.031**	**0.028**	**0.000**	0.480	−0.025	0.029	0.000
MA	**0.549**	**−0.043**	**0.045**	**0.000**	0.435	−0.035	0.045	0.000
TRANS	0.420	0.039	0.054	1.000	0.166	0.014	0.036	1.000
HUMAN	0.358	0.055	0.086	1.000	0.123	0.018	0.054	1.000
ARABLE	0.354	0.001	0.001	1.000	0.122	0.000	0.001	1.000
OILpc	0.350	0.000	0.000	0.998	0.166	0.000	0.000	1.000
FDI	0.305	0.002	0.003	1.000	0.112	0.001	0.002	1.000
POPDIFF	0.275	0.000	0.000	0.999	0.142	0.000	0.000	1.000
EPCpc	0.239	0.000	0.000	0.972	0.088	0.000	0.000	0.979
URBAN	0.197	0.000	0.000	0.895	0.100	0.000	0.000	0.950
L	0.192	−0.022	0.055	0.000	0.054	−0.005	0.027	0.000
RGDPDIFF	0.174	0.000	0.000	0.875	0.091	0.000	0.000	0.947
CAPFLOW	0.161	0.007	0.021	1.000	0.087	0.004	0.016	1.000
CPWDIFF	0.150	0.000	0.000	0.000	0.052	0.000	0.000	0.000
CAPDIFF	0.140	0.000	0.000	0.819	0.072	0.000	0.000	0.914
IITT	0.127	1.133	4.488	0.996	0.048	0.349	2.206	0.998
RGDPPROD	0.123	0.000	0.000	0.997	0.039	0.000	0.000	0.997
MONET	0.110	0.001	0.006	0.967	0.035	0.000	0.003	0.961
TRADE2	0.098	0.067	0.332	0.943	0.039	0.027	0.192	0.976
TRADE1	0.097	0.116	1.092	0.885	0.039	0.060	0.551	0.954
EU	0.091	0.008	0.047	0.901	0.030	0.002	0.021	0.913
RGDPpc	0.087	0.005	0.029	0.856	0.025	0.001	0.012	0.758
OPEN	0.087	−0.003	0.015	0.041	0.028	−0.001	0.007	0.042
OLDUE	0.087	0.003	0.017	0.936	0.031	0.001	0.009	0.961
POPPROD	0.085	0.000	0.000	0.752	0.028	0.000	0.000	0.788
GOV	0.082	−0.027	0.153	0.072	0.035	−0.014	0.102	0.022
ARABLEpw	0.079	0.000	0.000	0.450	0.029	0.000	0.000	0.782
INFVAR	0.072	0.000	0.002	0.102	0.026	0.000	0.001	0.145
DGEO	0.071	0.000	0.000	0.131	0.030	0.000	0.000	0.046
LAND	0.070	0.000	0.000	0.214	0.026	0.000	0.000	0.344
URBANshare	0.065	0.003	0.040	0.689	0.023	0.001	0.023	0.645
MU	0.063	−0.001	0.011	0.300	0.022	0.000	0.006	0.306
B	0.062	−0.001	0.013	0.340	0.021	0.000	0.007	0.617
AGROWTH	0.060	−0.034	0.377	0.118	0.024	−0.015	0.243	0.130
Burn-ins		4 m				4 m		
Iterations		40 m				40 m		
Cor PMP		0.9985				0.9999		

Note: Variables robust under at least one prior specification are written in bold.

effective adjustment mechanism under asymmetric shocks. Migration flows here are not calculated bilaterally for two reasons. Firstly, the degree of bilateral migration flows is negligible for most pairs of countries. Secondly, labour force mobility can lessen the effects of asymmetric shocks not only bilaterally but also through third countries, and this effect is seen in the results.[5]

The similarity in production structures measured by bilateral Krugman specialization index is positively associated with BCS. This outcome supports the notion that countries with more similar production structures are more prone to symmetric shocks. Exchange

Table 2. BMA statistics under *RIC* g prior and *EMS* = 21.5.

Model prior	Uniform				Binomial-beta			
Variable	PIP	PM	PSD	*P*(+)	PIP	PM	PSD	*P*(+)
MIGR	**1.000**	**0.026**	**0.004**	**1.000**	**1.000**	**0.026**	**0.004**	**1.000**
KSI	**1.000**	**−0.779**	**0.161**	**0.000**	**1.000**	**−0.799**	**0.146**	**0.000**
EXCHANGE	**1.000**	**−1.258**	**0.161**	**0.000**	**1.000**	**−1.275**	**0.148**	**0.000**
TFP	**0.997**	**0.268**	**0.063**	**1.000**	**0.993**	**0.273**	**0.065**	**1.000**
RESERV	**0.992**	**0.116**	**0.029**	**1.000**	**0.993**	**0.120**	**0.030**	**1.000**
IIT	**0.952**	**0.679**	**0.243**	**1.000**	**0.954**	**0.673**	**0.229**	**1.000**
RISK	**0.860**	**−0.161**	**0.083**	**0.000**	**0.738**	**−0.140**	**0.096**	**0.000**
MOBILITY	**0.793**	**0.111**	**0.068**	**1.000**	**0.584**	**0.083**	**0.077**	**1.000**
RWELASTIC	**0.527**	**−0.028**	**0.030**	**0.000**	0.272	−0.015	0.026	0.000
MA	0.470	−0.038	0.045	0.000	0.279	−0.023	0.040	0.000
FISCAL	0.381	−0.008	0.011	0.000	0.163	−0.003	0.008	0.000
TRANS	0.196	0.017	0.039	1.000	0.049	0.004	0.020	1.000
OILpc	0.190	0.000	0.000	1.000	0.062	0.000	0.000	1.000
POPDIFF	0.158	0.000	0.000	1.000	0.068	0.000	0.000	1.000
ARABLE	0.142	0.000	0.001	1.000	0.034	0.000	0.000	1.000
HUMAN	0.141	0.020	0.057	1.000	0.036	0.005	0.029	1.000
FDI	0.127	0.001	0.002	1.000	0.039	0.000	0.001	1.000
URBAN	0.111	0.000	0.000	0.947	0.047	0.000	0.000	0.982
EPCpc	0.102	0.000	0.000	0.978	0.026	0.000	0.000	0.989
RGDPDIFF	0.101	0.000	0.000	0.942	0.048	0.000	0.000	0.987
CAPFLOW	0.093	0.005	0.017	1.000	0.054	0.003	0.014	1.000
CAPDIFF	0.080	0.000	0.000	0.909	0.035	0.000	0.000	0.972
L	0.061	−0.006	0.028	0.000	0.014	−0.001	0.012	0.000
CPWDIFF	0.060	0.000	0.000	0.000	0.016	0.000	0.000	0.000
IITT	0.054	0.393	2.314	0.997	0.015	0.100	1.080	0.999
TRADE2	0.045	0.030	0.204	0.977	0.013	0.009	0.108	0.993
TRADE1	0.044	0.070	0.583	0.957	0.013	0.021	0.278	0.984
RGDPPROD	0.044	0.000	0.000	0.997	0.012	0.000	0.000	0.999
GOV	0.040	−0.015	0.109	0.022	0.014	−0.006	0.066	0.007
MONET	0.040	0.000	0.003	0.957	0.010	0.000	0.001	0.975
OLDUE	0.035	0.001	0.009	0.960	0.010	0.000	0.005	0.987
DGEO	0.034	0.000	0.000	0.043	0.012	0.000	0.000	0.012
EU	0.034	0.002	0.022	0.910	0.009	0.000	0.009	0.957
ARABLEpw	0.033	0.000	0.000	0.794	0.010	0.000	0.000	0.940
OPEN	0.032	−0.001	0.007	0.044	0.008	0.000	0.003	0.023
POPPROD	0.031	0.000	0.000	0.790	0.009	0.000	0.000	0.821
INFVAR	0.030	0.000	0.002	0.124	0.008	0.000	0.001	0.320
LAND	0.029	0.000	0.000	0.342	0.008	0.000	0.000	0.446
RGDPpc	0.029	0.001	0.012	0.746	0.007	0.000	0.005	0.821
URBANshare	0.027	0.001	0.025	0.635	0.008	0.000	0.013	0.726
AGROWTH	0.026	−0.016	0.257	0.135	0.008	−0.006	0.145	0.094
MU	0.026	0.000	0.006	0.301	0.007	0.000	0.003	0.312
B	0.025	0.000	0.007	0.612	0.007	0.000	0.004	0.833
Burn-ins		4 m				4 m		
Iterations		40 m				40 m		
Cor PMP		0.9999				1.0000		

Note: Variables robust under at least one prior specification are written in bold.

rate volatility is negatively related to BCS. This conclusion is not intact with the notion of exchange rate serving as an adjustment mechanism after the occurrence of an asymmetric shock. In the context of the European Union, exchange rate volatility can serve as a proxy for monetary union membership and a common monetary policy as well as a higher degree of trade in both goods and assets associated with the elimination of exchange rate risk. This might also explain why monetary union membership, monetary policy similarity, and bilateral trade are classified as fragile.

Correlation of total factor productivity shocks is positively associated with the degree of business cycle synchronization. This result is not unanticipated and testifies that BCS is driven in part by the real shocks. Similarities in exchange rate policy proxied by the correlation of changes in the currency reserves are positively associated with BCS. It shows that countries conducting similar exchange rate policies are characterized by tighter business cycle synchronization, although the opposite can be true as well: countries with higher BCS will be conducting more similar exchange rate policies. The direction cannot be unambiguously determined within the BMA framework.

Intra-industry trade is positively associated with the BCS. This result suggests that economic shocks are better transmitted within the same industries and/or that countries trading goods within the same industries are more prone to symmetric shocks. Risk sharing, in accordance with the theory, is negatively associated with business cycle synchronization. Countries that are able to share risk better can specialize in accordance with their comparative advantage. A higher degree of specialization results in susceptibility to asymmetric shocks and, consequently, lowers the degree of business cycle synchronization.

Differences in capital mobility are characterized by a positive posterior mean, which indicates that countries characterized by low as well as high capital mobility experience lower business cycle synchronization. The highest degree of BSC is present between countries characterized by different degrees of capital mobility. This result is consistent with the international real business cycle theory, which predicts that high capital mobility decreases BCS. The chosen measure here, like in Imbs (2004) and Monnet and Puy (2016), is not bilateral. This choice has the advantage of taking into consideration the effect of third countries and supports results obtained with bilateral flows (e.g. Kalemli-Ozcan et al., 2013). Interestingly, countries with low capital mobility are also described by low BCS, but this might be ascribed to the imperfect nature of the used measure.

Differences in real wage elasticity are robust under the uniform model prior for both g priors, with a negative posterior mean. This result suggests that after symmetric shocks countries characterized by high wage elasticity can undergo the adjustment process faster, while countries with low wage elasticity are adjusting more slowly, which results in tighter business cycle synchronization in both cases. Countries characterized by a different degree of wage elasticity will be adjusting to symmetric shocks at a different phase, which leads to lower BCS.

Finally, under a uniform model prior and *UIP* g prior, two more variables are classified as robust. Fiscal policy similarity is characterized by the negative posterior mean. This suggests that the fiscal policy can be a source of asymmetric shocks, and better fiscal policy coordination can contribute to higher business cycle synchronization. Finally, if two European countries both have access to the sea or the ocean, they are characterized by lower business cycle synchronization. This points to the fact that continental Europe countries with close proximity are on average characterized by higher BCS. The Bayesian model selection shows that *MIGR, EXCHANGE, KSI, TFP, RESERV, IIT, RISK, MOBILITY,* and *RWELASTIC* are always significant at 0.01 level in the best models, while *FISCA*L and *MA* at 0.05.

To check whether results obtained here depend on undertaken assumptions, various exercises on them are commenced.[6] Firstly, g prior is set to $\ln(N)^3$ in order to imitate Hannan-Quinn information criterion and various fixed values under uniform and

binomial-beta model priors. The obtained results are virtually identical to those reported in the main text. To deal with potential multicollinearity, dilution priors are employed (George, 2010). The tessellation dilution prior implemented through MC^3 combined with uniform, binomial-beta, *RIC* and *UIP* as well as multicollinearity adjusted dilution prior combined with *RIC* and *UIP* reproduce virtually identical results to the ones presented in the main text. This comes as no surprise since out of all 903 pairs of variables in the correlation matrix, only 14 are characterized by an absolute value of correlation coefficient higher than 0.7, and none of the variables in these pairs have been classified as robust.

The changes in the results come only from the employment of flexible g priors. Under empirical Bayesian local (*EBL*) g prior (George & Foster, 2000; Hansen & Yu, 2001) and uniform model prior, except for 11 variables that were found robust under uniform and *UIP* prior, 6 more have *PIP* higher than prior inclusion probability, namely: *L* (negative *PM*) and *HUMAN, FDI, ARABLE, TRANS*, *EPCpc* (positive *PM*). Except for those 17, the combination of *EBL* with a binomial-beta model prior classifies additional 6 as robust: *RGDPpc, OILpc, CAPFLOW,* and *POPDIFF* (with positive *PM*), as well as *CPWDIFF* and *OPEN* (with negative *PM*). These extensions to the list of robust variables can be attributed to the fact that *EBL* is based on F statistic, and can assign too much prior probability mass to overspecified models. Moreover, the 11 variables maintain their high values of PIP, while additional ones are characterized by medium values of PIP, with the exception of *HUMAN, FDI,* and *ARABLE*.

Finally, hyper-g (Feldkircher & Zeugner, 2009; Liang, Paulo, Molina, Clyde, & Berger, 2008) with the shrinkage factor given by beta distribution $-\frac{1}{1+g} \sim B\left(1, \frac{\alpha}{2} - 1\right)$ – is employed along with a uniform and binomial-beta model prior, with different values of α parameter. The results obtained are comparable with the use of EBL: the leading 11 retain their high PIP, while the additional ones move above the marginal value of 0.5. Both hyper-g and EBL as flexible priors are more susceptible to the noise in the data. The dataset under consideration contains an active noise component, as even clearly overspecified models cannot explain more than 60% of the variability in the dependent variable. This final robustness check confirms results obtained in the main estimation, while still leaving an open window for additional determinants.

Even though the analysis points to the determinants of BSC along with the theoretical prediction, some of the regressors well rooted in theory are classified as fragile. In order to shed some light on these results, jointness measures are applied, and the output is presented in Table 3.[7] The number of measures makes the description of all the relationships infeasible; hence, only the chosen ones are presented here. It is worth pointing out that Ley and Steel's measure (LS) finds an overwhelming magnitude of substitutional relationships between variables, while Doppelhofer and Weeks's measure (DW) results are rather diversified, which can be attributed to the differences in their construction (Beck, 2017).

Firstly, bilateral trade, which is very strongly affirmed in the literature, turned out fragile regardless of the used measure. As it is pointed out in the literature review, bilateral trade has not always been found significant. Duval et al. (2014) and Duval, Li, Saraf, and Seneviratne (2015) explain this by the usage of gross data and show a significant impact of value added in trade. Still, this does not seem to be the case here, as trade is significant in simple model specifications with few regressors and loses significance when more variables are added to the model. LS shows that trade is a strong substitute for every variable in the set. On the other hand, DW is silent about any substitutional relationships. Similarly, to

Table 3. *LS* (above diagonal) and *DW* (below diagonal) measures under beta-binomial model prior with *EMS* = 21.5 and *RIC* g prior.

LS / DW	EU	MU	B	DGEO	L	FISCAL	MONET	EXCHANGE	RGDPPROD	POPPROD	RGDPpc	OPEN	GOV	HUMAN	CPWDIFF	ARABLE	ARABLEpw	LAND	EPCpc	OILpc	MIGR	URBANshare
EU		−4.1	−4.1	−4.2	−3.7	−3.8	−3.6	−3.3	−5.0	−4.3	−3.5	−4.3	−4.2	−3.6	−4.0	−3.3	−4.1	−4.3	−3.6	−3.6	−3.3	−4.1
MU	0.2		−4.3	−4.7	−4.2	−3.6	−4.1	−3.7	−3.9	−4.6	−4.2	−4.2	−3.9	−3.7	−3.7	−3.7	−4.0	−4.1	−3.9	−3.6	−3.7	−4.2
B	−0.2	−0.2		−4.4	−3.9	−3.8	−4.4	−3.7	−4.1	−4.2	−4.1	−4.2	−4.2	−3.8	−4.6	−3.7	−4.2	−4.1	−3.8	−3.7	−3.8	−4.3
DGEO	0.2	0.2	−0.2		−3.4	−3.5	−4.0	−3.4	−3.7	−4.4	−4.0	−4.1	−4.8	−3.2	−3.7	−3.6	−4.7	−4.1	−3.7	−3.4	−3.4	−4.3
L	0.4	−1.0	0.2	0.1		−2.7	−3.6	−2.8	−3.6	−3.8	−3.9	−3.5	−3.5	−2.7	−3.2	−3.2	−3.7	−3.9	−2.9	−2.9	−2.8	−3.8
FISCAL	0.5	0.2	−0.9	−0.2	0.2		−3.0	−0.5	−3.1	−3.5	−3.4	−3.4	−3.1	−2.2	−2.8	−1.7	−3.5	−3.5	−1.7	−1.3	−0.5	−3.7
MONET	0.2	−0.2	0.2	−0.3	0.3	0.5		−3.2	−3.6	−4.5	−4.3	−3.8	−3.6	−3.3	−3.4	−3.3	−4.3	−4.2	−3.3	−3.1	−3.3	−4.2
EXCHANGE	−0.5	−1.8	inf	inf	−0.5	−0.6	inf		−4.0	−3.4	−3.5	−3.4	−3.1	−1.8	−2.8	−1.8	−3.4	−3.5	−2.2	−1.5	7.6	−3.7
RGDPPROD	−0.6	−0.1	−0.4	0.3	−0.2	0.2	0.4	−1.2		−3.1	−4.0	−3.9	−3.9	−3.4	−3.8	−3.5	−4.7	−3.9	−3.3	−3.8	−4.0	−4.2
POPPROD	−0.7	0.2	−0.7	1.0	−0.1	0.5	0.4	1.4	0.7		−3.9	−4.1	−3.9	−3.3	−4.0	−3.4	−3.8	−4.3	−3.6	−3.4	−3.4	−4.3
RGDPpc	1.0	0.2	−0.3	−1.0	−0.6	0.2	−0.2	−1.6	0.3	0.2		−3.9	−3.8	−3.6	−3.5	−3.6	−3.9	−4.7	−3.9	−3.7	−3.5	−4.3
OPEN	0.8	0.4	0.2	0.1	0.4	0.2	0.5	−1.7	0.7	0.4	0.3		−4.2	−3.1	−4.8	−3.8	−3.8	−3.9	−3.5	−3.4	−3.4	−4.3
GOV	−0.1	0.1	−0.1	0.2	0.2	−0.6	0.7	−1.8	−0.3	0.5	0.3	−0.4		−3.2	−4.0	−3.2	−4.3	−4.3	−3.6	−3.5	−3.1	−4.3
HUMAN	0.7	−0.7	0.3	0.5	0.3	−0.2	0.3	1.4	0.3	0.3	0.2	0.4	0.1		−3.3	−2.3	−3.4	−3.7	−2.2	−1.9	−1.8	−3.7
CPWDIFF	−0.5	0.2	−0.5	−0.1	0.3	0.5	0.4	3.6	0.4	−0.9	0.6	0.2	−0.4	0.2		−3.9	−3.7	−3.9	−3.0	−2.6	−2.8	−3.9
ARABLE	0.3	−0.2	0.2	0.1	−0.2	0.5	0.1	−0.4	0.3	0.4	0.3	−0.8	0.3	0.3	0.2		−3.5	−3.8	−3.0	−2.1	−1.8	−3.7
ARABLEpw	−0.3	0.8	−0.3	−1.0	0.1	−0.1	0.2	−0.7	0.9	0.4	0.1	0.3	−0.2	0.2	−0.1	−0.2		−4.4	−3.8	−3.7	−3.4	−4.4
LAND	−0.2	−0.3	−0.2	0.2	0.1	0.7	−0.1	inf	0.2	−0.1	0.7	−0.3	0.2	−0.4	0.2	0.7	0.1		−3.5	−3.6	−3.5	−4.6
EPCpc	0.1	−0.8	0.4	0.2	0.2	1.2	0.2	−0.4	0.5	0.3	0.1	1.0	−0.4	0.7	0.4	−0.3	−0.4	0.5		−4.2	−2.2	−3.8
OILpc	−0.2	1.0	−0.3	0.2	0.4	0.8	0.3	2.1	0.3	0.1	−0.1	0.5	−0.3	0.6	0.5	0.2	−0.1	0.5	−1.5		−1.5	−3.7
MIGR	inf	inf	inf	−0.3	1.9	-inf	-inf	-inf	inf	−1.7	0.1	0.5	inf	inf	0.3	inf	inf	−0.3	−0.5	−1.9		−3.6
URBANshare	1.0	0.3	0.5	0.2	0.2	−0.5	0.2	−2.3	0.1	−0.1	0.4	−0.3	−0.6	0.2	−0.8	0.9	−0.4	0.4	−0.8	0.2	−0.6	
FDI	−0.1	0.9	0.8	−0.2	1.2	0.2	0.5	−1.7	0.4	0.4	−0.7	0.7	0.3	0.9	1.0	0.7	−0.3	−0.9	0.5	−0.9	−2.0	1.0
TRADE1	−0.3	−0.2	0.3	−0.2	0.6	−0.9	0.2	1.4	−0.6	0.2	0.3	0.2	−0.6	0.1	0.8	0.1	1.0	0.6	0.3	0.3	−3.6	0.9
TRADE2	−0.3	0.2	0.2	−0.1	0.5	−0.2	0.1	inf	−0.3	−0.4	−1.0	−0.2	0.7	0.2	−0.1	0.3	−0.9	−0.7	0.3	0.2	inf	−0.2
TFP	−0.5	−0.9	0.8	−0.3	0.6	−0.3	0.6	2.8	0.3	−0.1	2.2	0.7	−0.2	0.7	0.1	−0.2	−0.5	−0.5	0.1	0.4	−22.0	0.2
RESERV	−1.5	−0.5	0.1	−0.3	−0.8	−3.2	−1.9	-inf	−1.5	−0.7	−1.7	−0.5	−0.6	−0.6	−0.9	−0.2	0.1	−0.2	−1.5	−0.7	4.5	−0.4
CAPFLOW	0.4	−0.2	0.1	0.2	0.5	−0.3	−0.2	0.3	0.3	0.3	−0.6	−0.7	0.1	0.5	0.1	0.2	0.2	0.3	0.2	−0.7	inf	−0.2
MOBILITY	−0.3	0.1	0.7	−0.3	−0.3	0.7	−0.2	2.9	−0.1	−0.1	−0.2	−0.4	−0.1	−0.4	0.2	−0.3	−0.1	−0.1	0.3	0.4	0.3	−0.3
RWELASTIC	0.8	−0.3	0.9	0.5	0.1	0.1	−0.2	−2.2	0.2	0.3	0.4	0.5	−0.2	−0.7	−0.3	−0.8	−0.6	−0.2	−0.1	−0.6	2.3	−0.8
KSI	−2.4	inf	−1.2	inf	−0.2	-inf	−1.7	-inf	inf	−1.5	−2.8	0.9	inf	−0.4	3.3	−1.2	inf	inf	0.6	0.9	7.0	inf
IIT	0.1	−0.2	−0.3	−0.1	−0.8	−0.6	−0.4	−1.7	−0.8	−0.8	0.1	−0.9	0.2	−1.9	−0.4	0.1	−0.2	0.3	−1.3	−1.8	2.2	−0.3
IITT	0.9	0.8	0.1	−0.4	0.8	−0.8	0.1	1.8	−0.2	−0.2	0.4	0.4	−0.8	0.5	−0.2	0.3	0.2	0.9	0.4	0.5	−0.9	0.9
MA	−0.4	−0.4	−0.2	0.2	−0.2	−0.6	−0.2	−2.3	−0.6	−0.3	−0.1	−0.2	−0.2	0.1	0.1	0.5	0.3	−0.8	−0.9	−0.5	1.0	−0.1
AGROWTH	1.0	0.2	−0.4	−0.1	−0.2	−0.5	0.1	−1.4	0.8	0.2	0.3	−0.2	0.3	0.2	−0.5	−0.1	0.9	−0.2	0.2	−0.2	inf	−0.3
INFVAR	0.2	0.9	−0.6	0.8	−0.2	0.2	−0.1	nan	0.1	−0.4	1.0	−0.3	0.2	−0.2	−0.2	0.2	−0.6	−0.3	0.6	−0.7	−1.6	0.2
TRANS	0.6	−0.6	0.2	−0.4	−0.2	−0.1	−0.6	3.2	0.3	0.6	0.5	−0.2	−0.4	0.2	−0.4	0.4	−0.2	0.9	0.3	0.5	inf	0.3
RISK	−0.1	−0.1	−0.4	−0.5	−0.2	−0.9	−0.5	−1.6	−0.4	−0.2	−0.2	−0.7	0.5	0.2	0.3	0.2	−0.9	−0.8	−0.9	−0.6	1.2	−0.1
RGDPDIFF	−0.6	0.4	0.6	−0.2	0.4	−0.9	−0.2	−0.7	0.2	0.8	0.2	−0.2	−0.1	0.4	−0.2	0.8	−0.7	0.2	0.5	0.5	inf	0.9

(*Continued*)

Table 3. Continued.

LS DW	EU	MU	B	DGEO	L	FISCAL	MONET	EXCHANGE	RGDPPROD	POPPROD	RGDPpc	OPEN	GOV	HUMAN	CPWDIFF	ARABLE	ARABLEpw	LAND	EPCpc	OILpc	MIGR	URBANshare
POPDIFF	−0.8	0.1	0.2	0.7	0.4	0.8	−0.4	−0.3	0.2	0.1	0.4	0.3	−0.1	0.4	0.1	−0.4	−0.6	0.4	0.6	0.6	−1.8	0.7
OLDUE	−0.5	0.4	0.3	0.6	0.2	0.5	0.9	−0.7	−0.3	−0.2	0.7	−0.2	−0.2	0.2	−0.4	0.7	−0.7	−0.2	0.2	0.1	−2.7	0.5
CAPDIFF	0.3	−0.1	0.2	0.2	0.2	−0.2	0.8	−0.9	0.2	0.7	−0.3	−0.3	0.7	0.2	0.1	−0.8	−0.1	−0.2	0.5	0.5	inf	0.2
URBAN	−0.2	0.2	0.4	−0.9	0.3	−0.6	0.9	inf	0.3	0.2	0.4	0.3	−0.1	0.3	−0.9	−0.4	0.8	0.1	0.5	0.4	3.2	0.4

LS DW	FDI	TRADE1	TRADE2	TFP	RESERV	CAPFLOW	MOBILITY	RWELASTIC	KSI	IIT	IITT	MA	AGROWTH	INFVAR	TRANS	RISK	RGDPDIFF	POPDIFF	OLDUE	CAPDIFF	URBAN
EU	−3.8	−4.9	−4.2	−3.3	−3.4	−3.1	−3.5	−3.3	−3.3	−3.3	−4.2	−3.5	−4.3	−4.4	−3.0	−3.4	−3.7	−3.6	−4.2	−3.6	−3.5
MU	−3.7	−4.1	−5.0	−3.7	−3.7	−3.9	−3.6	−3.7	−3.7	−3.7	−4.0	−3.7	−4.4	−4.5	−3.7	−3.8	−3.7	−3.7	−3.8	−3.9	−3.9
B	−3.7	−3.8	−4.0	−3.7	−3.7	−3.8	−3.8	−3.7	−3.8	−3.7	−3.7	−3.8	−4.1	−4.1	−3.9	−3.7	−3.8	−3.6	−4.1	−3.9	−4.0
DGEO	−3.8	−4.2	−4.3	−3.4	−3.4	−3.5	−3.5	−3.5	−3.4	−3.4	−3.9	−3.3	−4.2	−4.2	−3.6	−3.5	−3.5	−3.5	−4.8	−3.8	−3.5
L	−2.1	−3.5	−3.2	−2.8	−2.8	−4.0	−2.9	−2.7	−2.8	−2.8	−2.8	−3.2	−4.0	−3.7	−3.8	−2.8	−2.8	−2.8	−3.9	−3.1	−2.8
FISCAL	−2.1	−3.9	−3.1	−0.5	−0.5	−2.6	−0.6	−0.9	−0.5	−0.5	−3.2	−1.4	−3.6	−3.4	−1.8	−0.8	−2.4	−1.9	−3.2	−2.6	−2.2
MONET	−3.2	−3.6	−3.6	−3.2	−3.2	−3.7	−3.2	−3.3	−3.2	−3.3	−3.6	−3.4	−3.8	−4.2	−3.8	−3.2	−3.3	−3.3	−3.6	−3.4	−3.6
EXCHANGE	−1.9	−3.5	−3.6	5.6	4.8	−2.2	1.3	1.0	7.6	3.9	−2.9	−0.1	−3.6	−3.5	−1.4	1.8	−2.2	−1.7	−3.3	−2.4	−2.4
RGDPPROD	−3.9	−4.7	−4.1	−3.9	−3.1	−3.4	−3.1	−3.6	−3.9	−3.2	−3.9	−3.6	−4.2	−3.9	−3.0	−3.2	−3.2	−3.6	−4.3	−3.5	−3.7
POPPROD	−3.4	−4.2	−4.1	−3.4	−3.4	−3.7	−3.5	−3.4	−3.4	−3.5	−4.9	−3.7	−4.3	−4.8	−3.4	−3.5	−3.7	−3.4	−4.0	−3.7	−3.5
RGDPpc	−3.8	−4.6	−3.7	−3.5	−3.5	−3.7	−3.6	−3.5	−3.5	−3.5	−4.2	−3.5	−4.2	−4.2	−3.2	−3.5	−3.6	−3.6	−3.4	−3.9	−3.7
OPEN	−2.9	−3.8	−4.2	−3.4	−3.5	−3.7	−3.5	−3.4	−3.4	−3.5	−3.6	−3.6	−4.1	−4.5	−3.6	−3.5	−3.5	−3.4	−3.9	−3.7	−3.4
GOV	−3.3	−4.0	−3.8	−3.1	−3.1	−3.4	−3.2	−3.3	−3.1	−3.1	−3.9	−3.4	−4.3	−4.3	−3.6	−3.1	−3.5	−3.3	−4.2	−3.6	−3.7
HUMAN	−1.8	−3.2	−3.1	−1.8	−1.8	−2.2	−2.0	−2.4	−1.8	−2.0	−2.8	−1.9	−3.6	−3.9	−2.2	−1.8	−2.4	−2.2	−3.4	−2.8	−2.3
CPWDIFF	−3.2	−3.7	−3.6	−2.9	−2.8	−3.1	−2.9	−3.0	−2.8	−2.8	−3.5	−2.9	−4.2	−4.0	−3.4	−2.8	−3.2	−3.8	−3.9	−3.2	−3.3
ARABLE	−2.0	−3.1	−3.9	−1.8	−1.8	−2.4	−2.0	−2.4	−1.8	−1.8	−2.9	−1.7	−3.8	−3.6	−2.0	−1.8	−2.6	−2.5	−3.4	−2.9	−2.6
ARABLEpw	−3.5	−3.8	−4.1	−3.4	−3.4	−3.5	−3.4	−3.5	−3.4	−3.4	−3.8	−3.2	−5.0	−4.1	−3.4	−3.4	−3.7	−3.6	−3.9	−3.9	−3.7
LAND	−3.8	−4.1	−3.9	−3.5	−3.5	−3.8	−3.5	−3.6	−3.5	−3.5	−3.7	−3.6	−4.8	−4.3	−3.7	−3.6	−3.7	−3.4	−4.2	−3.9	−3.6
EPCpc	−2.4	−3.8	−3.9	−2.2	−2.2	−2.9	−2.1	−2.4	−2.2	−2.3	−2.9	−2.9	−3.7	−3.6	−2.3	−2.4	−2.3	−2.2	−3.6	−2.7	−2.4
OILpc	−3.2	−3.1	−3.0	−1.5	−1.5	−2.6	−1.5	−2.0	−1.5	−1.6	−2.7	−2.7	−3.7	−3.5	−2.7	−1.6	−2.2	−1.9	−3.6	−2.3	−2.9
MIGR	−1.9	−3.5	−3.6	5.7	4.9	−2.2	1.3	1.0	8.4	3.1	−2.9	−0.1	−3.6	−3.5	−1.4	1.8	−2.2	−1.7	−3.3	−2.4	−2.4
URBANshare	−3.8	−4.5	−4.3	−3.7	−3.6	−3.8	−3.7	−3.7	−3.6	−3.6	−4.3	−3.7	−4.1	−4.1	−3.5	−3.6	−3.7	−3.6	−4.1	−3.8	−3.7
FDI		−3.4	−3.5	−1.9	−1.9	−2.8	−2.2	−2.3	−1.9	−2.9	−3.1	−1.9	−3.7	−3.7	−2.5	−2.0	−2.3	−2.4	−3.7	−2.8	−2.4
TRADE1	−0.3		−4.1	−3.5	−3.5	−3.6	−3.0	−3.5	−3.5	−3.9	−4.2	−3.5	−3.9	−4.8	−3.5	−3.9	−3.3	−3.3	−3.9	−3.4	−3.3
TRADE2	−0.5	−0.4		−3.6	−3.7	−3.5	−3.8	−3.8	−3.7	−4.0	−4.3	−3.5	−4.2	−4.4	−3.2	−3.9	−3.2	−3.1	−4.2	−3.4	−3.3
TFP	−1.8	−0.7	0.3		4.5	−2.2	1.3	1.0	5.7	2.9	−2.9	−0.1	−3.6	−3.5	−1.4	1.8	−2.2	−1.7	−3.3	−2.4	−2.3
RESERV	−1.3	−0.7	−0.4	-inf		−2.2	1.3	0.8	4.8	2.9	−2.9	−0.1	−3.6	−3.4	−1.4	1.8	−2.2	−1.7	−3.3	−2.4	−2.4
CAPFLOW	0.7	−1.0	−0.1	1.6	−0.5		−3.3	−2.6	−2.2	−2.2	−3.3	−2.2	−3.8	−3.8	−3.0	−2.3	−2.8	−2.6	−3.2	−3.5	−2.8
MOBILITY	−0.9	0.5	0.5	−0.3	3.6	−2.5		−0.2	1.3	1.2	−2.8	−0.6	−3.6	−3.5	−1.6	0.8	−2.2	−1.8	−3.4	−2.4	−2.2
RWELASTIC	−0.5	0.1	0.9	−0.4	−1.1	−0.4	0.5		1.0	0.1	−3.0	−1.9	−3.7	−3.4	−1.6	−0.2	−2.1	−1.8	−3.3	−2.4	−2.0
KSI	1.5	−0.8	−0.4	−22.7	1.7	−0.1	0.1	−0.3		3.2	−2.9	−0.1	−3.6	−3.5	−1.4	1.8	−2.2	−1.7	−3.3	−2.4	−2.4
IIT	−1.7	−0.6	−0.5	0.7	1.3	0.2	−0.5	1.3	−25.6		−3.8	−0.4	−3.6	−3.4	−1.5	1.6	−2.3	−1.8	−3.3	−2.5	−2.1
IITT	0.1	−0.3	−0.6	0.8	−0.3	−0.3	0.4	−0.4	−1.3	−1.4		−3.3	−3.8	−3.7	−3.3	−2.9	−3.0	−2.8	−4.2	−3.2	−2.9
MA	0.4	−0.6	−0.6	−0.2	1.2	0.3	−0.8	−0.7	−0.2	2.6	−0.7		−3.5	−3.4	−1.2	0.8	−3.0	−2.6	−3.5	−3.6	−2.8

AGROWTH	0.3	0.9	0.5	−0.5	0.3	−0.6	−0.8	−0.3	inf	−0.1	−0.3	0.1		−4.5	−3.6	−3.6	−3.7	−3.6	−4.6	−3.8	−4.0	
		INFVAR	0.8	0.7	−0.7	−0.4	−0.9	0.1	−0.3	0.4	−0.6	0.6	−0.8	0.3	−0.1		−3.7	−3.4	−3.7	−3.6	−3.8	−3.6
−3.8																						
TRANS	−0.8	−0.2	0.9	−0.7	−1.0	−0.5	−0.5	−0.2	−1.5	0.6	−0.2	0.9	0.9	−0.2		−1.4	−2.4	−2.3	−3.3	−2.7	−2.4	
RISK	−0.2	−0.2	−0.2	−1.2	0.6	−0.6	0.3	−0.6	1.4	0.4	−0.1	2.9	0.2	0.3	0.6		−2.4	−1.9	−3.3	−2.6	−2.2	
RGDPDIFF	0.5	0.3	0.1	0.8	−0.5	0.1	0.7	0.3	inf	−1.2	0.3	−1.0	0.5	0.8	0.3	−1.6		−3.9	−3.8	−4.3	−4.4	
POPDIFF	0.3	0.3	0.3	1.2	−0.5	0.6	0.3	0.3	4.4	−1.2	0.3	−1.4	1.0	−0.2	−0.5	−0.7	−1.3		−3.4	−3.9	−3.9	
OLDUE	−0.2	−0.3	−0.3	−0.2	−1.6	0.3	−0.2	−0.9	−1.3	−0.2	−0.2	−0.3	−0.5	−1.0	0.2	−0.2	−0.5	−0.4		−3.8	−3.7	
CAPDIFF	0.2	0.2	0.4	0.4	−0.8	−0.6	0.2	0.4	−1.1	−0.7	0.3	−0.9	−0.4	0.8	0.1	−1.3	−1.3	−1.2	−0.1		−4.5	
URBAN	0.3	0.2	0.2	0.4	−0.6	0.8	0.2	0.4	inf	−0.9	0.3	−1.0	−0.2	0.6	0.1	−0.7	−1.5	−1.4	−0.9	−1.3		

Baxter and Kouparitsas (2005), all the variables representing differences in factor endowments were fragile. The fragility of trade and factor endowments cannot be attributed to multicollinearity between them, as estimation results remained unchanged under dilution and tessellation priors. The obtained results point towards the conclusion that it is not the bilateral trade itself that is a driver of BCS, but rather the type of trade, which is reflected by the robustness of intra-industry trade and structural similarity. The notion that intra-industry trade takes explanatory power from total trade was raised by Gruben et al. (2002), Fidrmuc (2004) and Duval et al. (2014). Moreover, intra-industry trade variable, in contrast to total trade, is calculated for intermediate inputs. Consequently, *IIT* takes into account not only trade effect but also incorporates information about the degree of vertical integration and entanglement in the European value chains.

Participation in a monetary union is also classified as fragile, even though the variable is significant in smaller models. LS points to substitutional relationships with all the variables in the set, while DW finds it only with exchange rate variability. This result seems very plausible, and the inclusion of exchange rate variability in the model makes *MU* insignificant. A similar situation can be seen in the case of participation in the European Union. According to the DW measure, there is one strong substitute in the set, *KSI*, which suggests that more similar production structures characterize countries that have been members of the EU longer. This result finds strong support in the time series used to create the dataset employed here. According to DW, the variable capturing the differences in FDI is a substitute with *EXCHANGE, TFP,* and *IIT*. Intra-industry can be thought of as an integral part of FDI, especially in the case of vertical integration of production process on the international scale, which might explain why both variables contain the same information about the variation in BCS. The fragility of monetary policy similarity could be explained by the fact that the difference in the real interest rate is a poor proxy for this variable. Still, among others, Duval et al. (2014) find a significant impact of this variable on BCS while using the same measure. However, in the dataset used in the present paper, even when included alone, the difference in real interest rates is not significant. DW shows a very strong complementary relationship between *MONET* and *EXCHANGE*, but the inclusion of the latter in the model is still not sufficient to make the former significant at any conventional level.

4.2. Panel data setting

The results of the application of the Moral-Benito (2016) approach to Bayesian model averaging for dynamic panels with weakly exogenous regressors are depicted in Table 4. Posterior inclusion probability is higher than prior inclusion probability (0.5) in case of all analyzed variables and for all four measures of BCS indicating that all of them could be classified as robust determinants of business cycle synchronization. PIP values obtained in a panel data setting are smaller than the ones in cross-sectional setting, showing that in the dynamic panel setting the evidence is less clear cut. Still, this could be explained otherwise. In the case of a uniform model prior and all robust variables, posterior model distribution will be flattened around models of above average value sizes, consequently driving the individual posterior inclusion probabilities down. With a binomial-beta model prior, there will be a heavy concentration of posterior at large models: in the present case, the model with all variables accounts for around 40% of the total probability mass in all four cases.

Table 4. Moral-Benito dynamic panel BMA statistics under *UIP* g prior and *EMS* = 5.5.

BCS measure		CFy						CFdlny					
Model prior		Uniform			Binomial-beta			Uniform			Binomial-beta		
Statistic		PIP	PM	PSD	PIP	PM	PSD	PIP	PM	PSD	PIP	PM	PSD
Regressor	LAG BCS	–	0,168	0,047	–	0,171	0,038	–	0,129	0,037	–	0,128	0,032
	KSIp	0,845	−0,223	0,095	0,947	−0,144	0,060	0,828	−0,076	0,072	0,944	−0,069	0,025
	RWELASTICp	0,719	−0,089	0,035	0,909	−0,079	0,027	0,724	−0,045	0,025	0,911	−0,042	0,020
	IITp	0,714	0,165	0,083	0,908	0,317	0,134	0,715	0,251	0,151	0,908	0,340	0,176
	CAPFLOWp	0,698	−0,018	0,053	0,901	−0,038	0,028	0,702	−0,045	0,020	0,902	−0,046	0,024
	TFPp	0,632	0,087	0,087	0,875	0,052	0,022	0,637	−0,020	0,011	0,877	−0,043	0,022
	EXCHANGEp	0,621	0,019	0,013	0,869	0,017	0,006	0,615	−0,030	0,018	0,867	−0,028	0,014
	FISCALp	0,599	−0,104	0,051	0,860	0,035	0,023	0,603	−0,098	0,047	0,860	−0,053	0,027
	MIGRp	0,597	0,037	0,108	0,859	−0,058	0,031	0,598	−0,017	0,009	0,858	−0,008	0,004
	RISKp	0,580	−0,037	0,029	0,856	−0,048	0,022	0,575	−0,018	0,014	0,852	−0,018	0,014
	RESERVp	0,561	0,036	0,027	0,843	0,039	0,010	0,555	0,026	0,016	0,839	0,016	0,015
BCS measure		BKy						Bkdlny					
Regressor	LAG BCS	–	0,407	0,058	–	0,427	0,048	–	0,107	0,051	–	0,122	0,038
	KSIp	0,841	−0,812	0,189	0,950	−0,783	0,148	0,831	−0,152	0,092	0,946	−0,132	0,087
	RWELASTICp	0,736	−0,088	0,039	0,913	−0,076	0,028	0,723	−0,055	0,022	0,911	−0,060	0,018
	IITp	0,706	0,296	0,144	0,905	0,413	0,208	0,712	0,270	0,140	0,907	0,321	0,126
	CAPFLOWp	0,695	−0,040	0,085	0,900	−0,032	0,052	0,704	−0,024	0,049	0,903	−0,046	0,047
	TFPp	0,633	0,148	0,087	0,875	0,105	0,062	0,636	0,089	0,061	0,874	0,090	0,042
	EXCHANGEp	0,625	−0,051	0,028	0,870	−0,039	0,023	0,628	−0,057	0,018	0,872	−0,060	0,015
	FISCALp	0,602	−0,147	0,067	0,860	−0,106	0,051	0,601	−0,069	0,035	0,860	−0,017	0,016
	MIGRp	0,597	−0,119	0,066	0,860	−0,119	0,057	0,597	−0,031	0,041	0,858	−0,014	0,008
	RISKp	0,576	−0,046	0,044	0,853	−0,053	0,043	0,579	−0,030	0,029	0,855	−0,050	0,030
	RESERVp	0,559	0,033	0,046	0,842	0,087	0,047	0,558	0,048	0,025	0,841	0,054	0,021

Interestingly, the ordering of the variables according to PIP changed, as exemplified by the difference in wage elasticity reaching a second position. The ratios of the posterior means to posterior standard deviations are generally smaller in comparison with cross-sectional exercises. They also vary significantly between the BCS measures, with measures based on Baxter-King filter associated with the lowest posterior standard deviations, where the ratios are above 2 in most cases. Still, the evidence from the panel exercise is less convincing in comparison with the cross-sectional setting.

A posterior mean on the lagged measures of business cycle synchronization (*CFylag, CFdlnylag, BKylag,* and *BKdlnylag*) is positive, indicating the persistence of the BCS over time. The extent of intra-industry trade (*IITp*) is characterized by the highest posterior inclusion probability for *CFy* measure of BCS. A positive posterior mean and high PIP are assuring robustness of this variable in determining business cycle synchronization. This reaffirms the conclusion that economic shocks are better transmitted within the same industries and/or that countries trading goods within the same industries are more prone to symmetric shocks. A negative posterior mean for *KSIp* shows that a more similar production structure fosters tighter business cycle synchronization, which can be explained by proneness to symmetrical shocks by economies characterized by a high degree of structural convergence. The differences in real wage elasticity (*RWELASTICp*) impact BCS negatively, implying that during the occurrence of symmetric shocks countries characterized by high wage elasticity can go through the adjustment process faster, while countries with low wage elasticity are adjusting more slowly. In both instances, it is associated with a higher degree of business cycle synchronization.

A negative posterior mean characterizes the absolute value of the difference in total factor productivity (*TFPp*). This confirms the result from a cross-sectional setting that business cycle synchronization is in part driven by real shocks. Posterior mean *RISKp* is negative, indicating that countries engaged in more risk sharing are characterized by more synchronized business cycles. This result can be explained by a higher degree of specialization associated with risk sharing (Kalemli-Ozcan et al., 2001). The absolute value of the difference in capital flows (*CAPFLOWp*) has a negative posterior mean. This ascertains the conclusions from the cross-sectional setting that countries characterized by a similar level of capital mobility exhibit more correlated business cycles. It should be noted that out of all variables analyzed in the panel setting *CAPFLOWp* is associated with the lowest PM to PSD ratios. This outcome should not be surprising as the variable is a panel counterpart of *CAPFLOW* from cross-section setting and not *MOBILITY*, which could not be calculated in the panel setting. The cross-sectional exercise demonstrated that *MOBILITY* is a better proxy for capital mobility than *CAPFLOW*, and consequently *CAPFLOW* posterior mean to posterior standard deviation ratio is accordingly smaller.

Similarly to the cross-sectional setting, fiscal policy similarity (*FISCALp*) positively affects business cycle synchronization. This result implies that improvements in international macroeconomic policy coordination can improve synchronization of business cycles. Exchange rate volatility (*EXCHANGEp*) is characterized by a negative posterior mean, which implies that it is negatively related to business cycle correlations. This result is a contradiction of the role of nominal exchange rate serving as an adjustment mechanism after asymmetric shocks. It also indicates that membership in the currency union associated with no exchange rate volatility fosters tighter business cycle synchronization.

The most unusual developments in panel data setting concern migration and changes in currency reserves. PM on differences in net migration is negative for all four BCS measures, contrary to the value obtained in a cross-sectional setting where the posterior mean was positive. The change in the sign can be attributed to accounting for reverse causality between synchronization of business cycles and migration. Consequently, the result in the cross-sectional setting suffers from a simultaneity bias.[8] A negative posterior mean on *MIGRp* indicates that the inflow or outflow of the labour force can initiate a change in the GDP and, consequently, foster synchronization of business cycles. This outcome supports the notion of migration, promoting divergence through changes in pressure on wage adjustment, put forward by Krugman (1993). Summarizing, elimination of the endogeneity bias between migration and BCS shows that the impact of the former on the latter is negative, which shows that migration of labour force does not work in the European Union as an adjustment mechanism after asymmetric shocks.

Finally, the sign of PM for exchange rate policy similarity has also changed in the panel setting in comparison with cross-sectional analysis. Accordingly, accounting for simultaneity resulted in the change in conclusions about the impact of exchange rate policy on the synchronization of business cycles. A negative posterior mean on *RESERVp* indicates that in instances of asymmetric shocks exchange rate policy can be used to stabilize the economy and consequently improve synchronization of business cycles.

5. Conclusions

Since the seminal work of Frankel and Rose (1998), researchers have been investigating the determinants of business cycle synchronization. As shown in the literature review, researchers focus their attention on a limited number of potential BCS drivers at once, which leads to many conflicting conclusions. For these reasons, the present paper is an attempt to bring all the past research together under one unified framework in order to assess which of the variables proposed in the literature are in fact drivers of business cycle synchronization.

The application of BMA to the dataset with 43 potential determinants of BCS for a rather homogenous group of European Union countries under different prior structures allows to draw the following conclusions. There is overwhelming evidence that migration, exchange rate variability, similarity of production structures, correlation of TFP shocks, similarity in exchange rate policy, intra-industry trade, risk sharing, and capital mobility are robust determinants of business cycle synchronization. There is also evidence that wage elasticity and fiscal policy similarity impacts the correlation of business cycles. All these variables find strong support in theory and the direction of their impact is in accordance with theoretical predictions, with the exemption of migration flows.

Interestingly, accounting for simultaneity demonstrates that in the case of migration its impact on the synchronization of business cycles is negative. Consequently, one of the main criteria of the Optimum Currency Areas theory contributes to business cycle divergence in the European Union, as demonstrated on theoretical grounds by Krugman (1993). On the other hand, central bank interventions on the currency market can contribute to a higher degree of business cycle synchronization.

Some of the variables strongly affirmed in the literature are classified as fragile: bilateral trade, monetary policy similarity, and participation in the European Union have turned out

fragile. Finally, there is some rather weak evidence of the impact of FDI on business cycle synchronization. This result may be attributed to the fact that robust intra-industry trade can be thought of as a form of vertical integration through FDI. In future research, the scope of data should be extended geographically to make a complete picture of the global business cycle synchronization.

Notes

1. For elaboration, see Beck (2011).
2. Other methods of filtration have been applied: logarithmized first differences, Hodrick-Prescott, and Baxter-King filter. Results are qualitatively similar, so they are not reported here for brevity.
3. The choice of three-year period was dictated by the need to obtain meaningful values of the correlation coefficient, which could be doubtful with less than 10 observations.
4. A thorough and accessible explanation of jointness measures can be found in Beck (2017).
5. Bilateral migration flows turned out fragile for all prior specifications.
6. Robustness checks are not reported here for brevity, but they are available upon request.
7. Jointness tables under different combinations of prior assumptions are available upon request.
8. A change in the sign of the coefficient is not the result of the different data structure, in cases of both migration and exchange rate policy similarity. BMA in panel data setting without accounting for reverse causality yields a positive posterior mean.

Disclosure statement

No potential conflict of interest was reported by the author.

Notes on contributor

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