Beck, K. (2020). What drives international trade? Robust analysis for the European Union. *Journal of International Studies, 13*(3), 68-84. doi:10.14254/2071-8330.2020/13-3/5

Journal of International Studies

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Scientific Papers

What drives international trade? Robust analysis for the European Union

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Abstract. Economic literature is full of theories explaining international trade flows and empirical studies striving to verify them. Most of these attempts focus on the verification of single theory at a time without regard to the problem of model uncertainty. As a consequence, empirical research has brought a bulk of inconsistent results. The aim of the present paper is to validate which theories are correct on a purely empirical basis. To accomplish this, Bayesian model averaging was employed to 71 potential determinants of international trade for a sample of EU countries over the 1995-2015 period. The results show that the gravity model takes the lead in the explanation of trade flows. Membership in the EU has also a profound impact on trade, as each year of membership in the EU is associated with a growth rate of bilateral trade between 0.5 and 1.5. Finally, the analysis provides support to the predictions under Heckscher-Ohlin model of trade.

Received: December, 2019
1st Revision: May, 2020
Accepted: August, 2020

DOI: 10.14254/2071-8330.2020/13-3/5

Keywords: international trade, European Union, trade policy, economic integration, Bayesian model averaging.

JEL Classification: C11, F14, F15

1. INTRODUCTION

Economic literature is full of theories trying to explain international trade flows. A brief look at an advanced international trade textbook (e.g., Helpman & Krugman, 1987; Feenstra, 2015) points to the vast body of models showing the rationale behind trade flows: from Ricardian and Heckscher-Ohlin type, through new trade models based on imperfect competition, increasing returns and gravity equation, to geographical economics and models stressing on multinationals. Beyond those models, economic theory stresses the importance of trade impediments: tariff and nontariff barriers, as well as free trade agreements, customs, and monetary unions.

All those theoretical considerations were met with an extensive strain of empirical research striving for their verifications. To enlist just a few, researchers were investigating the impact of: exchange rates (Bahmani-Oskooee, 1986; Brada & Méndez, 1988), exchange rate variability (Arizeet *al.*, 2003; Klein &

Shambaugh, 2006; Miron *et al.*, 2013), factor endowments (Baldwin, 1971; Bowen *et al.*, 1987; Staiger, 1988; Davis & Weinstein, 2001; Debaere, 2003), gravity variables (McCallum, 1995; Anderson & van Wincoop, 2003; Wang *et al.*, 2010), free trade agreements (Frankel *et al.*, 1995; Baier & Bergstrand, 2007; Beck *et al.*, 2019; Gawrońska-Nowak *et al.,* 2019), currency unions (Rose & van Wincoop, 2001; Frankel & Rose, 2002; Glick & Rose, 2002; Beck, 2014), institutions (de Groot *et al.*, 2004; Kuncic, 2012), cultural factors (Carrère & Masood, 2018; Egger & Lassmann, 2018; Egger & Toubal, 2018).

The abovementioned list is in no way exhaustive, but the articles share one common trait: their focus is highly concentrated on a limited number of regressors, usually combined with gravity variables. For that reason, the research has led to many contradictory results, in terms of the sign, magnitude and significance of the determinants in international trade. It was all due to the fact that the researchers were not accounting properly for model uncertainty, which is one of the main issues in cases of theories' open-endedness (Brock and Durlauf, 2001). The listed papers clearly demonstrate to what extent the results obtained in the previous investigations are sensitive to model specification. Consequently, this paper attempts at filling the gap in the research by performing Bayesian model averaging (BMA) in order to find which out of 71 regressors are in fact the robust determinants of international trade.

To the best of the author's knowledge, there have been so far only four attempts at sensitivity analysis of the determinants of bilateral trade[1]. The first was made by Leamer (1984) who used Bayesian sensitivity analysis to examine the impact of different production factors on net trade as a whole and within 10 different product categories. The results heavily depend on the specific product category. The second attempt was made by Ghosh and Yamarik (2004), who examined the sensitivity of various free trade agreements using Extreme Bounds Analysis (EBA) (Leamer and Leonard, 1983) and found fragility of all of them in trade regressions. Later on, Yamarik and Ghosh (2005) applied a more restrictive version of EBA (Leamer, 1983) to a set of 47 potential determinants of trade under the gravity model framework. The authors found 20 out of them to be robust, yet they used only 19 model specifications per variable under investigation in the sensitivity analysis, so their results should be treated with caution. The last attempt was made by Baxter and Kouparitsas (2006), who applied EBA, its extension proposed by Sala-I-Martin (1997) to a set of 24 variables. Among them, they found factor endowments, fixed exchange rates, development level, and current account restrictions to be robust determinants of bilateral trade under all three estimation strategies.

All the abovementioned articles were using a rather outdated methodology and a limited number of regressors. For that reason, this paper investigates the robustness of 71 different potential determinants of international trade using BMA to account properly for model uncertainty. The paper is structured as follows. Section 2 deals with methodology and comprises two subsections. The first subsection describes measures used in the analysis along with the data sources, while the second presents BMA estimation strategy. Estimation results are described in section 3. Section 4 concludes.

2. METHODOLOGY

The first part of the methodology presents variables used in the estimations. Due to the fact, that the dataset contains a lot of variables characterized by multicollinearity and functional interdependence two different strategies have been used to deal with that problem. Those strategies are described in the second subsection.

[1] Chen *et al.* (2016) and Beck (2017) applied BMA to the gravity model of trade along with the short list of additional variables. In both instances, trade data was used to illustrate the method and analysis of trade patterns was not of the primary concern.

2.1. Data and measurement

The analysis covers 26 European Union (without Croatia and Malta). All variables are in bilateral form – for 26 countries, it amounts to 325 country pairs. The time span of the research covers the period between 1995 and 2015. The research undertakes the task of the examination of the long-term forces governing international trade flows, as the ones considered in international trade models, and consequently, takes the long-run perspective. Accordingly, the validity of the results can be extrapolated into the near future (2016-2020 perspective).

The dependent variable in the study is a natural logarithm of the sum of annual real exports and imports (in 2015 US dollars) between country *i* and *j* averaged over the 1995-2015 period:

$$TRADE_{ij} = \ln[\frac{1}{T}\sum_{t=1}^{T}(IMPORT_{ijt} + EXPORT_{ijt})]. \quad (1)$$

Data for exports and imports was taken from IMF Directions of Trade and deflated using price levels from Penn World Table (PWT) as in Feenstra *et al.* (2015). Averaging over the analyzed period was undertaken to capture the long-term behavior of international trade.

Independent variables used in the research can be divided into five categories. Of course, the division is somewhat arbitrary as some of the variables could belong to more than one group. Still, it serves as a convenient device for organizing the regressors. The first group comprises gravity variables. The group starts with a natural logarithm of products of real GDPs and populations of two countries averaged over the 1995-2015period, denoted as $RGDPPROD_{ij}$ and $POPPROD_{ij}$ respectively. $RGDPDIFF_{ij}$ and $POPDIFF_{ij}$ denote absolute value of the differences in real GDP and population respectively, averaged over 1995-2015 period. Data for all four above-mentioned variables comes from PWT. $DGEO_{ij}$ is a natural logarithm of a geographical distance between the capital cities of 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 one 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 marine border, $TRANS_{ij}$ is a binary variable taking the value of 1 if both countries are transition countries (classification according to IMF), and $OLDEU_{ij}$ is a binary variable taking the value of 1 if both countries were members of the EU before 2004.

The second group contains differences in factor endowments. Variables from this group are calculated in two ways. Firstly, as an average value over the 1999-2011 period of the absolute value of the difference in an absolute:

$$FACTORx_{ij} = \frac{1}{T}\sum_{t=1}^{T}\left|FACTORx_i - FACTORx_j\right| \quad (2)$$

and relative factor endowments:

$$FACTORxFACTORy_{ij} = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{FACTORx_i}{FACTORy_i} - \frac{FACTORx_j}{FACTORy_j}\right|, \quad (3)$$

where$FACTORx_i$*and* $FACTORx_j$ denote factor endowment x of country *i*and *j* respectively, while $FACTORy_i$and$FACTORy_i$ denote factor endowment *y* of country *i*and *j* respectively. Next, formulas (2) and (3) are used with factors listed below. Data from PWT was taken for EMP– employment, $HUMAN$– human capital index (Barro and Lee, 2013), CAP – capital, and CPW – capital per worker. From World Bank (WB), comes data for: $ARABLE$ – arable land, $LAND$ – land, $EPCpc$ – electricity consumption *per capita*, $OILpc$ – oil usage per capita, and $IUp100$ – the number of Internet users per 100 inhabitants. Data from Eurostat was used for $PATENT$ – the number of patents per 1 million of inhabitants. Data from PWT and WB was taken for $ARABLEpw$ – arable land per worker, and $LANDpc$ - arable land *per capita*.

For example, CAP_{ij} is the absolute value of the difference in capital endowment, while $CAPLAND_{ij}$ is the absolute value of the difference in ratios of capital to land. The list of all the variables can be found in the data appendix.

Secondly, to account for nonlinearities, all aforementioned measures were recalculated as an average value over the 1995-2015 period of the absolute value of logarithmic differences in factor endowments in absolute:

$$FACTORx1_{ij} = \frac{1}{T}\sum_{t=1}^{T}\left|\ln(FACTORx_i) - \ln(FACTORx_j)\right| \tag{4}$$

or relative terms:

$$FACTORxFACTORy1_{ij} = \frac{1}{T}\sum_{t=1}^{T}\left|\ln(\frac{FACTORx_i}{FACTORy_i}) - \ln(\frac{FACTORx_j}{FACTORy_j})\right|. \tag{5}$$

The third category contains variables associated with new trade theories. The first of them measures the similarity of production structures of 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:

$$KSI_{ij} = \frac{1}{T}\sum_{t=1}^{T}\sum_{l=1}^{L}\left|v_{lit} - v_{ljt}\right|, \tag{6}$$

wherev_{lit} denotes value added in sector l for country i at time t, and L is a total number of sectors. This variable takes values from 0 to 2, where 0 represent identical production structure in both countries. Data for KSI_{ij} is annual and was taken from World Output-Input Database (WOID).

The second variable in this group captures real GDP *per capita* distance. It is calculated with annual data from PWT as:

$$RGDPpcDIFF_{ij} = \frac{1}{T}\sum_{t=1}^{T}\left|\ln(\frac{REAL\ GDP\ per\ capita_{it}}{REAL\ GDP\ per\ capita_{jt}})\right|. \tag{7}$$

Another variable associated with new trade theories (denoted by $RGDPpcPROD_{ij}$) is the product of real GDP *per capita* of two countries averaged over the 1995-2015 period.

The last two variables in this category are average absolute values of differences in urban population $(URBAN_{ij})$ and share of the urban population $(URBANshare_{ij})$ calculated using formula (2). Data for urban population differences comes from WB and for differences in urban population shares was taken from WB and PWT.

The fourth group consists of macroeconomic variables. To capture the impact of exchange rate volatility on international trade coefficient of variation of the bilateral nominal exchange rate for the 1995-2015 period was calculated using data from AMECO:

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

$INFVAR_{ij}$is computed as an absolute value of a difference between standard deviations of inflation rates in two countries over the 1995-2015 period. Data for $INFVAR_{ij}$ was taken from IMF World Economic Outlook (WEO). Variable $AGROWTH_{ij}$ is calculated as an absolute value of a difference between mean GDP growth rates over the 1995-2015period between two countries. The next 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 1995-2015 period. To assess the impact of technological shocks, variable TFP_{ij} was calculated as the correlation coefficient of growth rates of total factor productivity in two countries over the 1995-2015period. Data for all three above-mentioned variables comes from PWT. The last macroeconomic measure is the absolute value of the difference of FDI flows between country i and j. The data used is annual, covers the period between 1995 and 2015, and the measure is the mean value for the entire period. Data for FDI_{ij}, was taken from UNCTAD database.

Finally, the fifth group captures the variables that are associated with participation in supra-national agreements and corruption. The impact of participation in a monetary union is captured by variable MU_{ij}. It is constructed for the 1995-2015 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 mean value for the entire period is calculated. The variable expressing participation in free trade area – EU_{ij} – was calculated in the same fashion, with value 1 assigned to years where both countries were members of the European Union. To measure the impact of corruption on international trade two additional variables were calculated using Bayesian Corruption Index (Standaert, 2015): the higher the value of the index the higher is the degree of perceived corruption. One, $BCIPROD_{ij}$ is calculated as the product, while $BCIDIFF_{ij}$ measures the absolute value of the difference in the values of the indicator for two countries under consideration.

2.2. BMA estimation strategy

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

$$P(\beta|y) = \sum_{j=1}^{2^K} P(\beta|M_j, y) * P(M_j|y) \tag{9}$$

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:

$$PMP = p(M_j|y) = \frac{l(y|M_j) * p(M_j)}{p(y)} = \frac{l(y|M_j) * P(M_j)}{\sum_{j=1}^{2^K} l(y|M_j) * P(M_j)}. \tag{10}$$

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 (Beck, 2019).

Applying BMA requires specifying 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:

$$P(\beta|\sigma^2, M_j) \sim N(0, \sigma^2 V_j). \tag{11}$$

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

$$V_j = (g X_j' X_j)^{-1}, \tag{12}$$

where$g$ is the proportionality coefficient and it is widely used in BMA applications. The so-called 'benchmark prior' (Fernández, *et al.* 2001) dictated the choice of risk inflation criterion (RIC) proposed by Foster and George (1994) for the dataset at hand. Additionally, unit information prior (UIP) put forward by Kass and Wasserman (1995) was employed in the main results.

In the empirical part of the paper, two main estimation strategies have been undertaken. Due to a large degree of multicollinearity and functional interdependence between regressors standard BMA structure has been extended by means of dilution priors in two ways. Firstly, by implementing multicollinearity prior into model prior, and secondly by using tessellation prior through Metropolis-Hestings algorithm. Both strategies are described below in detail.

In the first strategy binomial model prior (Ley and Steel, 2009) is supplemented with function accounting for multicollinearity (George, 2010):

$$P(M_j) \propto |R_j|^{0.5} \left(\frac{EMS}{K}\right)^{k_j} * \left(1 - \frac{EMS}{K}\right)^{K-k_j}, \tag{13}$$

where EMS denotes expected model size, k_j is a number of covariates in a model *j*, K is the total number of regressors, while $|R_j|$ is the determinant of the correlation matrix for all the regressors in the model *j*. Whit $EMS = \frac{K}{2}$, it turns into uniform model prior – priors on all the models are all equal $(P(M_j) \propto 1)$. The higher the multicollinearity between the variables, the closer is the value of $|R_j|$ to 0, and the lower is the prior ascribed to a given model. Model space is reduced with MC^3 (Markov Chain Monte Carlo Model Composition) sampler (Madigan *et al.*, 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.

In the second strategy binomial-beta model prior (Ley and Steel, 2009) is utilized:

$$P(M_j) \propto \Gamma(1 + k_j) * \Gamma\left(\frac{K - EMS}{EMS} + K - k_j\right); \tag{14}$$

with $EMS = \frac{K}{2}$ probability of each model size is equal $(= \frac{1}{K+1})$. Dilution is implemented trough MCMC search. Tessellation is achieved through the "Spinner Process", which uses following method of sampling from a subspace of models $P_V(M_j)$ (George, 2010):

1. Sample the model size *k* from K,
2. Simulate $Y^* \sim N_n(0, I)$, where Y^* could be thought of as an 'imaginary data',
3. Select the matrix of covariates with $k_j = k$ that is 'closest' to Y^* – select *j* for which R^2 is the highest in the regression ofY^*on the matrix of covariates.

Along the lines of the second strategy using correlation coefficient of analytical and MC^3 PMP is inadequate to assess convergence of the chain. For that reason, empirical exercise was repeated 10 times with different numbers of burn-ins and iterations. In all cases, obtained results were qualitatively and quantitatively similar to results reported here.

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

$$PM = E(\beta_i|y) = \sum_{j=1}^{2^K} P(M_j|y) * \hat{\beta}_{ij}, \tag{15}$$

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:

$$PSD = \sqrt{\sum_{j=1}^{2^K} P(M_j|y) * V(\beta_j|y, M_j) + \sum_{j=1}^{2^K} P(M_j|y) * [\hat{\beta}_{ij} - E(\beta_i|y, M_j)]^2}, \tag{16}$$

where$V(\beta_j|y, M_j)$ denotes the conditional variance of the parameter for the model M_j. To better capture the relative impact of the determinants on the international trade standardized coefficients were calculated and BMA statistics based on their values (Beck, 2020). SPM denotes standardized posterior mean, while SPSD denotes standardized posterior standard deviation[2].

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

$$PIP = P(x_i|y) = \sum_{j=1}^{2^K} 1(\varphi_i = 1|y, M_j) * P(M_j|y) \tag{17}$$

where$\varphi_i = 1$ signifies including the variable x_i in the model. In both applied strategies of estimation, prior inclusion probability is 0.5, and a variable is classified as robust if PIP is above that value.

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

$$P(+) = P[sign(x_i)|y] = \begin{cases} \sum_{j=1}^{2^K} P(M_j|y) * CDF(t_{ij}|M_j), & if\ sign[E(\beta_i|y)] = 1 \\ 1 - \sum_{j=1}^{2^K} P(M_j|y) * CDF(t_{ij}|M_j), & if\ sign[E(\beta_i|y)] = -1 \end{cases} \tag{18}$$

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

Details about the BMA can be found in Hoeting*et al.* (1999) and Błażejowski*et al.* (2016); g prior structure in Fernández, *et al.* (2001), Ley and Steel (2009), and Eicher, *et al.* (2011); model prior structure in Ley and Steel, (2009); and dilution priors in George (2010).

3. EMPIRICAL RESULTS

Results of the application of the strategy 1 are reported in Table 1 (Annex), while for strategy 2 in Table 2 (Annex), for both risk inflation criterion and unit information prior g priors. In all four cases variable with the highest posterior inclusion probability is natural logarithm of geographical distance. Values of PM are extremely stable across experiments as they range from -1.219 to -1.150 indicating that 1% increase in distance is associated with approximately 1.2% drop in trade. The result reinforces the notion that trade costs associated with distance are increasing at the decreasing rate[3]. The second variable with the highest PIP is natural logarithm of real GDP products with PM ranging from 0.780 to 0.874. In accordance with this result 1% increase in real GDP product causes increase in trade by approximately 0.85%. On the outset, these results reinforce the validity of the gravity model of trade as a backbone of the empirical research on international trade. By estimating a single equation with these variables, one finds that coefficients on LNRGDPROD and LNDGEO are respectively 0.841 and -0.401, with R^2 equal to 0.905. The difference in PMs and estimated coefficients is very small for LNRGDPROD and rather large for LNDGEO, which points to the notion that impact of the geographical distance, used as a proxy for the cost of transportation is amplified when other variables are being included in the model. Still, LNRGDPROD and LNDGEO alone can explain lion's share of the variation in the bilateral international trade.

The third variable with PIP above the prior value of 0.5 is the absolute value of the difference in capital to land ratios with rather stable PM ranging from 0.016 to 0.021. These values are decidedly lower than a

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[2] See Doppelhofer and Weeks (2009) for elaboration.

[3] When the distance was included in the set of regressors set without logarithm, the variable turned out fragile and border dummy was the variable characterized by the highest posterior inclusion probability.

0.035 implied by estimation of the model with this variable alone. The difference in capital to labor ratios is positively associated with international trade, which is the exact prediction of the H-O theory and pointing to inter-industry trade based on specialization. It is worth mentioning that variable is not expressed in natural logarithms, as one would expect from the construction of the dependent variable – absolute value of the natural logarithm of the difference in capital to land ratio was classified fragile with PIP ranging from 0.003 to 0.056. Another robust variable is common border dummy. Its posterior mean ranges from 0.405 to 0.513. This implies that countries sharing common border trade more on average by 49.9 to 67 percent, than countries not sharing a border. Estimation of a single equation with B led to the value of the coefficient equal to 2.728. Border effect is very well documented in international trade research (ex. McCallum, 1995).

An average number of years when both countries were members of the European Union in the analyzed period (EU) is characterized by PIP higher than the prior value in all four BMA specifications. The PM ranges from 1.116 to 1.396, which implies that pairs of countries that were members of the EU for the entire analyzed period trade on average more by from 111.6 to 136.6 percent. This extremely enthusiastic result for the free trade agreements proponents should be taken with caution. Firstly, the analyzed period covers only years from 1995 to 2015, and six of the countries that were members of the EU during the entire period, were the same countries that started economic integration with the commencement of the European Communities in 1950. The other nine still had significantly more time, in comparison with new members, to engage in the integration process. In light of that, the high differences can be attributed to pairs of countries that have been members of FTA for a longer period of time. Yet this argument can be rebutted by the results. OLDEU – a dummy variable taking the value of 1, if both countries were members of the European Union before 2004 – is fragile in all the BMA specifications. OLDEU is characterized be very low positive posterior mean and is unstable across models, which can be seen from the values of posterior probability of a positive sign of the coefficient – P(+). This contrasts with results obtained using a single variable equation, where OLDEU is positive and significant.

Secondly, as the sample covers only countries that were members of the EU by 2015, there is no pair that would have a value of the EU variable equal to 0 (the minimum value for the EU variable is 0.476), which makes exact interpretation more difficult. Alternative interpretation says that one more year of participation in the EU on average increases bilateral trade between 0.53 and 1.49 percent. This outcome can also be accounted for by the pairs of countries that were trading very little before entering the EU. Still the results showed here point that the EU members trade with each other vastly more than countries outside the EU, as well as the EU members with non-members. Moreover, this result should not be taken as a proof that free trade areas are extremely effective in trade creation – this could be just one of the explanations for the high posterior mean. The other one being trade diversion away from the countries outside the EU. Another issue that can be taken up here is the problem of endogeneity – countries that already trade with one another a lot, are more likely to establish the free trade area. Yet this seems not to be the problem here, as the sample covers only countries that have eventually established FTA, and the question in the research was concerning how much time did they spend in it? Finally, membership in the European Union is more than just FTA or customs union. Harmonization of law and standards, free movement of factors of production, as well as common institutions are all factors that can contribute to elevated trade.

The last variable classified as robust in all four BMA specifications is the absolute value of the difference in arable land per worker. The posterior mean for ARABLEpw is in a range from -0.021 to -0.009. Contrary to CAPLAND, this result contradicts the predictions coming from the H-O theory, that the differences in relative factor abundance stimulate international trade. Here increasing the gap in arable land to labor ratio seems to hamper bilateral trade. The explanation for this result might be found outside the realm of comparative advantage theories. Negative PM suggests that arable land abundant countries trade with each other more. So maybe ARABLEpw can be thought of as a proxy for the difference in the stage of development, and indeed correlation coefficient between ARABLEpw and an absolute value of the difference in real GDP *per capita* is equal to 0.292 (95% confidence interval ranges from 0.19 to 0.389). As RGDPpc variable was classified as fragile, ARABLEpw might capture differences in stage of development not inherent to differences in real GDP *per capita*. Furthermore, an absolute value of natural logarithm of differences in arable land per worker was classified as fragile.

It is worth mentioning, that the first six most robust determinants are characterized by posterior probability sign approaching either one or zero, which indicates that the direction of their effect is stable regardless of the particular model specification. Turning to standardized posterior means, product of real GDPs and geographical distance, no surprisingly appear to have the strongest impact on the bilateral trade flows. The next two variables in line are membership in the European Union and differences in the arable land per worker. Differences in capital to land ratios are fifth in line, while common border show the lowest influence on trade out of all the robust variables.

Three more variables were classified as robust under the first strategy and unit information prior. The first of them is the absolute value of the difference in human capital to employment ratio with posterior inclusion probability of 0.798 and posterior mean equal to 114261. This result can be explained by H-O theory, in this instance emphasizing the difference in the level of education of workers as a source of trade. Just like in the case of CAPLAND, this result indicates the presence of inter-industry trade, due to specialization. The second variable is transition country dummy with PIP equal to 0.631. The posterior mean of 0.291 implies that transition country pairs trade with each other on average more by 33.8%, which strongly contrast with -72% obtained for single variable model with the coefficient equal to -1.272. This result might imply presence of post-soviet ties between the transition countries, as well as that TRANS is being good a proxy for cultural similarities between those countries. The last variable marked as robust is the absolute value of the difference in capital to arable land ratio with PIP of 0.572. The regressor is characterized by the positive but very small value of the posterior mean of 0.000002. This result is another testament to the trade based on specialization predicted by the H-O theory. Values of the standardized posterior mean suggest that human capital to labor ratio has the strongest effect on bilateral trade out of all three aforementioned variables.

4. CONCLUSION

The analysis carried out with Bayesian model averaging allowed to identify robust determinants of bilateral trade in the European Union countries. First of all, it affirmed that real GDP and geographical distance are two main driving forces of international trade accreting validity of the gravity model. Membership in the European Union has also a very profound impact on trade. On average each year of membership in the EU is associated with a growth rate of bilateral trade between 0.52 and 1.49 percent, which is rather impressive result. On course this cannot be solely attributed to trade creation, as it can be the result of trade diversion from the countries outside of the European Union. Nevertheless, this result demonstrates effectiveness of elimination of consecutive impediments in facilitating trade.

Border effect is also listed among the robust determinants of international trade, yet its effect on trade is rather small in comparison with other determinants when one looks at the results from the standardized posterior mean. Heckscher-Ohlin theory predictions are also reflected in the data as three measures of the difference in relative factor abundance are classified as influencing bilateral trade flows, namely: capital to land, capital to arable land, and human capital to employment ratio. Finally, differences in arable land per worker have a negative effect on trade flows. An explanation for this result might be found outside the realm of comparative advantage theories, as the variable can be thought of as a proxy for the difference in the stage of development not inherent to differences in real GDP *per capita*.

ACKNOWLEDGEMENT

Article was prepared within the research project "Structural and regional aspects of international business cycles" funded by the Polish National Science Centre, on the basis of the decision No. DEC-2019/35/D/HS4/03636.

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DATA APPENDIX

VARIABLE	DESCRIPTION	SOURCE
AGROWTH	ABV of the difference between mean GDP growth rates over 1999-2011 period	PWT
ARABLE	AV of ABV of the difference in arable land	WB
ARABLE1	AV of LN of the ABV of the difference in arable land	WB
ARABLEpw	AV of ABV of the difference in arable land per worker	PWT & WB
ARABLEpw1	AV of LN of the ABV of the difference in arable l& per worker	PWT & WB
B	common border dummy	-
BCIDIFF	AV of the ABV of the difference in Bayesian corruption Index	S
BCIPROD	AV of the product of the values of Bayesian Corruption Index	S
CAP	AV ABV of the difference in capital	PWT
CAP1	AV of LN of the ABV of the difference in capital	PWT
CAPAREABLE	AV ABV of the difference in capital to arable land ratio	PWT & WB
CAPAREABLE1	AV of LN of the ABV of the difference in capital to arable land ratio	PWT & WB
CAPLAND	AV ABV of the difference in capital to land ratio	PWT & WB
CAPLAND1	AV of LN of the ABV of the difference in capital to land ratio	PWT & WB
CPW	AV ABV of the difference in capital per worker	PWT
CPW1	AV of LN of the ABV of the difference in capital per worker	PWT
CPWARABLE	AV ABV of the difference in capital per worker to arable land ratio	PWT & WB
CPWARABLE1	AV of LN of the ABV of the difference in capital per worker to arable land ratio	PWT & WB
CPWLAND	AV ABV of the difference in capital per worker to land ratio	PWT & WB
CPWLAND1	AV of LN of the ABV of the difference in capital per worker to land ratio	PWT & WB
DGEO	LN of geographical distance between capitals	-
EMP	AV ABV of the difference in employment	PWT
EMP1	AV of LN of the ABV of the difference in employment	PWT
EMPARABLE	AV ABV of the difference in employment to arable land ratio	PWT & WB
EMPLAND	AV ABV of the difference in employment to land ratio	PWT & WB
EMPLAND1	AV of LN of the ABV of the difference in employment to land ratio	PWT & WB
EPCpc	AV ABV of the difference in electricity consumption per capita	WB
EPCpc1	AV of LN of the ABV of the difference in electricity consumption per capita	WB
EU	AV number of years both countries spend in the European Union together between 1999 & 2011	-
EXCHANGE	coefficient of variation of bilateral nominal exchange rate	AMECO
FDI	AV ABV of the difference in FDI flows	UNCTAD
GOV	AV ABV of the difference of government shares in GDP	PWT
HUMAN	AV ABV of the difference in human capital	PWT
HUMAN1	AV of LN of the ABV of the difference in human capital	PWT
HUMANARABLE	AV ABV of the difference in human capital to arable land ratio	PWT & WB
HUMANARABLE1	AV of LN of the ABV of the difference in human capital to arable land ratio	PWT & WB
HUMANCAP	AV ABV of the difference in human capital to capital ratio	PWT
HUMANCAP1	AV of LN of the ABV of the difference in human capital to capital ratio	PWT
HUMANEMP	AV ABV of the difference in human capital to employment ratio	PWT
HUMANEMP1	AV of LN of the ABV of the difference in human capital to employment ratio	PWT
HUMANLAND	AV ABV of the difference in human capital to land ratio	PWT & WB
HUMANLAND1	AV of LN of the ABV of the difference in human capital to land ratio	PWT & WB
INFVAR	ABV of the difference between std of inflation rates in two countries over the 1999-2011 period	IMF
IUp100	AV ABV of the difference in number of internet users per 100 inhabitants	WB
IUp1001	AV of LN of the ABV of the difference in number of internet users per 100 inhabitants	WB
KSI	AV of Krugman specialization index for value added for 35 sectors	WOID
L	common language dummy (at least on official common language)	-
LAND	AV ABV of the difference in land	WB
LAND1	AV of LN of the ABV of the difference in land	WB
LANDpc	AV ABV of the difference in land per capita	WB
LANDpc1	AV of LN of the ABV of the difference in land per capita	PWT & WB
MA	dummy variable for a pair of countries sharing a marine border	-

MB	dummy variable for a pair of countries with access to the ocean or the sea	-
MU	Average number of years both countries spend in the euro area together between 1999 and 2011	-
OILpc	AV of ABV of the difference in number of internet users per 100 inhabitants	WB
OILpc1	AV of LN of the ABV of the difference in oil usage per capita	WB
OLDEU	dummy variable for a pair of countries that were members of the European Union before 2004	-
PATENT	AV ABV of the difference in number of patents per 1 million inhabitants	WB
PATENT1	AV of LN of the ABV of the difference in number of patents per 1 million inhabitants	WB
POPDIFF	AV ABV of the difference in population	PWT
POPPROD	AV of LN of population product	PWT
RGDPDIFF	AV ABV of the difference in real GDP	PWT
RGDPpcDIFF	AV ABV of LN of the difference in real GDP per capita	PWT
RGDPpcPROD	AV of the real GDP per capita product	PWT
RGDPPROD	AV of LN of real GDP product	PWT
TFP	correlation coefficient of growth rates of total factor productivity in two countries	PWT
TRADE	natural logarithm of the AV of real imports plus exports	IMF & PWT
TRANS	dummy variable for a pair of transition countries	IMF
URBAN	AV of the ABV of the difference in the urban population	WB
URBAN1	AV of LN of the ABV of the difference in the urban population	WB
URBANshare	AV of the ABV of the difference in share of the urban population	PWT & WB
URBANshare1	AV of LN of the ABV of the difference in share of the urban population	PWT & WB

Abbreviations: ABV – absolute value; AV – average value; LN – natural logarithm; S – Standaert (2015).

Table 1

BMA statistics under strategy 1 – dependent variable TRADE

g prior	Risk Inflation Criterion						Unit Information Prior					
VARIABLE	PIP	PM	PSD	SPM	SPSD	P(+)	PIP	PM	PSD	SPM	SPSD	P(+)
LNDGEO	1,000	-1,192	0,067	-0,365	0,021	0,000	1,000	-1,150	0,081	-0,352	0,025	0,000
LNRGDPPROD	1,000	0,780	0,043	0,715	0,040	1,000	1,000	0,790	0,059	0,724	0,054	1,000
CAPLAND	0,995	0,019	0,005	0,104	0,026	1,000	0,986	0,021	0,007	0,118	0,038	1,000
EU	0,983	1,356	0,300	0,138	0,030	1,000	0,982	0,498	0,145	0,071	0,021	1,000
B	0,972	0,510	0,152	0,072	0,022	1,000	0,951	1,342	0,417	0,136	0,042	1,000
ARABLEpw	0,816	-0,012	0,008	-0,104	0,070	0,000	0,907	-0,021	0,011	-0,177	0,090	0,000
GOV	0,472	-1,327	1,550	-0,025	0,030	0,000	0,387	-1,032	1,464	-0,020	0,028	0,000
HUMANARABLE	0,369	0,421	0,597	0,022	0,031	1,000	0,216	0,250	0,543	0,013	0,028	0,997
CAPAREABLE	0,362	0,000	0,000	0,029	0,043	1,000	0,572	0,000	0,000	0,058	0,056	1,000
HUMANEMPL	0,344	35049	54540	0,048	0,074	0,999	0,798	114261	70866	0,155	0,096	1,000
PATENT	0,229	0,000	0,001	0,013	0,026	1,000	0,442	0,001	0,001	0,030	0,038	1,000
ARABLE1	0,177	0,038	0,089	0,008	0,020	0,999	0,230	0,051	0,103	0,011	0,023	0,997
HUMANARABLE1	0,114	0,023	0,072	0,005	0,016	0,993	0,162	0,033	0,095	0,007	0,022	0,986
EMP1	0,099	-0,022	0,073	-0,011	0,037	0,027	0,397	-0,112	0,156	-0,057	0,080	0,002
TRANS	0,094	0,034	0,119	0,005	0,019	0,993	0,637	0,291	0,255	0,047	0,041	1,000
HUMANEMPL1	0,091	-0,018	0,064	-0,009	0,033	0,027	0,306	-0,077	0,128	-0,040	0,066	0,003
EPCpc1	0,086	0,02	0,1	0,004	0,014	0,998	0,194	0,05	0,12	0,010	0,023	0,997
EPCpc	0,086	0,000	0,000	0,004	0,016	0,994	0,192	0,000	0,000	0,012	0,029	0,995
HUMANLAND	0,084	-50,771	181,039	-0,007	0,023	0,008	0,056	-56,731	272,765	-0,007	0,035	0,037
ARABLE	0,082	0,001	0,002	0,003	0,011	0,990	0,285	0,002	0,004	0,012	0,021	0,996
CPWLAND	0,081	0,000	0,002	-0,006	0,023	0,011	0,044	0,000	0,002	-0,005	0,026	0,075
EMPLLAND1	0,071	-0,015	0,059	-0,005	0,019	0,001	0,245	-0,059	0,116	-0,019	0,037	0,000
OILpc1	0,066	0,018	0,078	0,003	0,011	0,998	0,116	0,034	0,110	0,005	0,016	0,989
L	0,059	0,020	0,092	0,002	0,008	1,000	0,271	0,105	0,198	0,010	0,018	1,000
EXCHANGE	0,048	-0,042	0,213	-0,002	0,009	0,000	0,088	-0,063	0,255	-0,003	0,011	0,008
BCIDIFF	0,047	0,000	0,003	-0,002	0,012	0,032	0,099	-0,001	0,003	-0,004	0,015	0,026

URBANshare	0,046	0,137	1,072	0,006	0,050	0,999	0,162	0,873	2,820	0,040	0,131	0,994
LAND	0,044	0,000	0,000	0,001	0,008	0,998	0,099	0,000	0,000	0,003	0,011	0,995
CPWARABLE	0,044	0,000	0,000	0,002	0,009	0,976	0,042	0,000	0,000	0,001	0,007	0,755
CAP	0,041	0,000	0,000	0,002	0,013	0,986	0,064	0,000	0,000	0,004	0,021	0,935
IUp1001	0,039	-0,012	0,074	-0,002	0,011	0,010	0,195	-0,071	0,169	-0,011	0,025	0,002
CAPAREABLE1	0,039	0,004	0,024	0,002	0,012	0,946	0,167	0,027	0,070	0,014	0,036	0,981
EMPLARABLE	0,038	0,000	0,000	0,002	0,012	0,984	0,082	0,000	0,000	0,007	0,026	0,978
OILpc	0,038	0,000	0,000	0,002	0,010	0,984	0,076	0,000	0,000	0,003	0,015	0,976
PATENT1	0,035	0,002	0,013	0,001	0,009	0,987	0,075	0,005	0,022	0,003	0,015	0,975
BCIPROD	0,035	0,000	0,000	-0,002	0,012	0,011	0,129	0,000	0,000	-0,008	0,025	0,013
CPWLAND1	0,033	0,002	0,014	0,001	0,008	0,993	0,056	0,003	0,017	0,002	0,010	0,971
URBANshare1	0,031	-0,078	0,723	-0,005	0,047	0,541	0,135	-0,562	1,922	-0,037	0,125	0,317
LANDpc1	0,027	-0,004	0,030	-0,001	0,009	0,014	0,111	-0,022	0,072	-0,007	0,022	0,010
IUp100	0,027	0,000	0,001	-0,001	0,007	0,083	0,110	-0,001	0,003	-0,004	0,016	0,023
CPWARABLE1	0,026	0,003	0,023	0,001	0,007	0,847	0,046	0,000	0,027	0,000	0,008	0,484
ARABLEpw1	0,025	0,001	0,029	0,001	0,013	0,667	0,130	0,030	0,095	0,014	0,043	0,923
LAND1	0,025	0,002	0,015	0,001	0,008	0,981	0,034	0,002	0,014	0,001	0,007	0,931
TFP	0,023	0,004	0,037	0,000	0,004	0,989	0,114	0,026	0,094	0,002	0,009	0,986
RGDPDIFF	0,022	0,000	0,000	0,001	0,009	0,958	0,048	0,000	0,000	0,004	0,020	0,928
HUMANLAND1	0,021	0,001	0,012	0,001	0,006	0,975	0,033	0,002	0,014	0,001	0,007	0,912
MB	0,020	0,001	0,017	0,000	0,003	0,864	0,055	0,003	0,028	0,000	0,005	0,735
FDI	0,020	0,000	0,003	0,001	0,008	0,979	0,146	0,003	0,008	0,009	0,025	0,995
HUMANCAP	0,019	-104,7	1028,9	-0,001	0,008	0,095	0,089	-736,5	2792,5	-0,006	0,023	0,019
KSI	0,019	-0,011	0,105	-0,001	0,006	0,022	0,052	-0,029	0,171	-0,002	0,010	0,035
CAP1	0,017	-0,001	0,013	0,000	0,007	0,308	0,030	-0,003	0,025	-0,001	0,014	0,205
HUMANCAP1	0,017	-0,001	0,012	0,000	0,007	0,317	0,029	-0,002	0,022	-0,001	0,012	0,275
LANDpc	0,016	0,000	0,000	0,000	0,005	0,175	0,058	0,000	0,000	-0,001	0,013	0,144
EMPLLAND	0,015	0,000	0,000	0,000	0,011	0,330	0,033	0,000	0,001	0,000	0,018	0,418
URBAN1	0,015	-0,001	0,014	0,000	0,007	0,248	0,034	-0,002	0,034	-0,001	0,017	0,223
URBAN	0,014	0,000	0,000	0,001	0,009	0,858	0,057	0,000	0,000	0,005	0,027	0,905
AGROWTH	0,014	-0,001	0,457	0,000	0,002	0,340	0,064	0,152	1,131	0,001	0,004	0,891
HUMAN1	0,014	-0,002	0,068	0,000	0,002	0,144	0,049	-0,003	0,148	0,000	0,004	0,350
HUMAN	0,014	0,000	0,023	0,000	0,002	0,273	0,050	0,000	0,050	0,000	0,004	0,469
CPW	0,013	0,000	0,000	0,000	0,003	0,492	0,037	0,000	0,000	0,000	0,005	0,473
OLDUE	0,013	0,005	0,054	0,001	0,012	0,874	0,046	0,019	0,107	0,004	0,023	0,868
MA	0,013	0,000	0,008	0,000	0,002	0,735	0,049	0,001	0,017	0,000	0,004	0,785
RGDPpc	0,012	-0,002	0,038	0,000	0,007	0,265	0,023	0,001	0,043	0,000	0,008	0,638
INFVAR	0,012	0,000	0,002	0,000	0,003	0,105	0,041	0,000	0,004	0,000	0,006	0,355
POPDIFF	0,011	0,000	0,000	0,000	0,007	0,512	0,036	0,000	0,000	0,000	0,018	0,446
CPW1	0,011	-0,001	0,016	0,000	0,003	0,257	0,034	-0,002	0,030	0,000	0,006	0,263
EMP	0,011	0,000	0,000	0,000	0,006	0,682	0,038	0,000	0,000	0,002	0,019	0,723
RGDPpcPROD	0,011	0,000	0,000	0,001	0,007	0,983	0,059	0,000	0,000	0,004	0,018	0,995
CAPLAND1	0,010	-0,001	0,010	0,000	0,004	0,079	0,024	-0,001	0,015	0,000	0,006	0,245
MU	0,010	0,001	0,014	0,000	0,003	0,782	0,032	0,001	0,026	0,000	0,005	0,654
LNPOPPROD	0,003	-0,001	0,022	-0,001	0,019	0,008	0,009	-0,003	0,043	-0,003	0,037	0,019
Burn-ins	10m											
Itertions	100m											
Cor PMP	0.9998						0.9946					

*Cor PMP -correlation coefficient for MC^3 and analytical PMP.

Table 2

BMA statistics under strategy 2 – dependent variable TRADE

g prior	Risk Inflation Criterion						Unit Information Prior					
VARIABLE	PIP	PM	PSD	SPM	SPSD	P(+)	PIP	PM	PSD	SPM	SPSD	P(+)
LNDGEO	1,000	-1,219	0,082	-0,373	0,025	0,000	1,000	-1,164	0,087	-0,356	0,026	0,000
LNRGDPPROD	1,000	0,806	0,062	0,739	0,057	1,000	1,000	0,874	0,209	0,800	0,192	1,000
EU	0,978	1,396	0,304	0,142	0,031	1,000	0,864	1,166	0,538	0,118	0,055	1,000
CAPLAND	0,968	0,016	0,004	0,092	0,025	1,000	0,963	0,018	0,007	0,098	0,038	1,000
B	0,771	0,405	0,248	0,058	0,035	1,000	0,960	0,513	0,166	0,073	0,024	1,000
ARABLEpw	0,728	-0,009	0,007	-0,074	0,057	0,000	0,871	-0,015	0,010	-0,128	0,081	0,000
HUMANARABLE	0,448	0,538	0,632	0,028	0,033	1,000	0,371	0,453	0,678	0,023	0,035	1,000
HUMANEMPL	0,156	11406	28065	0,015	0,038	0,999	0,438	48070	64670	0,065	0,088	0,999
CPWLAND	0,104	-0,001	0,002	-0,008	0,024	0,003	0,061	0,000	0,003	-0,003	0,037	0,142
GOV	0,103	-0,308	0,970	-0,006	0,018	0,000	0,281	-0,771	1,354	-0,015	0,026	0,000
ARABLE1	0,052	0,012	0,101	0,003	0,012	1,000	0,104	0,021	0,082	0,005	0,017	0,992
HUMANLAND	0,046	-25,4	124,5	-0,003	0,016	0,004	0,055	-38,9	290,1	-0,005	0,037	0,081
PATENT	0,041	0,000	0,000	0,002	0,012	1,000	0,230	0,000	0,001	0,015	0,030	1,000
HUMANARABLE1	0,038	0,009	0,047	0,002	0,011	0,986	0,070	0,009	0,103	0,002	0,023	0,922
CAPAREABLE	0,028	0,000	0,000	0,002	0,011	1,000	0,338	0,000	0,000	0,030	0,047	1,000
EMPLLAND	0,026	0,000	0,000	0,001	0,012	0,779	0,063	0,000	0,001	-0,002	0,022	0,346
EPCpc	0,021	0,000	0,000	0,001	0,008	0,996	0,080	0,000	0,000	0,004	0,017	0,988
CPWARABLE	0,018	0,000	0,000	0,001	0,006	0,995	0,037	0,000	0,000	0,001	0,008	0,934
EPCpc1	0,016	0,004	0,034	0,001	0,007	0,999	0,079	0,020	0,076	0,004	0,015	0,993
LNPOPPROD	0,016	-0,007	0,056	-0,006	0,048	0,002	0,168	-0,086	0,209	-0,074	0,180	0,003
KSI	0,014	-0,014	0,130	-0,001	0,007	0,000	0,038	-0,026	0,161	-0,001	0,009	0,014
EXCHANGE	0,013	-0,016	0,158	-0,001	0,007	0,000	0,040	-0,031	0,192	-0,001	0,008	0,030
LAND	0,012	0,000	0,000	0,000	0,005	0,995	0,037	0,000	0,000	0,001	0,007	0,995
L	0,010	0,004	0,043	0,000	0,004	1,000	0,062	0,020	0,093	0,002	0,008	1,000
OILpc1	0,010	0,003	0,038	0,000	0,005	0,996	0,049	0,014	0,083	0,002	0,012	0,968
LAND1	0,009	0,001	0,013	0,001	0,007	0,986	0,016	0,001	0,017	0,001	0,009	0,938
CPWLAND1	0,009	0,001	0,008	0,000	0,005	0,995	0,029	0,002	0,012	0,001	0,007	0,913
ARABLE	0,008	0,000	0,001	0,000	0,003	0,990	0,081	0,001	0,003	0,003	0,015	0,980
BCIPROD	0,008	0,000	0,000	0,000	0,005	0,003	0,095	0,000	0,000	-0,007	0,023	0,008
URBANshare	0,007	0,041	0,614	0,002	0,028	1,000	0,275	2,616	4,580	0,121	0,212	1,000
EMPLLAND1	0,007	-0,001	0,018	0,000	0,006	0,082	0,095	-0,024	0,084	-0,007	0,026	0,006
RGDPpc	0,007	-0,004	0,054	-0,001	0,009	0,027	0,024	-0,002	0,057	0,000	0,010	0,450
HUMANLAND1	0,006	0,001	0,011	0,000	0,005	0,954	0,016	0,001	0,016	0,000	0,008	0,911
URBANshare1	0,006	-0,025	0,409	-0,002	0,027	0,261	0,269	-1,749	3,082	-0,114	0,201	0,023
OILpc	0,006	0,000	0,000	0,000	0,005	0,945	0,032	0,000	0,000	0,001	0,012	0,922
LANDpc1	0,006	0,000	0,015	0,000	0,005	0,646	0,045	-0,009	0,052	-0,003	0,016	0,064
TRANS	0,005	0,002	0,030	0,000	0,005	0,979	0,346	0,200	0,300	0,032	0,048	0,999
BCIDIFF	0,005	0,000	0,001	0,000	0,004	0,028	0,090	-0,001	0,004	-0,005	0,018	0,015
PATENT1	0,004	0,000	0,006	0,000	0,004	0,999	0,042	0,003	0,019	0,002	0,012	0,979
EMPLARABLE	0,004	0,000	0,000	0,000	0,003	0,983	0,038	0,000	0,000	0,002	0,014	0,895
CPWARABLE1	0,004	0,000	0,009	0,000	0,003	0,791	0,071	0,010	0,044	0,005	0,023	0,964
CAP	0,004	0,000	0,000	0,000	0,003	0,994	0,037	0,000	0,000	0,002	0,015	0,843
ARABLEpw1	0,003	0,000	0,007	0,000	0,003	0,680	0,063	0,010	0,064	0,004	0,029	0,816
FDI	0,003	0,000	0,001	0,000	0,003	0,540	0,049	0,001	0,005	0,002	0,014	0,915
RGDPpcPROD	0,003	0,000	0,000	0,000	0,004	0,911	0,039	0,000	0,000	0,002	0,015	0,963
CAPLAND1	0,003	0,000	0,006	0,000	0,003	0,364	0,019	0,000	0,014	0,000	0,006	0,284
MU	0,003	0,000	0,009	0,000	0,002	0,872	0,022	0,002	0,024	0,000	0,004	0,836
OLDUE	0,002	0,000	0,016	0,000	0,003	0,396	0,029	0,005	0,063	0,001	0,014	0,633

HUMANEMPL1	0,002	0,000	0,008	0,000	0,004	0,077	0,104	-0,024	0,085	-0,012	0,044	0,030
CAPAREABLE1	0,002	0,000	0,005	0,000	0,002	0,935	0,022	0,001	0,020	0,000	0,006	0,663
TFP	0,002	0,000	0,000	0,000	0,001	0,993	0,024	0,000	0,000	0,000	0,004	0,905
LANDpc	0,002	0,000	0,000	0,000	0,002	0,526	0,022	0,000	0,000	0,000	0,010	0,454
HUMANCAP	0,002	-8,029	274,9	0,000	0,002	0,194	0,047	-373,5	2016	-0,003	0,016	0,030
URBAN1	0,002	0,000	0,003	0,000	0,002	0,477	0,033	0,004	0,043	0,002	0,022	0,678
EMP1	0,001	0,000	0,006	0,000	0,003	0,295	0,118	-0,036	0,115	-0,018	0,059	0,005
MB	0,001	0,000	0,004	0,000	0,001	0,862	0,019	0,000	0,017	0,000	0,003	0,452
MA	0,001	0,000	0,003	0,000	0,001	0,390	0,014	0,000	0,009	0,000	0,002	0,575
RGDPDIFF	0,001	0,000	0,000	0,000	0,002	0,962	0,021	0,000	0,000	0,001	0,014	0,810
AGROWTH	0,001	-0,002	0,149	0,000	0,001	0,162	0,017	0,023	0,547	0,000	0,002	0,719
IUp1001	0,001	0,000	0,009	0,000	0,001	0,036	0,047	-0,016	0,085	-0,002	0,013	0,007
POPDIFF	0,001	0,000	0,000	0,000	0,002	0,789	0,030	0,000	0,000	-0,001	0,019	0,350
IUp100	0,001	0,000	0,000	0,000	0,001	0,222	0,031	0,000	0,002	-0,001	0,008	0,066
HUMAN	0,001	0,000	0,006	0,000	0,000	0,186	0,011	0,000	0,142	0,000	0,011	0,567
CPW1	0,001	0,000	0,004	0,000	0,001	0,174	0,012	-0,001	0,024	0,000	0,005	0,234
CPW	0,001	0,000	0,000	0,000	0,001	0,334	0,013	0,000	0,000	0,000	0,004	0,551
INFVAR	0,001	0,000	0,001	0,000	0,001	0,119	0,017	0,000	0,003	0,000	0,004	0,621
HUMAN1	0,001	0,000	0,016	0,000	0,000	0,168	0,010	0,000	0,421	0,000	0,012	0,540
EMP	0,001	0,000	0,000	0,000	0,001	0,899	0,016	0,000	0,000	0,000	0,012	0,550
HUMANCAP1	0,001	0,000	0,002	0,000	0,001	0,397	0,015	-0,001	0,020	-0,001	0,012	0,248
CAP1	0,001	0,000	0,002	0,000	0,001	0,236	0,017	-0,001	0,021	-0,001	0,012	0,204
URBAN	0,000	0,000	0,000	0,000	0,002	0,950	0,023	0,000	0,000	0,002	0,018	0,837
Burn-ins	10m											
Itertions	100m											