Determinants of Foreign Direct Investment in Europe: Bayesian Model Averaging in the Presence of Weak Exogeneity

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Abstract

This paper derives the robust determinants of Foreign Direct Investment (FDI) in Europe under model uncertainty and weak exogeneity issues. For this reason, Bayesian Averaging of Limited Information Maximum Likelihood Estimates (BALIMLE) approach was utilized. The chosen methodology allows for the estimation of a dynamic panel model with fixed effects. Also, the jointness measures were computed. The considered sample includes bilateral FDI flows between 36 European countries over the 2004 – 2017 period. The empirical evidence shows the importance of the endowment theory and the significance of output per worker and labor force variables in explaining the FDI flows. A market size theory was proposed to be augmented with a relative growth hypothesis. The calculated jointness measures indicated the complementary nature of considered regressors and theories.

Introduction

The recent globalization has led to the liberalization of political and economic restrictions resulting in more vague borders for trade, economic activity, migration, and investment. Now, multinational enterprises (MNEs) have received an opportunity to access previously unavailable immobile factors of production via moving the capital in a foreign direct investment (FDI) form. Accordingly, the possibility of more efficient utilization of the economies of scale and operating in various developed markets significantly boosted the role of MNEs and their FDI. Thus, the activity of MNEs totaled 10% of world Gross Domestic Product (GDP) and more than half of world research and development (Blonigen and Piger 2014). Despite that, MNEs, which transfer intangible assets such as managerial practices, patents, and specific knowledge to developing markets, largely increase local competition. Later, the spillover of this transfer of knowledge significantly accelerates the process of convergence to the level of the developed countries, enhancing the well-being of the local population. Moreover, the promotion of FDI, in contrast to portfolio investment, is more attractive to policymakers because MNEs produce working places and FDI is not ready to flee after the first expectation of the recession. Also, MNEs generate high corporate tax revenues in the host economies.

The by-products of MNEs' FDI activity are too benefiting to be ignored. Thus, two important questions whether there exist some factors largely attracting or impacting MNEs' investment decisions and whether they can be effectively influenced arise. For this reason, the bulk of theoretical, empirical, and survey literature has developed a diversity of hypotheses. Despite the joint theoretical foundation, econometrical studies on this matter showed that variables considered as robust in one part of the studies appear to be completely irrelevant in the other. Moreover, some researchers find the positive relationship between a specific regressor and FDI, while others –

negative. This phenomenon may be attributed to different country, time, and hypotheses' combinations. This paper, in its turn, does not claim to discover the only relevant set of dynamically stable determinants of global FDI; instead, it tests the behaviour of the most influential FDI theories in the sample of European countries over time. In addition, this paper tries to address the almost universally ignored issue of weak exogeneity of the majority of classical determinants of FDI. For this purpose, the econometric framework proposed by Moral-Benito (2013 and 2016) is for the first time applied to the FDI flows data. The chosen methodology combines the Bayesian Model Averaging (BMA) techniques with the appropriate likelihood function in the so-called Bayesian Averaging of Limited Information Maximum Likelihood Estimates (BALIMLE) dynamic panel model with fixed effects.

Thus, the goal of the research was finding theories and regressors capable of interpreting European FDI flows, which do not lose their explanatory power and robustness under the weak exogeneity.

The first chapter surveys the relevant literature and hypotheses. The next chapter consists of a thorough description of the concepts of the chosen methodology and utilized data. The third (empirical results and discussion) chapter comprises the overview of statistics obtained from the empirical regression and consideration of variable-specific estimates. The concluding chapter summarizes the main findings obtained during the research process.

Literature Review

Foreign Direct Investment (FDI) is defined as the direct investment in a company located not in the investor's country, where direct investment implies either purchasing 10% or more of the voting stock or founding a new business. The fast growth of worldwide FDI flows has put a spotlight on determining the factors and hypotheses capable of explaining companies' decisions to engage in affiliate production instead of, for example, exporting.

Prior to the emergence of a diversity of macroeconomic FDI theories, FDI, as a relatively uncharted concept, was attempted to be explored as a part of the capital trade. MacDougall (1960), Jasay (1960), and Kemp (1966) utilized the Hecksher-Ohlin framework with the extra assumption of perfect capital mobility to indicate the effects and principles of FDI. Under this structure, a relatively capital-abundant home country is expected to invest in the foreign economy to make use of the recipient's relatively higher marginal product of capital or, accordingly, a higher unit return (rent) on capital. According to Frankel (1965), the premium on rent in the recipient's economy should offset the lost opportunity of home technological expansion.

The depreciation and the appreciation of the currency are essential under Mundell's (1957) "Anti-trade" or the U.S. FDI style. If FDI is intended to serve as a substitute to trade, i.e. the production is transferred to a foreign country to satisfy local demand, the appreciation of the host-country currency attracts investors. On the other hand, under Kojima's (1973) "Pro-trade" Japanese FDI style, FDI in the production line, e.g. FDI in labor-abundant or resource-rich countries to produce labor- or resource-intensive goods, flourishes trade between the host- and the source-country. Here, the appreciation of the host-country currency results in less affordable exports and repels FDI. MNEs' resolution on pro- or anti-trade, i.e. "vertical" and "horizontal" FDI accordingly, is summarized in Caves (1971) and influenced by micro, macro, and strategic factors. The empirical research in this sphere utilized the U.S. data and showed the evidence of the inflow of FDI in the U.S. due to dollar depreciation (Froot and Stein 1991, Blonigen 1997 and 2005).

Dunning (1977, 1979, and 2000) was first to integrate Hymer's (1976) international production "O", Southard's (1931) location "L", and Buckley's and Casson's (1976) internalization "I" theories into eclectic or OLI paradigm (Moosa 2002). Briefly, "Ownership" advantages employed in the foreign market such as intangible assets like trademarks, brand name, patents, innovative technologies, operating experience, etc. should outweigh the costs of operating in, sometimes, alien legislation, currency, language or religion areas. "Internalization", when "O" conditions are met, helps to deal with market failures, time lags, transaction, negotiation, and marketing costs via substituting open market transactions with intra-firm transactions (Moosa 2002). Thus, "O" and "I" advantages manage greatly to meet the challenge of explaining MNEs' investing behavior on the industry and the firm levels. However, strategic and microeconomic characteristics of MNEs are hardly assessable and usually concealed from public. "Location" as the country level advantages is to be discussed more thoroughly.

A cluster of empirical researches and possible determinants proposals followed the appearance of statistical data on FDI. Dunning (1979) has outlined them in four groups: production costs, government intervention, movement costs, and risk factors, later expanded according to contemporary views by the variety of appearing theories.

Production costs. The relocation of the manufacture of labor-intensive goods to labor-abundant countries is a regular solution to shrink the production costs. Hence, the low local wage level theoretically should determine huge FDI inflows. On the other hand, asset-seeking or cutting-edge technology FDI demands high labor productivity and quality (human capital). Moosa (2002) illustrates a bunch of studies supporting the hypothesis that the rise in wages results in reduced FDI inflows. Conversely, there is evidence of the reverse results (Yang et al. 2000). Yang et al. (2000) pointed out the market imperfections assuming that labor productivity may grow faster than wages, lessening the unit labor cost. Despite the existence of different hypotheses, some policymakers in developing countries recognize the maintenance of competitively low wages as the main FDI attracting policy sometimes deterring the enhancement of workers' well-being (Bayraktar-Sağlam and Böke 2017).

The manufacturing industry is highly dependent on cheap and timely supplies of raw materials. As an alternative or a complement to locating their business in the labor-abundant countries, investors may want to move their affiliates in the countries abundant with natural resources. By doing so, MNEs may benefit from the existing local supply chains or from building their own infrastructure focused on the home country. Moreover, one should not forget that some companies specializing in the extraction of subsoil assets are constantly looking for FDI opportunities to exploit new deposits. It should be noted that this part of the production costs hypothesis represents the classical endowment-based theory, namely that countries endowed with capital tend to invest in countries endowed with natural resources and labor (Campos and Kinoshita 2003).

Government intervention. Dunning (1979) describes government intervention as tariff barriers, taxation, and the environment for FDI. Jun (1989) emphasizes the influence of the domestic taxation policy on MNEs' engagement in outward FDI. De Mooij and Ederveen (2003) recapitulated the empirical literature, examining the relationship between taxes and FDI. The mean tax-rate elasticity of FDI computed from 351 elasticities from 25 different studies amounted to -3.3; however, 20% of elasticities were, de facto, positive. Scholes and Wolfson (1990) show how an increase in explicit and a decrease in implicit taxes in the U.S. resulted in a higher inflow of FDI due to higher domestic tax credits under "residence" legislation.

Traditional literature considers tariff barriers or trade protectionism an explicit cause for horizontal or trade-substitution FDI. Blonigen (1997) provides the results, questioning the significance of trade barriers in MNEs' decision making, although, in the later study, Blonigen (2002) found robust evidence that only MNEs from developed countries undertake tariff-jumping FDI. Besides, Blonigen and Feenstra (1996) verified statistically the hypothesis of increased FDI flows due to a protectionist threat.

Agarwal (1980) concludes from the previous survey studies that, in the process of choosing the location, MNEs generally disregard incentives provided by local governments. On the other hand, developing countries tend to harm FDI flows by imposing too strict conditions that MNEs have to obey to obtain some incentives (Situmeang 1978, cited in Agarwal 1980).

Regional integration agreements (RIAs) encourage both trade and FDI through the elimination of trade barriers and the stimulation of capital mobility. Hence, the question which factor benefits from RIAs more arises. Early studies on RIAs' effects on FDI mentioned in Nayak and Choudhury (2014) produced inconclusive results stressing the need for a new theoretical framework. Salike (2010) considers both vertical and horizontal FDI to observe the effects of RIA in the case of tariff jumping and internalization. The generalized conclusion is that integrated regions receive more FDI, especially when the previous pattern of investment demonstrated the uncommonness of intra-region FDI. Nonetheless, the distribution of FDI flows in the region is expected to be unequal, favoring previously closed economies.

Movement costs. Movement costs are transport costs and psychic distance (Dunning 1979). Transport costs contain both an increased cost of trade and investment transactions. Markusen

(2002) concentrated on the distinction of horizontal and vertical FDI and deduced the positive correlation between the distance and horizontal FDI and vice versa. This empirical finding implies that the trade costs outweigh investment costs for MNEs. Regarding psychic distance, Johanson and Vahlne (1977, p. 24) provide the following definition: "the psychic distance is defined as the sum of factors preventing the flow of information from and to the market. Examples are differences in language, education, business practices, culture, and industrial development". Psychic distance results in miscommunications and a lack of experience in operating in the local culture, which, in turn, leads to raised business risks and costs discouraging foreign investors (Jiménez and de la Fuente 2016). Yet, there is some evidence of the "psychic distance paradox", when Canadian retail companies were performing poorly because they underestimated the dissimilarity between the Canadian and the U.S. markets basing on geographical and seemingly cultural proximity (O'Grady and Lane 1996).

Risk factors. Apart from Aliber's (1970) currency risk theory, Ragazzi (1973) proposed FDI as more efficient for MNEs' industrial risk-reducing analogy to portfolio investment. Rugman (1977) argued that if a foreign country's market behaves even slightly asymmetrically, a domestic firm can diversify the risk by investing directly. Individual investors who may find it difficult to create a diversified portfolio at a reasonable price due to capital trade limitations and obstacles, e.g. Interest Equalization Tax, will diversify risk through buying shares of the firms integrated into FDI activity, i.e. funding MNEs' further enlargement and growth. Rugman's (1976 and 1977) and Thompson's (1985) empirical findings broadly support the diversification hypothesis.

Clearly, both economic and political stability substantially determine the FDI attractiveness. The propensity to invest in the growing and prosperous economy may be undermined by the threat of nationalization or a coup. The most frequently used proxies for economic stability are GDP as a measure of the market size (positive relation with FDI), GDP per capita which stands for nation’s well-being (positive), rate of growth of GDP as a potential for progress (positive), and inflation rate as a symptom of internal monetary malfunction (negative) (Agarwal 1980, Schneider and Frey 1985, Assunção et al. 2011, Bajrami and Zeqiri 2019).

2. Methods and Data

2.1 Methods

The discussed FDI literature provides some insight into the diversity of approaches and hypotheses capable of explaining the amount and the direction of FDI flows. On the other hand, a researcher is obscured by the variety of combinations of theories and possible discrepancies among them. The subjective selection of one model questions the legitimacy of the results and the robustness of the determinants used. Utilization of every possible variable hurts the degrees of freedom and often leads to the risk of overfitting the model. Fortunately, recent enhancement of computational powers and statistical techniques allows researchers to address the model uncertainty issue through Bayesian Model Averaging (BMA).

BMA solves uncertainty through considering and assigning probabilities to all 2^k possible models obtained from combining k variables of interest. Thus, each model has the power to influence parameter estimates constructed as a weighted-average (Chen et al. 2009). Also, BMA provides scholars with a possibility to benefit from the prior knowledge, expectations, or research in the field of interest.

This paper follows Moral-Benito's (2013 and 2016) expanded BMA framework, which allows for considering the potential weak exogeneity of the regressors under the dynamic panel model with fixed effects[1]. The dynamic panel model setting is desired while explaining FDI flows for several reasons (Campos and Kinoshita 2003, Moral-Benito 2016). First, the agglomeration theory stresses the importance of self-reinforcement effects, i.e. the activity of FDI flows vastly

[1] The method is relatively new; however, it was already applied in the analysis of the determinants of economic growth (Moral-Benito 2013 and 2016), business cycle synchronization (Beck 2019, 2020, and 2021a) and structural convergence (Beck 2021b).

depends on the previous success in attracting FDI because newcomers tend to mimic the behavior of experienced investors. Once the ice is broken and MNEs have started investing, maintaining the existing political and economic conditions is sufficient to promote constantly growing inflows. As a result, the lagged dependent variable and time series part of the panel should incorporate self-reinforcing. Second, it is important to ascertain the dynamic consistency of the obtained model structure. Third, extension in time allows for inner changes such as an entrance in RIAs or market reforms to come into effect. The cross-sectional dimension of the panel accounts for the heterogeneity of FDI types and motives explaining them. The inclusion of countries displaying distinct features helps not to stuck in determining regressors for one category of FDI and to expand the focus of the study.

The predetermined or weakly exogenous nature of several or all explanatory variables should not be ignored. This notion admits the presence of correlation between past values of the error term and current values of regressors in contrast to the more common yet more limiting assumption of strict exogeneity, which forbids any correlation between the variable and the residuals (Moral-Benito 2016). To put it in the empirical context, one of the most commonly included independent variables, the market size, is expected to attract FDI flows that stimulate economic activity, which results in a growing market. The evidence of this feedback process is found in various studies for different mainstream right-hand side variables discussed more thoroughly in the Data Description section. The most popular way to address the predeterminedness issue so far is to employ instrumental variables (IV). However, to avoid inconsistent and inefficient estimates, one has to be certain that he or she has chosen such instruments that are simultaneously uncorrelated with the omitted regressors, not potential determinants themselves, and strongly correlated to the endogenous variables (Pruefer and Tondl

2008). Durlauf et al. (2005) caution about the difficulty to find valid instruments in such a setting. Moreover, the dynamic panel framework does not allow for the utilization of commonly used stable geographical instruments.

The starting point of the Bayesian Averaging of Limited Information Maximum Likelihood Estimates (BALIMLE) is the following linear equation:

$$y_{it} = \alpha y_{it-1} + x_{it}\beta + \eta_i + \zeta_t + v_{it} \qquad (i = 1, \dots., N; t = 1, \dots, T), \tag{1}$$

where y_{it} denotes FDI flows in a country pair i at time t, x_{it} is a matrix of regressors, β represents coefficients, η_i means fixed effects of each country pair, ζ_t is a time-specific shock, and v_{it} is a matrix of time-varying residuals. The weak exogeneity is described formally in the following equation:

$$\mathrm{E}(v_{it} | y_i^{t-1}, x_i^t, \eta_i) = 0 \quad (i = 1, \dots., N; t = 1, \dots, T) \tag{2}$$

where $y_i^{t-1} = (y_{i0}, \dots, y_{it-1})'$ and $x_i^t = (x_{i0}, \dots, x_{it})'$ are vectors of values up to time t. The set of moment conditions described in equation (2) is commonly used in standard Generalized Method of Moments (GMM) and is sufficient to design a reliable and asymptotically normal maximum likelihood function (Moral-Benito 2013). The alternative estimators described in Hsiao et al. (2002) and Binder et al. (2005) impose extra restrictions on a time-series not allowing for heteroscedasticity and nonstationary mean respectively. In addition, the maximizer of the likelihood function in equation (6) produces more accurate estimations in the finite-set design compared to GMM and system GMM estimators (Moral-Benito 2013).

Moral-Benito (2013 and 2016) supplements the equation (1) with a set of reduced-form equations, which expresses the unrestricted feedback process, i.e. include information from all existing lags ($t = 2, \dots, T$):

$$x_{it} = \gamma_{t0} y_{i0} + \cdots + \gamma_{t,t-1} y_{i,t-1} + \Lambda_{t1} x_{i0} + \cdots + \Lambda_{t,t-1} x_{it-1} + c_t \eta_i + \vartheta_{it} \quad (3)$$

where c_t is the $k \times 1$ coefficient vector. For $h < t$, γ_{th} is the $k \times 1$ vector $(y_{th}^1, \ldots, y_{th}^k)'$, $h = 0, \ldots, T-1$; Λ_{th} is the coefficient matrix of order $k \times k$, and ϑ_{it} is the $k \times 1$ residuals vector. The mean vector and covariance matrix of the joint distribution of the initial observations and country-specific fixed effects η_i are unconstrained considering the following:

$$y_{i0} = c_0 \eta_i + v_{i0} \quad (4)$$

$$x_{i1} = \gamma_{10} y_{i0} + c_1 \eta_i + \vartheta_{i1} \quad (5)$$

where c_0 is a scalar, and c_1 and γ_{10} are $k \times 1$ vectors. Finally, the Gaussian log-likelihood function resulting from combining sets of equations (1) and (3–5) is defined as:

$$\log f(data|\theta) \propto \frac{N}{2} \log \det(B^{-1} D \Sigma D' B'^{-1}) - \frac{1}{2} \sum_{i=1}^{N} \{R'_i (B^{-1} D \Sigma D' B'^{-1})^{-1} R_i\}, \quad (6)$$

where θ is the vector of estimated coefficients specific to each model, $R_i = (y_{i0}, x'_{i1}, y_{i1}, \ldots, x'_{iT}, y_{iT})'$ is the vector of data, $\Sigma = \mathrm{diag}\{\sigma_\eta^2, \sigma_{v_0}^2, \Sigma_{\vartheta_1}, \sigma_{v_1}^2, \ldots, \Sigma_{\vartheta_T}, \sigma_{v_T}^2\}$ is the block-diagonal variance-covariance matrix of the residuals vector $U_i = (\eta_i, v_{i0}, \vartheta'_{i0}, v_{i1}, \ldots, \vartheta'_{iT}, v_{iT})$. B and D contain equations' parameters:

$$B = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\ -\gamma_{10} & I_0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\ -\alpha & -\beta' & 1 & 0 & 0 & \cdots & 0 & 0 & 0 \\ -\gamma_{20} & -\Lambda_{21} & -\gamma_{21} & I_k & 0 & \cdots & 0 & 0 & 0 \\ 0 & 0 & -\alpha & -\beta' & 1 & \cdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & 0 & 0 & 0 \\ -\gamma_{T0} & -\Lambda_{T1} & -\gamma_{T1} & -\Lambda_{T2} & -\gamma_{T2} & \cdots & -\gamma_{T,t-1} & I_k & 0 \\ 0 & 0 & 0 & 0 & 0 & \cdots & -\alpha & -\beta' & 1 \end{bmatrix}, \quad (7)$$

$$D = \begin{bmatrix} [c_0 & c'_1 & 1 & c'_2 & 1 & \cdots & c'_T & 1] \\ & & & I_{T(k+1)} & & & & \end{bmatrix}. \quad (8)$$

Once the problem-specific marginal likelihood in equation (6) is defined, it can be combined with the classical BMA approach. Generally, to estimate a posterior distribution of any parameter of interest β unconditional on a model, i.e. to solve model uncertainty, BMA computes the following:

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

where $P(\beta|M_j, y)$ denotes the probability distribution of a parameter β conditional on a model M_j, and $P(M_j|y)$ is the Posterior Model Probability (PMP). $P(M_j|y)$ is expressed employing the Bayes' rule:

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

where $l(y|M_j)$ denotes the marginal likelihood of each model, and $P(M_j)$ is the prior probability of each model. The following property $p(y) = \sum_{j=1}^{2^K} l(y|M_j) * P(M_j)$ allows to consider PMP of a model as this model's weight in the whole model space. In the BALIMLE case, the joint distribution of both dependent and independent variables is always the reference point for each model-specific marginal likelihood. This is explained by the fact that the set of simultaneous equations is the same no matter if any or all determinants are excluded from the specific model (Moral-Benito 2016).

The derivation of posterior distributions bases on specifying beliefs about prior probability distributions. A parameter β is assumed to be distributed normally with zero mean and variance $\sigma^2 V_j$:

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

In its turn, the prior variance matrix V_j represents the relationship between the hyperparameter g and the data covariance structure:

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

The proportionality coefficient g initially proposed by Zellner (1986) reflects the degree of the conservativeness of one's beliefs about β's variability. Fernández et al. (2001) encourage employing the 'benchmark prior':

$$g = \frac{1}{\max(n, k^2)}, \tag{13}$$

where $g = \frac{1}{n}$ denotes Unit Information Prior (UIP) (Kass and Wasserman 1995), while $g = \frac{1}{k^2}$ means Risk Inflation Criterion (RIC) (Foster and George 1994). Eicher et al. (2011b) found some compelling evidence in favor of the superiority of UIP estimates over 11 other examined priors in both simulated and economic growth data. Also, Eicher et al. (2011a) suggest applying it in the FDI context to promote the approximation of the Bayes factor by the Bayesian Information Criterion.

Concerning prior model probability, it is common to use so-called "non-informative" priors. The binomial model prior is defined as follows (Sala-i-Martin *et al.* 2004, Ley and Steel 2009):

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

where EMS is an abbreviation for the expected model size and k_j is the model-specific number of regressors. In case when $EMS = \frac{K}{2}$, all models have uniform prior probability equal to $\frac{1}{2^K}$. The binomial-beta model prior has the following form (Ley and Steel 2009):

$$P(M_j) \propto \Gamma(1 + k_j) * \Gamma\left(\frac{K - EMS}{EMS} + K - k_j\right). \tag{15}$$

When $EMS = \frac{K}{2}$, models have probability equal to $\frac{1}{K+1}$. Eicher et al. (2011b) advocate choosing the uniform binomial model prior in conjunction with the UIP prior as an adequate basic option.

Unconditional posterior mean (PM) of the parameter β_i is computed as a weighted average of $\hat{\beta}_{ij}$:

$$PM = E(\beta_i|y) = \sum_{j=1}^{2^K} P(M_j|y) * \hat{\beta}_{ij}, \tag{16}$$

where $\hat{\beta}_{ij} = E(\beta_i|y, M_j)$ is the parameter's value for the model M_j obtained employing the Ordinary Least Squares (OLS). The formula of posterior standard deviation (PSD) is given as:

$$PSD = \sqrt{\sum_{j=1}^{2^K} P(M_j|y) * V(\beta_j|y, M_j) + \sum_{j=1}^{2^K} P(M_j|y) * \left[\hat{\beta}_{ij} - E(\beta_i|y)\right]^2}, \tag{17}$$

where $V(\beta_j|y, M_j)$ is the variance of β_j conditional on the model M_j.

Posterior inclusion probability (PIP), i.e. the probability that the regressor, in fact, belongs to the posterior model, is formulated as follows:

$$PIP = P(x_i|y) = \sum_{j=1}^{2^K} 1(\varphi_i = 1|y, M_j) * P(M_j|y), \tag{18}$$

where $\varphi_i = 1$ when the regressor is included in the model M_j. If the inclusion probability of a regressor is higher than the applied prior probability, the regressor can be described as a robust factor causing FDI flows.

To estimate the sign of a parameter conditional on the presence in the model, the posterior probability of a positive sign is calculated as follows:

$$P(+) = P[sign(x_i)|y] = \begin{cases} \sum_{j=1}^{2^K} P(M_j|y) * CDF(t_{ij}|M_j), & if \;\; sign[E(\beta_i|y)] = 1 \\ 1 - \sum_{j=1}^{2^K} P(M_j|y) * CDF(t_{ij}|M_j), if & sign[E(\beta_i|y)] = -1 \end{cases} \qquad (19)$$

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

Thus, Moral-Benito's (2013 and 2016) BALIMLE approach integrates BMA techniques described in equations (9-19) with specific marginal likelihood function in equation (6) allowing one to simultaneously address reverse causality and model uncertainty issues in the dynamic panel data setting with fixed effects. Unfortunately, available gradient optimization methods, the inaccessibility of Markov chain Monte Carlo model composition algorithm (used to approximate the PMPs in order to make the estimation feasible), and the complexity of the likelihood function presented in equation (6) put constraints on the number of periods and determinants possible to be estimated.

After the estimation, if one is interested in figuring out the relationship between the posterior determinants, jointness measures can be applied. The jointness of a pair is commonly computed as in seminal papers by Doppelhofer and Week (2009) or Ley and Steel (2007). More recently, Hofmarcher et al. (2018) modified the existing measures to ascertain the fulfillment of standard BMA measures properties (Ley and Steel 2007) and augment them with other characteristics inherent in the data mining literature. Their measure of jointness has the following form:

$$J_{YQM} = \frac{(P(AB|y) + \alpha_k) * (P(\overline{AB}|y) + \alpha_k) - (P(A\bar{B}|y) + \alpha_k) * (P(\bar{A}B|y) + \alpha_k)}{(P(AB|y) + \alpha_k) * (P(\overline{AB}|y) + \alpha_k) + (P(A\bar{B}|y) + \alpha_k) * (P(\bar{A}B|y) + \alpha_k) - \alpha_k}, \quad (20)$$

where $P(AB|y) \equiv P(A \cap B|\mathrm{y})$, A and B denote variables of interest, α_k is a correction factor, and $\bar{A}$ ($\bar{B}$) imply cases in which a variable did not appear in the model. Following the advice of Hofmarcher et al. (2018), the Jeffreys prior, namely $\alpha_k = \frac{1}{2}\ \forall\ k$, was utilized. The interpretation range is constrained in $[-1,1]$ brackets, where -1 implies very strong substitutes, while +1 indicates very strong complements.

2.2 Data Description

In their survey of the theoretical and empirical literature on FDI, Assunção et al. (2011) overview 10 different theoretical approaches as well as 59 determinants proposed as proxies in different econometric settings. However, BALIMLE, in contrast to the orthodox BMA, necessitates more strict limitation of the number of hypothetical regressors tested simultaneously. Generally, each additional regressor makes the process of the likelihood maximization substantially more complicated doubling the model space as well as increasing the maximum number of parameters to be optimized simultaneously by $\frac{t^2+t+2}{2}$, where t denotes the time dimension of the panel. If one is interested in expanding the panel's time dimension by one year, i.e. estimating $(t+1)$ periods, the maximum number of parameters increases by $1 + (t+1) * n$, where t denotes the initial time and n is the total number of regressors.

It was decided to concentrate on the European continent to make the estimation computationally feasible. The list of considered countries can be found in the Appendix.

In addition to the computational constraints, Ciccone and Jarociński (2010) conclude that the inference from the agnostic model specification is very sensitive to measurement errors and chosen data sources. For instance, World Development Indicators' (WDI) and Penn World Table's (PWT) 6.0, 6.1 and 6.2 revisions of 1960-1996 growth data produce different PIPs for the same proxy groups; hence, it interferes with solving the primary uncertainty issue. Moral-Benito (2012) finds that a decrease in the number of regressors boosts the robustness of the inference about the same proxy groups but from different sources. In addition, he suggests refraining from using distinct proxies for one theoretical aspect.

Thus, for all the reasons mentioned above, the set of countries, time periods and potential regressors overviewed in this research is quite compact.

The dependent variable, denoted as FDI_{ijt} and measured in millions of euro, is obtained from yearly bilateral financial flows database constructed by the European Commission. After dropping the country pairs with missing observations and unavailable data for regressors for at least one country, the final database amounted to 1031 pairs between 36 European countries for the period from 2006 to 2017 inclusively. The estimation of, for instance, 5 regressors for $t = 12$ requires the optimization of 410 parameters simultaneously. When $t = 6$, this number decreases to computationally feasible 119. Consequently, FDI_{ijt} is decided to be constructed as averages of FDI flows from the country i to the country j for two subsequent years:

$$FDI_{ij} = \frac{1}{2}\sum_{t=1}^{2} FDI_{ijt} \tag{21}$$

The dynamic panel also requires the values of the lagged FDI. Thus, $FDIlag_{ijt}$ is designed similarly but for the 2004-2015 period.

All determinants are specified in the following way: first, two-year averages of a regressor for the country i and the country j are calculated; second, differences between the country i's averages and the country j's averages for the same period of time are computed:

$$REG_{ij} = \frac{1}{2}\sum_{t=1}^{2} REG_{it} - \frac{1}{2}\sum_{t=1}^{2} REG_{jt} \tag{22}$$

where REG denotes the regressor of interest. In other words, variables are denoted to represent the gap between the source and the host economy.

YOS – Mean years of schooling attained by people aged 25 and older. In the context of globalization, MNEs seeking a way to enhance their competitiveness and business practices may turn to the countries with already available qualified labor force (Wendlassida Miningou et al. 2017). Also, educated labor demands less time and training to adopt new practices or technologies, which results in lower labor costs for MNEs (Campos and Kinoshita 2003). In contrast, MNEs may also benefit from unskilled labor force locating the production of labor-intensive goods in such countries. Due to the unavailability of human capital data or, at least, harmonized test scores to assess the efficiency of education, the mean years of schooling constructed by Human Development Reports were used to proxy the quality of labor. Indeed, this assumption does not take into consideration the diminishing returns of schooling; also, it does not allow to measure the differences in the country-specific and time-specific cognitive abilities and the quality of the educational system (Wossmann 2003). However, YOS is the most accessible measure of human capital, which allows for the evaluation of the stock of the already attained education. The endogeneity of human capital in the form of first attracting FDI and then spillover effects was discussed in a variety of studies (Borensztein et al. 1995, Blomstrom and Kokko 1997, Hoffmann 2003). In general, if the absorptive capacity of the labor force in the host country is sufficient, local employees may enjoy the accumulation of human capital stock through various training and transfers of specific knowledge and technology conducted by MNEs.

LLF – Natural logarithm of the total labor force. LLF, obtained from International Labour Organization (ILO), is one of the variables included to measure the differences in the factor endowment between countries. Generally, labor abundant countries are expected to attract FDI flows from the capital abundant countries. The reverse causality, in this case, has brought a lot of attention too, with almost a universal conclusion of increased demand for skilled labor and labor in general and increased median wages which influence previously unmotivated individuals to join the labor force (Hale and Xu 2016, Sharma and Cardenas 2018).

LOPW – The logarithm of total output per worker (GDP constant 2010 US $) is accessed from ILO. The large market size encourages investments from MNEs willing to make use of the economies of scale and market-seeking MNEs. Proxies for this hypothesis seem to belong to the most robust and significant group of variables explaining FDI (Chakrabarti 2001, Assunção et al. 2011, Camarero et al. 2019). However, Chakrabarti (2001) questions the sufficiency of absolute GDP or GDP per capita in representing the market size. For this purpose, Petrović-Ranđelović et al. (2017) advocate using GDP per capita and population size together to account for the scope of the domestic market. Alternatively, LOPW may proxy the productivity of labor or the country's capital abundance. The endogeneity is represented by the growth literature's attention to positive interaction between FDI spillover effects and human capital formation, market development, and political environment (Almfraji and Almsafir 2014).

RES – Total natural resources rents (% of GDP) are obtained from World Bank. RES includes oil, natural gas, coal (hard and soft), mineral, and forest rents to account for the country's factor endowment of natural resources that may attract FDI. Here, greenfield FDI is very likely to enlarge RES as the development of new deposits increases the quantity produced. Poelhekke and van der Ploeg (2010) found empirical evidence of a tradeoff between different types of FDI: resource abundance attracts subsoil assets-seeking FDI simultaneously damaging the other types of FDI.

EX – The official exchange rate in local currency units per US$ is provided by the World Bank. The exchange rate, exchange rate risks and volatility are among the variables that often have high PIPs (Antonakakis and Tondl 2015, Camarero et al. 2019). Russ (2007) shows that exchange rate volatility influences MNEs' decision of entrance and can both promote and discourage FDI flows dependent on whether the host or home country is the origin of shocks. The theory suggests the endogeneity of EX as well, as the increase in FDI flows results in higher demand for local currency raising the EX. In addition, there exists a link between the magnitude of MNEs' production in host markets and exchange rate volatility (Russ 2007).

Another potential, however, more invariant and similar in the majority of countries proxies like dummy variables for RIAs, psychic and physic distance, tariffs, and taxes are assumed to be absorbed and explained by fixed effects. To facilitate convergence and accommodate time-specific shocks ζ_t, all included variables were specified as a deviation from the cross-sectional mean (Moral-Benito 2016).

Chapter 3. Empirical Results and Discussion

3.1 Empirical Results

Table 1. BALIMLE statistics under EMS = 2.5 and UIP.

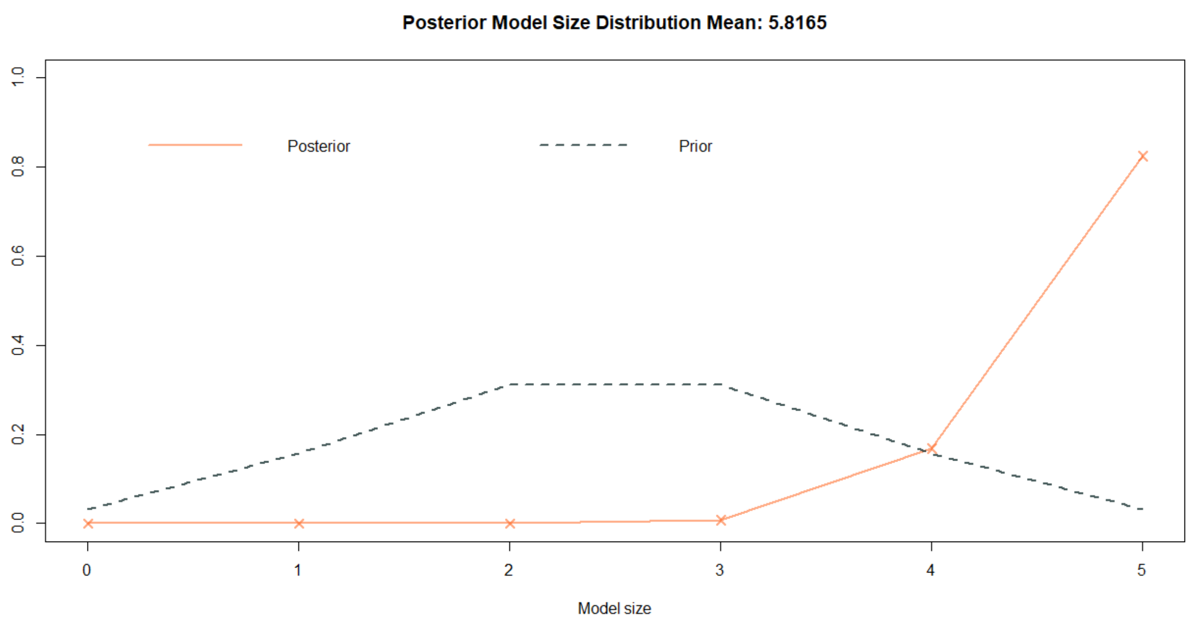
Variable	Posterior inclusion probability (1)	Posterior conditional mean (2)	Posterior robust conditional standard deviation (3)	|Mean/SD ratio| conditional on inclusion (4)	Posterior unconditional mean (5)	Posterior robust unconditional standard deviation (6)	|Mean/SD ratio| unconditional on inclusion (7)	Posterior sign certainty (8)
Dependent variable is FDI								
FDIlag	—	0.0974	0.1816	0.5363	0.0974	0.1816	0.5363	70.41%
LLF	99.41%	3.8947	0.6676	5.8339	3.8716	0.7298	5.3050	100%
LOPW	99.02%	1.3172	0.2585	5.0956	1.3042	0.2882	4.5253	100%
RES	98.45%	**-0.0812**	0.044	1.8455	**-0.08**	0.0448	1.7857	96.75%
EX	98.00%	**-0.0639**	0.0515	1.2408	**-0.0627**	0.0517	1.2128	89.27%
YOS	86.78%	0.0508	0.1006	0.5050	0.0441	0.0953	0.4627	69.32%
Posterior Mean Model Size = 5.8165135								

Note: The sample includes 1031 pairs composed of 36 countries located in Europe over the period 2004 – 2017, grouped in 2-year sub-periods. All variables are defined as a deviation from the cross-sectional mean. The posterior mean is bolded for the regressors with a negative sign. The regressors are sorted in descending order by the posterior inclusion probability.

Source: author's own estimation.

Table 1 presents the results of applying BALIMLE approach to the balanced panel assuming the uniform prior model probability and the UIP for the coefficients of the regression. The employment of the uniform prior results in putting the same 50% prior inclusion probability on all regressors under consideration. PIP measures the marginal contribution of a specific variable to the goodness-of-fit of the model adjusted for the number of variables included (Sala-i-Martin et al. 2004). As a result, regressors exceeding this threshold can be considered to belong to the true model. Column (1) shows that all regressors can be recognized as robust determinants of FDI flows. PIP for the lagged FDI is not exhibited because this regressor is designed to be present in every model to consider the self-reinforcement effects. Hence, PIP of the lagged FDI is 100% by definition. Raftery (1995) suggests studying the evidence for a determinant further using the following framework: the value of PIP located in 50-75% bracket corresponds to weak evidence, 75-95% suggests positive evidence, 95-99% bracket exhibits strong evidence, and values above 99% emphasize very strong evidence in favor of the determinant. Following this scale, very strong evidence is obtained in favor of the labor force and output per worker variables. PIPs of natural resources, as well as exchange rate variables, indicate strong evidence, while years of schooling show just positive evidence.

Figure 1. Prior and posterior model size distributions.



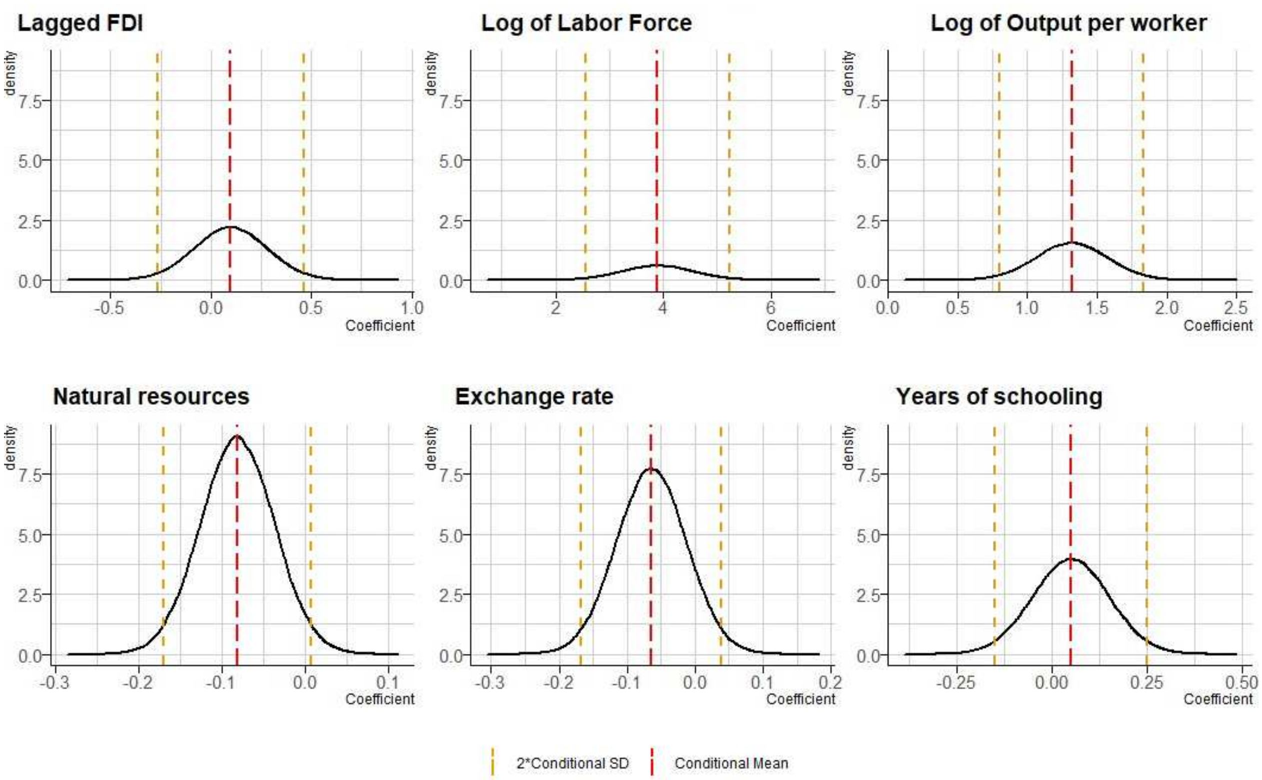
Source: author's own estimation.

The researcher is free to choose between the obtained conditional and unconditional statistics based on prior expectations. If one has a prior that all regressors are equally likely to constitute the true model, a regressor's statistic unconditional on the model inclusion should be considered. On the other hand, if the prior inclusion probability is one, i.e. if one is certain about the importance of some regressors, the conditional statistic should be taken into account. The reason for this is that the unconditional statistic incorporates zero values from the models in which the regressor is not included in this way handling the model uncertainty (Sala-i-Martin et al. 2004).

The ratio of mean to standard deviation is usually employed to test the significance hypotheses in the frequentist case. However, researchers do not seem to find a consensus in interpreting the Bayesian version of this ratio. Raftery (1995) advocates the following rule of thumb: if the regressor's PIP exceeds 50%, which corresponds to the absolute value of PM/PSD ratio equal to 1, this regressor enhances the true model. Masanjala and Papageorgiou (2008) find the threshold value of the ratio equal to 1.3 to approximate a standard 90% confidence region. In contrast, Eicher et al. (2011a) employ a value of 1.65 for the same region. Sala-i-Martin et al. (2004) and Eicher et al. (2011a) both consider the value of 2 to be roughly equivalent to the 5% frequentist significance level. According to the results in Table 1, LLF and LOPW are highly significant both in conditional (Column (4)) and unconditional (Column (7)) cases. At the same time, both EX and RES exceed the 1.3 threshold, with the latter approaching the value of 2 closely. The least significant variables are FDIlag and YOS with posterior mean/SD ratios below 1.

From the marginal densities of the regression coefficients depicted in Figure 2, one can obtain another measure of the regressor's significance, namely the posterior sign certainty that is also displayed in Column (8). This statistic indicates the value of the integral of the coefficient's distribution from $-\infty$ to 0, in other words, the probability that the coefficient and its conditional posterior mean are located on the same side of zero. Sala-i-Martin et al. (2004) use the standard two-tailed frequentist 5% significance test. In fact, if 97.5% mass of the coefficient's distribution is situated on the right side of zero, the regressor has a statistically significant positive sign. This phenomenon is visualized in Figure 2, where the red dashed line shows the conditional mean and orange dashed lines display the value of the coefficient estimate $\pm$ 2 conditional standard deviations. Thus, if zero is located outside the interval between two orange lines, the coefficient is 5% statistically significant. Again, the same three groups of regressors are obtained. Both labor force and output per worker variables prove their significance with approximately 100% positive sign certainty. The natural resources variable is 0.75% short from being included in the most significant group, while the exchange rate variable shows a robust 89.27% negative sign probability. The lagged FDI and years of schooling are situated around a 70% certainty level.

Figure 2. Posterior distributions of regressors' coefficients.



Note: The form of the distributions is visually affected by the same y-axis scaling, which is done for easier comparison.

Source: author's own estimation.

Table 2. Jointness measures under EMS = 2.5 and UIP.

Variable name	YOS	LLF	EX	RES	OPW
YOS	0	0.72511	0.69998	0.70764	0.71778
LLF	0.72511	0	0.94816	0.95707	0.96844
EX	0.69998	0.94816	0	0.9294	0.94055
RES	0.70764	0.95707	0.9294	0	0.94978
OPW	0.71778	0.96844	0.94055	0.94978	0

Source: author's own estimation.

Table 2 exhibits the symmetrical matrix containing the Hofmarcher et al. (2018) jointness measures applied to the results of the estimation. The obtained statistics indicate that all determinants are joint positively, part of that being the belonging to the endowment theory, while the other part is the fact that each variable has a very high PIP. The proxy for the human capital has the strongest complementary relationship with the labor force variable, suggesting the importance of the educated labor force. However, this statistic does not substantially differ from the other relatively fragile numbers in the YOS group. The remaining variables can be considered as very strong complements.

The review of the key concepts behind and the general statistics of the chosen regressors allows to take a closer look at the individual characteristics and to compare the results to the previous empirical studies. It is important to mention that despite the escalating interest to FDI, this phenomenon has not received a consensus on the data source and desired design of FDI. Based on the examined region and consequently the availability of data, researchers have employed different measures of FDI, namely stocks, flows, affiliate sales, and mergers and acquisitions. Also, theoretical concepts and empirical studies have primarily concentrated on static rather than on dynamically stable determinants of FDI (Blonigen and Piger 2014). Besides, independent variables are rarely designed as a difference: the researchers often include source and host countries' statistics simultaneously.

3.2 Discussion

Lagged FDI. Krifa-Schneider et al. (2010), Yu and Walsh (2010), Grubaugh (2013), Erdogan and Unver (2015), and Barrell et al. (2017) represent the most recent strain of literature applying the GMM dynamic panel approach to FDI. In contrast to the fragile results obtained in this estimation, they find the lagged values of FDI to be highly statistically significant and positive. This may be explained by the fact that FDI was designed as a stock variable in the majority of studies. As a result, this proves the importance of agglomeration effects in the form of an accumulated stock of FDI rather than the previous year flow. Also, the considered time period from 2004 to 2017 may be insufficient to build a decent investment infrastructure for MNEs inert clustering especially in the Eastern European countries with relatively new capitalist institutions. As an alternative to changing the design of the dependent variable or including a separate initial FDI stock regressor, one may experiment with considering the multiple higher-order lags to determine the average time period needed from the first brave investments to the establishment of favorable business conditions.

LLF. The natural logarithm of the labor force has turned up to be the most significant regressor. For instance, if the labor force difference increases by 2.11% (1 standard deviation%), the FDI flow from country i to country j at time t is expected to increase by €38.947 thousand. In other words, viewing this in the context of the endowment theory, if country j becomes relatively less labor abundant, it starts to receive more investments. Considering this aspect of LLF only, the empirical finding is contradictory to logic. However, Razin et al. (2003) show that the difference between the population of the source and the host countries is a highly significant positive determinant of FDI flows to the host country. They do not elaborate on reasons behind the sign of the variable, which was included to proxy the market size, as it is often done in various studies (Resmini 2000, Razin et al. 2003, Erdogan and Unver 2015, Petrović-Ranđelović et al. 2017). Indeed, if the market size of country i grew significantly as a result of the escalating labor force, this country becomes more likely to start investing in other economies. Thus, the growth of the home country should outweigh the loss of relative labor abundance advantages by the other countries. Nevertheless, from the perspective of country j, the labor force difference has decreased suggesting that FDI in the growing market of i should be reduced. Such a pattern favors the relative change rather than the size theory. In other words, the coefficient estimate suggests that countries tend to invest in markets that are growing more slow than the domestic one. In fact, this phenomenon may simply address the rising FDI flows from developing to developed countries.

LOPW. The natural logarithm of output per worker appears to be a robust determinant of FDI flows in Europe, as it was predicted by theory and prior empirical research. The price for its high significance is a vague interpretation, as LOPW may simultaneously proxy capital abundance, the productivity of labor, and the market size. The coefficient estimate, however, indicates that the increase in the LOPW gap by 1.09% results in €13.172 thousand higher FDI flows. The highly significant positive sign here goes in line with Razin et al. (2003) and the endowment theory, as the higher LOPW gap increases the relative capital abundance of the source country increasing the likelihood of transferring it in FDI form. With regard to the market size and labor productivity proxies, LOPW follows the same logic as LLF discussed above.

RES. A very close to being considered significant at 5% level variable, RES can be interpreted as follows: if a gap between the weights of natural resources rents in countries' GDP rises by 4.52, FDI flow declines by €81.2 thousand. To put it simply, if country's i rents grew significantly in contrast to rents of country j because of, say, a boom in prices of minerals, MNEs tend to invest domestically or in other countries experiencing even larger growth of rents. This finding conforms with the resource endowment hypothesis and the research conducted by Poelhekke and van der Ploeg (2010), who show that resource-seeking FDI favors booming resources. Grubaugh (2013) finds it to be more significant with the same sign, however using more country-diversified panel.

EX. The significance of the exchange rate coefficient is severely undermined in the transactions among the Eurozone members. On the other hand, Eicher et al. (2011a) caution that in larger FDI panels, the exchange rate is often insignificant too. Cavallari and d'Addona (2013) argue that exchange rate volatility primarily influences the MNEs' decision to start investing rather than the amounts of flows. The same conclusion, but for the timing of the investments is reached in a survey study by Agarwal (1980). Thus, despite the uncertainty of the magnitudes of flows, the exchange rate is an important determinant of FDI, which is additionally stressed by 98% PIP.

YOS. The distribution of the coefficient of years of schooling variable appears to be substantially concentrated near zero. Razin et al. (2003) also confirm that their measure of the human capital gap, the ratio of attained education, indicates its insignificance in different settings. The human capital measure proposed by Erdogan and Unver (2015), education expenditures in % of GDP, is not significant either. Blonigen and Piger (2014) found the host and source country education levels, as well as squared education difference, to have a maximum 7% PIP in OECD countries. There exist several explanations for such contrasting empirical evidence and theoretical conviction: either high-tech and labor-intense FDI flows balance each other, or popular proxies of human capital cannot properly incorporate the education efficiency, as it was argued by Wossmann (2003). Finally, the panel of countries should be more diversified for the endowment theory to work better (Blonigen and Piger 2014).

To conclude, it must be noted that the presented empirical evidence is substantially dependent on a compact panel size as well as little model space produced by 5 variables. This is the result of massive computational pressure during the optimization of coefficients – the main shortcoming of the chosen methodology.

Conclusion

Despite a large interest to the promoter of economic development and spillover effects, FDI, researchers cannot find a consensus on the robust theories and determinants of FDI flows. Numerous empirical studies investigated FDI using different theories and computational techniques. The utilization of BMA techniques, which were designed to solve the model uncertainty, shows the importance of data measurement errors, chosen proxies, and sets of countries in forming the results (Ciccone and Jarociński 2010, Blonigen and Piger 2014, Camarero et al. 2019). Thus, it is improper to claim the impeccability of the empirical estimation. Also, the review of literature signalled the need to carefully consider largely ignored reverse causality effects in the context of FDI. As a result, the main contribution of this paper in the extension of FDI literature is obtaining the empirical evidence from addressing the weak exogeneity and model uncertainty issue simultaneously.

For this purpose, the BALIMLE framework developed by Moral-Benito (2013 and 2016) was projected on FDI flows in Europe over the 2004 – 2017 period. As an outcome of the empirical estimation, only the size of the labor force and the output per worker can be considered as truly robust determinants of European FDI. The importance of both variables together with the natural resources' rents variable, which is very close to being significant, seemingly proves the classical endowment theory. However, the estimated sign of the labor force variable is contrary to common sense under the endowment theory setting. For this reason, the relative market growth hypothesis was put forward. This hypothesis is also applicable to the output per worker regressor – another variable very likely to proxy the market size. Despite the theoretical and empirical evidence of self-reinforcing effects, a one-year lag of FDI flow was not able to prove them statistically. The exchange rate variable, which is essential in the diversification theory, showed its inability to predict the direction of FDI flows, nonetheless showing 98% PIP. The last considered variable was the proxy for human capital. Despite positive posterior inclusion evidence, it appears to be the most fragile determinant of FDI. This finding is quite surprising because the endowment theory stresses the importance of the availability of the educated labor force. The complementary relationship of considered theories was indicated by jointness measures' statistic: all variables show positive J_{YQM} values close to one.

The price one has to pay to address the model uncertainty and weak exogeneity issues simultaneously is the constrained model and variable space. The available gradient optimization methods do not ascertain the finding of the global maxima, so the number of regressors optimized simultaneously should be limited. Also, the complex nature of the likelihood function further constraints the number of periods and determinants. Finally, the Markov chain Monte Carlo model composition (MC^3) algorithm is not available, so the number of models assessed has to be reduced.

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Appendix

Appendix 1. List of countries used in the estimation.

Albania	Estonia	Latvia	Romania
Austria	Finland	Lithuania	Russia
Belarus	France	Luxembourg	Serbia
Belgium	Germany	Malta	Slovakia
Bulgaria	Greece	Moldova	Slovenia
Croatia	Hungary	Netherlands	Spain
Cyprus	Iceland	Norway	Sweden
Czech Republic	Ireland	Poland	Switzerland
Denmark	Italy	Portugal	Ukraine