JPM
JOURNAL OF POSITIVE MANAGEMENT
Vol. 9, No. 2, 2018, pp. 74–88

ISSN 2083-103X
http://dx.doi.org/
10.12775/JPM.2018.143

SOCIAL EFFECTS OF FOREIGN DIRECT INVESTMENTS: A PANEL CAUSALITY ANALYSIS FOR THE CASE OF THE CEE

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Abstract

Purpose: The paper focus specifically on the impact of FDI and its contribution to the effectiveness of spending, a review of literature has revealed many attempts to evaluate the determinants of spending (i.e., education, health, and R&D). This study offers a modern approach to FDI and investigates the causal relationship between FDI and social effect in the Central and Eastern Europe.

Methodology: The study uses panel var for the period 2004–2015, and adopts a panel Granger causality analysis developed by Dumitrescu and Hurlin (2012) to assess the contribution FDI makes to social effect. The data were analysed with the use of R- Cran 3.5.1 (library: panelvar, plm).

Implications: Modelling these circumstances may be a potential direction for future studies aimed at investigating the causality between FDI and social effect in the CEE.

Keywords: foreign direct investment, social effect, dynamic panel, panel causality, Central and Eastern Europe

Paper type: Research paper

1. Introduction

The past few decades have seen a dramatic increase in world foreign direct investment (FDI) by multinational corporations (MNCs), with an annual average growth rate of world FDI inflows. For 20 years, Central and Eastern Europe has attracted investors. Since the post-communist transformation, the region has been known for its favorable labor cost ratio and rapidly growing markets. The process of integration with European structures, completed in 2004, had its impact on the increase in the share of the euro in direct foreign investments (FDI). Membership in the EU additionally guarantees access to numerous EU funds to the countries of the region (Białek, 2012). Human capital and the role of public policy, including education and health, is a further substantial research area. At the present time, the public sector in a large part of the world is the dominant activity, particularly in the provision of education and healthcare services, with the intention of developing human capital. Such a significant expansion of foreign capital flows promotes economic growth given certain social and/or economic as captured the attention of both policymakers and researchers.

This brings us to the relationship between FDI and social effects, particularly in the short-run, a yet unresolved question in both the theoretical and empirical literature. This paper contributes to be explore the role of social effect in affecting the impact of FDI on the CEE country. Using data for the time period from 2004 to 2015 for groups of CEE countries, we study the impact of FDI on macroeconomics variables. In this scientific article, we try to answer the following questions: To what extent can government policy stimulate the inflow of foreign direct investment? Do foreign direct investments affect government spending in the countries studied at the social and economic level?

2. Review of Literature

Literature aimed at identifying the relationship between social expenditures and investments was based rather on the levels of FDI inflow rather than the liberalization of capital flows, economic openness and globalization (Hecock, 2006; Hecock and Jepsen, 2013). There are many empirical studies assessing the importance of social spending. For example, M. Alsan, D.E. Bloom and D. Canning in 2006 investigates the effect of population health on gross inflows of FDI. They used panel data analysis of 74 industrialized and developing countries over 1980–2000. Main finding is that gross inflows of FDI are strongly and positively influenced by population health in low- and middle-income countries. They show that raising life expectancy by one year increases gross FDI inflows by 9%, after controlling for other relevant variables. These findings are consistent with the view that health is an integral component of human capital for developing countries (Alsan et al., 2006).

Recent research turns its attention toward whether FDI promotes economic growth given certain social and/or economic conditions. Borensztein et al. (1998), captures the positive effect of inward FDI on economic growth, given a sufficient level of secondary education in the host country. Using data on inward FDI over the period of 1970–1989, find that FDI promotes the host country's economic growth only if the host country reaches a threshold level of human capital, measured by the average years of secondary schooling. The authors point out that "… the main channel through which FDI contributes to economic growth is by stimulating technological progress" (Borensztein et al., 1998). Also, the statement that there is a complementarity between the incoming FDI and the level of education has been repeated and recognized by many other recent (Xu, 2000; Zhang, 2001; Durham, 2004; Chang et al., 2009). Asteriou and Agiomirgianakis (2001) analyzed causality between human capital (analyzed by rates in primary, secondary, and higher education) and economic growth in Greece. They found that causality runs through educational variables to economic growth, with the exception of higher education where reverse causality exists.

More precisely, the most important goal of governments is to increase economic and social well-being and human capital in their communities with expenditure on education, health and social security. There have been some specific remarks regarding the different impacts of FDI on education, health and social security expenditure. For example, Huber et al. predict overall the positive impact of FDI on education and health spending and the negative impact on social security spending, given that human capital is very important for maintaining competitiveness in the labor market (Huber et al., 2008). Furthermore, Gemmell et al. (2008) identified the relationship between FDI and government expenditure in the OECD countries in the period 1980–1997 and stated that FDI, as a measure of globalization, has a statistically significant and positive impact on health spending as one of the recipients of government spending.

There are a number of papers in literature defining the impact of FDI on R&D. R&D promotes the growth of knowledge capital, such as research papers and patents. Knowledge capital, in turn, influences the entire national economy through imitation and diffusion. FDI is considered to generate technological externalities and raise product market competition, both of which boost productivity and growth (Park, 2018). FDI has two facets – foreign firms invest in the domestic economy (inward FDI), and domestic firms invest abroad (outward FDI). Both forms of FDI foster technology diffusion and competition (Griffith et al., 2006).

3. Empirical methodology

The empirical analysis was carried out on the basis of unitary balanced panel data from the World Bank, World Development Indicators database for the period 2004–2015. The data set includes annual Foreign direct investment, net inflows, as percent of GDP (FDI), percentage growth rate of GDP (GDP), government expenditure on education as percent of GDP (Education), current health expenditure as percent of GDP and research and development expenditure as percent of GDP in the countries of Central and Eastern Europe: Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovak Republic and Slovenia.

Table 1 displays the descriptive statistics for all variables; these data define the extent of our panel dataset. To our knowledge, this is the largest sample of transition countries so far used to assess the determinants of FDI on social effects.

The first step for the investigation of panel data is to determine whether the series has any integration orders. For this purpose, this study employs panel unit

	FDI	GDP	Education	Health	RD
Min.	−15,989	−14,8	2,326	4,651	0,3826
1st	1,996	1,275	4,019	6,195	0,5676
Median	3,788	3,35	4,626	6,944	0,8266
Mean	5,409	2,78	4,559	6,905	0,9714
3rd	6,718	5,6	5,084	7,726	1,2347
Max.	50,505	11,9	6,972	9,275	2,6032

Table 1. Descriptive statistics for the whole sample

Source: own development using the R.

root tests to check the stationarity of the panel data developed by Levin, Lin and Chu (2002, hereafter LLC) and Im, Pesaran and Shin (2003, here-after IPS), test CADF (Covariate Augmented Dickey-Fuller) (Hansen, 1995b).

The LLC (2002) unit root test considers the following panel ADF specification:

$$\Delta y_{i,t} = \rho_i y_{i,t-1} + \sum_{j=1}^{p_i} \delta_{i,j} \Delta y_{i,t-j} + \varepsilon_{i,t}$$

The LLC (2002) assumes that the persistence parameters ρ_i are identical across cross-sections (i.e., $\rho_i = \rho$ r for all i), whereas the lag order ρ_i may freely vary. This procedure tests the null hypothesis $\rho_i = 0$ for all i against the alternative hypothesis $\rho_i < 0$ for all i. Rejection of the null hypothesis indicates a possible panel integration process.

The IPS (2003) proposed a testing procedure based on the mean group approach. The starting point of the IPS test is also the ADF regressions given in Eq. (1). But, the null and alternative hypotheses are different from that of the LLC test, where the rejection of the null hypothesis implies that all the series are stationary. We now have: $H0$: $\beta_1 = \beta_2 = \beta_N = 0$ vs. $H1$: *some but not necessarily all* $\beta_i \prec 0$.

IPS developed two test statistics and called them the LM-bar and the t-bar tests. The t-bar statistics is calculated using the average t-statistics for β_i from the separate ADF regressions in the following fashion:

$$\bar{t}_{nT} = \frac{\sum_{i=1}^{n} t_{iT_i}\left(\beta_i\right)}{n}$$

where $t_{iT_i}(\beta)$ is the calculated ADF test statistic for individual i of the panel (i = 1, 2,…, n).

The second step is to calculate the standardized t-bar statistic which is given by:

$$Z_{\bar{t}_{nT}} = \frac{\sqrt{n}\left[\bar{t}_{nT} - \frac{1}{n}\sum_{i=1}^{n} E\left(\bar{t}_{iT}\left(\beta_i\right)\right)\right]}{\sqrt{\frac{1}{n}\sum_{i=1}^{n} var\left(\bar{t}_{iT}\left(\beta_i\right)\right)}} \sim N\left(0,1\right)$$

where n is the size of the panel, which indicates the no. of individual, $E\left(\bar{t}_{iT}\left(\beta_i\right)\right)$ and $var\left(\bar{t}_{iT}\left(\beta_i\right)\right)$ are provided by IPS for various values of T and p. However, Im et al. (2003) suggested that in the presence of cross-sectional dependence, the data can be adjusted by demeaning and that the standardized demeaned t-bar statistic converges to the standard normal in the limit.

After analyzing cross-section dependency, we test the existence unit root in the series in order to get unbiased estimations. Several different panel unit root tests in accordance with the assumption of the cross-section dependence in the literature. In this study we take into account the averaged individual Cross-Sectionally Augmented Dickey Fuller (CADF). Pesaran (2003) proposes a test based on standard unit root statistics in a CADF regression. In general, the regression takes the form:

$$\Delta Y_{it} = \alpha_i + \beta_i Y_{i,t-1} + \sum_{j=1}^{pi} \delta_{ij} \Delta Y_{i,t-1} + d_i \tau + c_i \bar{Y}_{t-1} + \sum_{j=0}^{pi} \varphi_{ij} \Delta \bar{Y}_{i,t-j} + \varepsilon_{it}$$

where, $\bar{Y}_t = N^{-1}\sum_{j=1}^{N} Y_{jt}$, $\Delta \bar{Y}_t = N^{-1}\sum_{j=1}^{N} \Delta Y_{jt}$ and ε_{it} is the serially uncorrelated regression error. Let $CADF_i$ be the ADF statistics for the i-th cross-sectional unit given by the t-ratio of the OLS estimate $\hat{\beta}_i$ of β_i n the CADF regression.

One of the basic problems of panel data econometrics is cross-sectional dependence. It can be caused by high degrees of FDI or cross-unit relations may give rise to the existence of this problem. If the dependencies on the cross-sections appear in the panel data are the results generally become inconsistent and upward-biased (Bai and Kao, 2006). In this case, we intend to perform on test the existence of cross-sectional dependence before the analysis. Pesaran proposed a cross-sectional dependency (CD) test under the null hypothesis of no cross-sectional dependence, which is asymptotically distributed as standard normal and efficient even in panels with small sample sizes (Pesaran, 2004). The Pesaran's CD test statistic in the present study is as follows:

$$CD = \frac{2T}{\sqrt{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{p}_{ij}\right)$$

where T is the time interval, N is the number of cross-section units, and $\hat{p}_{ij}$ is the pair-wise correlation between cross-sections.

Next in this study, a panel causality test developed by Dumitrescu-Hurlin (2012) was used. The main benefit of this method is that it is appropriate for panel data. The main prerequisite of this method is that variables, which will be used in the analysis, should be stationary (Dumitrescu and Hurlin, 2012). The linear panel regression model followed by Dumitrescu and Hurlin (2012) is as follows:

$$Y_{i,t} = a_i + \sum_{k=1}^{K} Y_i^k Y_{i,t-k} + \sum_{k=1}^{K} B_i^k X_{i,t-k} + \varepsilon_{i,t}$$

where Y is FDI and x is the vector of the macroeconomics variable (i.e., GDP, Education, Health, RD). In addition to this situation, "i" represents the number of panel. Moreover, "K" demonstrates optimum lag interval and "ε" shows the error term.

Dumitrescu and Hurlin (2012) state that "a homogeneous specification of the relation between the variables x and y does not allow to interpret causality relations if any individual from the sample has an economic behaviour different from that of the others". Thus, they propose an average Wald statistic that tests the null of no causal relationship for any of the cross-section units, H0: $\beta_i = 0$, $(i = 1, \dots, N)$; against the alternative hypothesis that causal relationships occur for at least one subgroup of the panel, H0: $\beta_i = 0, (i = 1, \dots, N1)$; $\beta_i \neq 0$, $(i = N_1 + 1), N_2 + 2, \dots, N)$ Rejection of the null hypothesis with $N_1 = 0$ indicates that x Granger causes y for all i, whereas rejection of the null hypothesis with $N_1 > 0$ provides evidence that the regression model and the causal relations vary from one individual or the sample to another. Under these circumstances, the average of the individual Wald statistic generated by Dumitrescu and Hurlin (2012) assumes the following:

$$W_{N,T}^{Hnc} = \frac{1}{n}\sum_{i=1}^{N} W_{i,T}$$

where $W_{i,T}$ is the individual Wald statistic for the i-th cross-section unit.

The vector autoregressive model (VAR) regression on panel data goes back to the work of Love and Zicchino (2002), which examines the relationship between financial development and dynamics of firms' investment behavior in

36 countries. PVAR is the new macro-econometric approach, it was subsequently relayed in empirical studies seeking to understand the interaction between the different macroeconomic variables.

For conducting PVAR analyses, the standard procedure introduced in Sigmund and Ferstl (2017). The first step of the empirical analysis was to choose optimal lag order in PVAR and in the moment condition. According to Andrews and Lu (2001), consistent moment and model selection criteria (MMSC) for general method of moments (GMM) models are based on Hansen's (1982) J statistic of over-identifying restrictions (Andrews and Lu, 2001). However, the fixed effects are correlated with the regressors due to the lags of the dependent variable; therefore, we use forward mean-differencing, also known as the Helmert procedure (Arellano and Bover, 1995). In this case, the Helmert procedure removes the mean of all future observations available for each country and time in order to preserve the orthogonality between transformed variables and lagged independent variables (Love and Zicchino, 2006). Next, in addition to the GMM-estimators we contribute to the literature by providing specification tests (Hansen over identification test, lag selection criterion and stability test of the PVAR polynomial) and classical structural analysis for PVAR models such as orthogonal impulse response functions, which describe the reaction of one variable in the system to the innovations in another variable in the system, holding all other shocks at zero. We also present the forecast error variance decompositions expressing the magnitude of the overall effect of a shock, providing the proportion of the movement in one variable explained by the shock to another variable over time.

In this case, the analysis of the PVAR model combines, not only techniques of panel data treatment, but also those of VAR modeling. In view of these developments, the model which for the order p can be written following:

$$\begin{pmatrix} \dfrac{\dfrac{FDI}{GDP}}{\dfrac{Education}{\dfrac{Health}{RD}}} \end{pmatrix} = Y_{i,t} = \beta_0 + \sum_{j=1}^{p} \beta_j Y_{i,t-j} + \alpha Z_{i,t-1} + f_i + d_t + \varepsilon_{i,t}$$

where: Y – vector of endogenous variables, α, β – vector of parameter estimates with explanatory variables, Z – vector of control variables, f_i – Individual effects of individuals, d_t – zero-one variables corresponding to individual periods, ε – random error vector, i – observation index, t – time index.

4. Empirical Findings

We use Im, Pesaran and Shin (2003) (IPS) and the Levin, Lin and Chu (2002) (LLC) specifications to test for the presence of a unit root in the panel. The LLC and IPS tests were executed on data both in levels and first differences, and results were reported in Table 2. Tests show that all of the variables are stationary in level and first-difference.

Table 2. Results of panel unit root tests (LLC and IPS)

Source: own development using the R.

Variable	**LLC**		**IPS**	
	With constant and trend (level)	With constant (1st difference)	With constant and trend (level)	With constant (1st difference)
FDI	−10.844 (2.2e−16)	−15.715 (2.2e−16)	−7.5038 (3.099e−14)	−11.795 (2.2e−16)
GDPPC	−6.7725 (6.329e−12)	−11.797 (2.2e−16)	−3.3708 (0.0003748)	−5.1409 (1.367e−07)
Education	−8.0184 (5.355e−16)	−10.191 (2.2e−16)	−5.2081 (9.538e−08)	−8.0785 (3.279e−16)
Health	−7.0541 (8.688e−13)	−7.5553 (2.09e−14)	−4.4936 (3.502e−06)	−8.7826 (2.2e−16)
RD	−2.7694 (0.002808)	−6.7635 (6.737e−12)	−7.5038 (3.099e−14)	−11.795 (2.2e−16)

Note: numbers in parentheses are p-values

CADF is the Cross-sectionally Augmented Dickey-Fuller test of Pesaran (2007). This test was performed for all variables in order to take into account cross-sectional dependencies. The null hypothesis of the unit root is rejected for Education, Health and RD in level but all of the variables are stationary in first-difference (see Table 3).

Table 3. Results of panel unit root tests (CADF tests)

Source: own development using the R.

Variable	CADF	
	With constant and trend (level)	With constant (1st difference)
FDI	−5.9501 (8.190820e−06 2)	−12.596 (2.2e−16)
GDPPC	−6.7282 (2.698e−07)	−11.954 (3.178552e−12 2)
Education	−2.5456 (0.306)	−11.763 (1.198636e−11 2)
Health	−2.7056 (0.2363)	−8.714(3.972e−12)
RD	−1.9805 (0.6061)	−7.4299 (1.241e−09)

Note: numbers in parentheses are p-values.

We test the existence of cross-sectional dependence before the analysis. According to test results given in Table 4, the null hypothesis is not rejected for

Table 4. Cross-sectional dependence test results

Source: own development using the R.

the panel even at the 10% level of significance, indicating that there is no strong dependence on the cross-section.

	Statistic – CD	P-value
Pesaran's test	-4.4974	0,6878

Knowing the causal direction between macroeconomic imbalances is obviously useful for decision-making in economic policy. We therefore perform use Dumitrescu and Hurlin (2012) [1] test for the causality from variables (FDI, GDP, Education, Health and RD), which correspond to the tests reported in Table 5. The idea to determine the existence of causality is to test for significant effect of past values of x on the present value of y which implements a procedure recently, in order to test for Granger causality in panel datasets. The empirical results presented in this paper are based on a bivariate causality test between the five variables stated earlier. There are four sets of bidirectional hypotheses to be tested:

1. GDP Granger causes FDI and vice versa;
2. Education Granger causes FDI and vice versa;
3. Health Granger causes FDI and vice versa;
4. RD Granger causes FDI and vice versa.

Table 5. Pairwise Dumitrescu-Hurlin Panel Causality Tests

Source: own development using the R.

Null Hypothesis:	**W-stat/wbar**	**Zbar-Stat.**	**P-Value**	**Decision**
FDI does not homogeneously cause GDP	3.1868	1.9682	0.04905	Rejecwt
GDP does not homogeneously cause FDI	3.684	2.7926	0.005228	Reject
FDI does not homogeneously cause Education	9.5236	12.476	2.2e-16	Reject
Education does not homogeneously cause FDI	7.7616	9.5546	2.2e-16	Reject
FDI does not homogeneously cause Health	7.3899	8.9382	2.2e-16	Reject
Health does not homogeneously cause FDI	5.7971	6.2968	3.039e-10	Reject
FDI does not homogeneously cause RD	4.3489	3.8952	9.812e-05	Reject
RD does not homogeneously cause FDI	6.0701	6.7495	1.484e-11	Reject

Note: alternative hypothesis: Granger causality for at least one individual. On the whole, our findings emphasize the existence of a causal relationship between macroeconomic variables.

Estimated causal relationships, which are presented in Table 5., indicate that in the null hypothesis is rejected for the all variables. Furthermore, a causal relationship from FDI to other variables seems to be clearly established, as well as from all variables to FDI. Such results have not been strongly highlighted in previous studies, mainly because of the a priori choice of model specification. The lag selection criteria showed that the best model is with three opposites. The results show no evidence of serial correlation and heteroscedasticity. Furthermore, the model also passes the normality test.

Sims et al. (1990) emphasize that non–stationary time series should not be transformed into the first differences when estimating the VAR model. Differencing the series may result in a loss of information about trend movements of variables. Following Sims et al. (1990) and Gambacorta et al. (2014), we decide not to use first differences due to the possible loss of some useful information included in the data and also because of the overall stability of our models. The overall stability of the system is sufficient to interpret the PVAR model results. We test the stability of the PVAR system by examining the stability condition and find that the modulus of each eigenvalue is strictly less than 1 and thus the estimates satisfy the eigenvalue stability condition. We conclude that the system is stationary as a whole, and we proceed with the estimation of the PVAR in levels.

We apply a panel vector autoregression (3) on a sample of 11 countries over the period 2004–2015, with annual frequency. The coefficients of the PVAR estimation, which are used to construct the impulse response functions (IRFs) are depicted in Table 6 and the impulse-response graphs are presented in Figure 1.

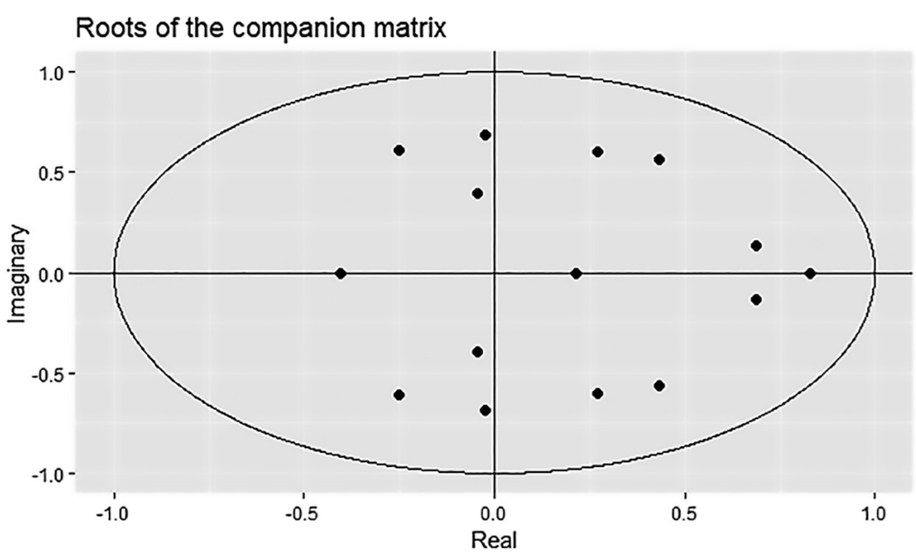

Figure 1. Eigenvalue stability condition.

Source: own development using the R.

Table 6. Detailed PVAR results

Source: own development using the R.

	FDI	GDP	Education	Health	RD
FDI(t-1)	0.8104 *** (0.1026)	−0.1212 (0.0693)	0.0197 *** (0.0049)	−0.0080 (0.0103)	−0.0005 (0.0023)
GDP(t-1)	0.0095 (0.1247)	0.5270 *** (0.1042)	−0.0147 (0.0116)	−0.0074 (0.0072)	0.0024 (0.0045)
Education(t-1)	0.1789 (1.6236)	0.3108 (1.6325)	0.2684 ** (0.0900)	0.2316 (0.1556)	0.1015 (0.0684)
Health(t-1)	−2.7939 (2.6493)	2.7818 (2.2574)	−0.0686 (0.1462)	0.5297 *** (0.1048)	0.0827 (0.0776)
RD(t-1)	15.2515 *** (3.0204)	−6.5334 (3.6194)	0.3884 (0.4705)	−0.5823 (0.4806)	0.6340 *** (0.1328)
FDI(t-2)	−0.6881 *** (0.1374)	0.0530 (0.0431)	−0.0043 (0.0033)	−0.0017 (0.0049)	0.0021 * (0.0008)
GDP(t-2)	0.1142 (0.2098)	−0.3422 *** (0.1018)	−0.0001 (0.0052)	0.0232 *** (0.0068)	−0.0090 * (0.0038)
Education(t-2)	−0.1661 (2.3283)	2.2303 (2.2278)	−0.3914 (0.2106)	−0.3577 *** (0.0828)	0.0648 (0.0338)
Health(t-2)	3.7745 (4.4468)	−3.0676 (2.7874)	0.0164 (0.0787)	0.1540 (0.1438)	−0.0655 (0.0514)
RD(t-2)	−18.8959 ** (6.3449)	7.9743 * (3.6752)	0.0383 (0.4802)	0.3224 (0.4246)	0.0288 (0.0658)
FDI(t-3)	0.2783 * (0.1218)	−0.1107 (0.0712)	0.0090 ** (0.0034)	0.0069 (0.0068)	−0.0037 *** (0.0011)
GDP(t-3)	0.4380* (0.2807)	−0.0711 (0.1078)	−0.0129 (0.0176)	−0.0025 (0.0091)	−0.0074 (0.0044)
Education(t-3)	−0.9486 (2.5078)	−1.8111 (1.8193)	0.1178 (0.0875)	0.0393 (0.1814)	−0.0312 (0.0523)
Health(t-3)	2.1164* (1.2799)	1.7478 (1.1984)	−0.2475 (0.1959)	0.0593 (0.1399)	−0.0051 (0.0325)
RD(t-3)	0.1610 (2.6726)	−4.9563 (3.0272)	−0.0486 (0.4643)	0.0705 (0.2339)	−0.0398 (0.0554)

Note: Five-variable PVAR *model is estimated by* GMM*, country and time fixed effects are removed prior to estimation. Reported numbers show the coefficients of regressing the column variables on lags of the row variables. Heteroscedasticity adjusted t-statistics are in parentheses. ***/**/* denotes significance at 1%, 5% and 10%, respectively.*

The PVAR results presented in Table 6 show in particular that only the variables RD (t-1), RD (t-2), GDP (t-3), Health (t-3) are statistically significant. A 1% increase in FDI leads to an approximately 15.3% increase in RD (t-1) followed by a 19% decrease RD(t-2). What's more, in the 1% increase, you can also see Health (t-3) increase by 2.1% and 0.43% GDP (t-3). The results of the impulse responses are shown in Figure 2. The continuous line represents the point estimate (response to a shock) of the impulse response and the broken lines represent the 95 percent confidence bands.

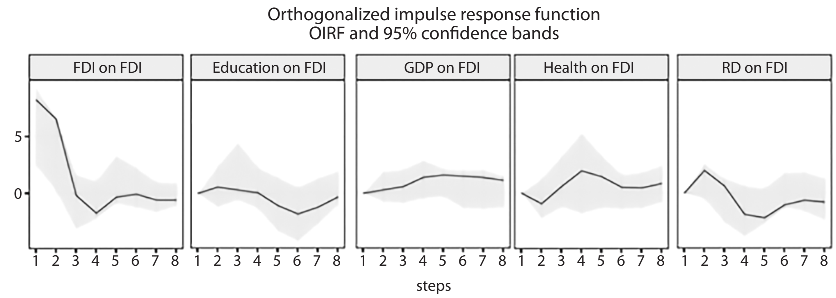

Figure 2. Orthogonalized impulse responses function

Source: own development using the R.

If we look, for example, at the impact of the impulse on the part of Education causes a short-term show a significantly positive adjustment process, followed by the decrease of FDI and return to the zero state. In turn, at the response of GDP we see the increase in FDI in subsequent periods. Impact of Heatlh in the first period show a significantly negative adjustment process, but in the next two periods periods of rapid growth, which ends in decline but in the final period calms down. RD, on the other hand, causes an increase in FDI in the initial period, but it is paid for by a decrease in a significant decrease lasting up to the 4th period, but it can be seen that at the end the peacock returns to the zero period state.

To determine the ability of Central and Eastern Europe repository shocks to explain the fluctuation of variables of interest, reports variance decompositions derived from the orthogonalized impulse–response coefficient matrices are presented in Table 7. The variance decompositions display the proportion of movements in the dependent variables that are due to their own shocks versus shocks to the other variables.

Table 7. Variance Decomposition for FDI

Variables	Forecast Horizon (Years)	FDI	GDP	Education	Health	RD
FDI	4	0,878014	0,071775	0,113547	0,122708	0,043372
	8	0,740674	0,076916	0,125492	0,133211	0,056317

Source: own development using the R.

Table 7 reports the results of variance decomposition and the estimates represent the percentage of variation in the row variable explained by the column variable. The first column shows the fraction of the 4 and 8 period-ahead forecast error that can be explained by CEE FDI shocks.At period 8, 7,69% of the variation of investment is explained by past economic growth, 12,54% by past education level, 13,32% by past health and 5,63% by past RD. That means education and health shocks are important for explaining investment level in the long-run.

5. Conclusion

To what extent can government policy stimulate the inflow of foreign direct investment? Do foreign direct investments affect government spending in the countries studied at the social and economic level? To answer for that question and to contribute to current literature in this paper we examine the relationship direction between foreign direct investment, economic growth, education, health and R&D for CEE countries. The main conclusion from dynamics analysis at annual frequencies is that education and health helps predict FDI exerting a positive influence on future outcomes of these variables. Increases in growth are led by surges in investment.

The findings of the PVAR shows 1% increase in FDI leads to an approximately 15.3% increase in RD (t-1) followed by a 19% decrease RD (t-2). Also, the 1% increase FDI increase Health (t-3) increase by 2.1% and 0.43% GDP (t-3). At the response of GDP we positive effect on FDI in subsequent periods, supporting the results of Makki and Somwaru (2004). They found a positive impact of exports and FDI on GDP using World Development Indicators database of 66 developing countries averaged over ten year periods, 1971–1980, 1981–1990, and 1991–2000 (Makki and Agapi, 2004).

The empirical findings of the study show that health expenditures in the the first period show a significantly negative adjustment process, but in the next two periods periods of rapid growth, which ends in decline but in the final period calms down. RD, on the other hand, causes an increase in FDI in the initial period, but it is paid for by a decrease in a significant decrease lasting up to the 4^{th} period, but it can be seen that at the end the peacock returns to the zero period state, supporting the results of Gemmell, Kneller and Sanz (2008).

The greatest contribution of this study to literature is the empirical evidence showing that, utilizing Dumitrescu and Hurlin test causality within the framework of a panel model, the results suggest that there is bidirectional relationship between all variables, implying that that a change in economic growth, education, health and R&D will affect foreign direct investment and vice versa.

Notes

[1] It is a test statistic for heterogeneous panels based on the individual Wald statistics of Granger non causality averaged across the cross-section units.

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