Impact of Foreign Direct Investment on Economic Growth: Do Host Country Social and Economic Conditions Matter?

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Abstract

Empirical studies analyzing the relationship between foreign direct investment (FDI) and economic growth haven't led to clear-cut conclusions yet. This paper investigates the causal link between FDI and economic growth by, contrary to most other studies, introducing host country characteristics directly into the econometric specification. A dynamic panel data model that relies on a system GMM specification approach is used for a panel of 54 developed and developing countries over the 1980 to 2013 period. Another important contribution is the use of a specific criterion (MMSC-BIC) to select the optimal lag lengths of the right-hand side variables. The main finding is that FDI and GDP per capita are both influenced by host country characteristics but that causality is present only from FDI to GDP per capita, whatever the income level of the country is.

Keywords: Foreign Direct Investment, Economic Growth, Granger-Causality, Model and moment selection Bayesian information criterion

1. Introduction

Since the late 1980s, foreign direct investment (FDI) inflows into developing countries have increased rapidly in almost every region of the world. After having reached a peak in 2007 with US$ 1,8 trillion, global FDI flows began to bottom out because of the worldwide financial and economic crisis. After a 16% decline in 2008, global FDI inflows fell a further 37% in 2009, while outflows fell some 43%. However, despite this worldwide decline, the share of FDI flows to developing and transition countries - compared to those to developed economies - has been steadily growing. This type of FDI has proved less volatile than the one going to industrialized countries and, in 2009, accounted for half of worldwide FDI flows. Recently, it can also be observed that one of the fastest-growing FDI segments are flows from developing countries into other developing economies (UNCTAD, 2010). In 2013, according to UNCTAD (2014), global FDI clearly returned to growth. FDI flows to developed countries increased by 9 per cent to $566 billion, leaving them at (39 per cent of global flows, while those to developing economies reached a new high of $778 billion, or 54 per cent of the total. The balance of $108 billion went to transition economies. Developing and transition economies now constitute half of the top 20 ranked by FDI inflows.

FDI-friendly policies are based on the belief that FDI, apart from bringing in capital and creating jobs, has several positive effects which include productivity gains, technology transfers and the introduction of new managerial skills and know-how into the domestic market. Nevertheless, it can also happen that FDI may harm the host economy (see Herzer, Klasen & Nowak-Lehmann D., 2006), for instance when foreign investors claim scarce resources or reduce investment opportunities for local investors. There is also some concern that no positive knowledge spillovers may finally occur within developing countries, because multinationals will prove able to protect their firm-specific knowledge, or because they may buy their inputs from foreign rather than domestic suppliers. These ambiguities have opened the scope for a large empirical literature on the benefits of FDI on growth, although it is fair to say that the evidence gathered so far remains ambiguous. While some authors found no significant relation between FDI and growth, others showed either an unconditional positive link between these two variables or a relationship that dependent upon to particular characteristics of the host country, such as the level of human capital or the depth of the financial system. At least two reasons explain these mixed results.

First, most of the authors analyzed the correlation between FDI and growth using a regression analysis framework that is silent on the causality between these two variables. Second, in the studies that do address the causality issue, the influence of other social and economic variables is most of the time simply ignored[1].

This paper is aimed at combining both approaches simultaneously. To our knowledge, there are only three studies that combine Granger-causality tests with the inclusion of control variables referring to host country characteristics in the empirical setting. The first one is Nair-Reichert & Weinhold (2000), who use a mixed fixed and random (MFR) panel data method to allow for cross country heterogeneity in the causal relationship between FDI and growth. They examine 24 developing economies from 1971 to 1995. Their results suggest that the relationship between FDI and economic growth in developing countries is highly heterogeneous and that there is some evidence that the impact of FDI on growth rate is higher in more open economies. The second paper is Omran & Bolbol (2003), who use cross-country regressions and Granger-causality to show that, in Arab countries, FDI will have a favorable effect on growth if interacted with financial variables at a given threshold level of development. The third study is Dhakal, Rahman & Upadhyaya (2007), who use regression techniques to analyze FDI-growth Granger-causality and the influence of institutional and economic factors. They consider only nine Asian countries and when they include host country variables into the specification, the sample size is very low (5 years). They conclude that FDI-to-growth as well as growth-to-FDI causality is reinforced by host countries characteristics, such as trade openness, bilateral aid or political rights. The present paper is close to the three above studies in terms of methodology, but tries to improve the analysis in several dimensions. First, rather than using a limited number of countries, it relies on a larger data set of 54 developed and developing economies, enlarging the scope to identify relevant host country characteristics. Second, it covers a long and more recent time period (1980-2013), which coincides with the moment of the upsurge of world FDI flows. Third, it considers systematically two-way Granger-causality tests (Nair-Reichert & Weinhold,2000 only consider one-way causality from FDI to growth) and a variety of host country indicators (Omran & Bolbol,2003 only examine financial indicators). The estimates are performed by means of a dynamic panel data model (system generalized method of moments (GMM) estimator). Fourth, as Granger-causality results are sensitive to the lags-length of the independent variables, this study follows for the first time a rigorous lags selection process based on the minimization of the model and moment selection Bayesian information criterion (MMSC-BIC). In the past, only a few authors (like Holtz-Eakin, Newey, & Rosen, 1988 and Choe, 2003, for example) have used a selection process but, in these cases, the lag length has been assumed to be the same for all right-hand side variables, which is a strong constraint. All the previous factors contribute to provide more systematic and robust evidence on the link between FDI and GDP per capita once controlling for host country characteristics.

The paper proceeds as follows. Section 2 describes the econometric framework for testing Granger-causality within a dynamic panel data model including the control variables and the optimal lag length selection procedure. Section 3 summarizes the empirical findings and section 4 concludes.

2. Econometric Methodology

2.1 Granger-Causality

Granger-causality states that if a series y is better predicted by the complete universe of past information than by that universe less the series x, then x Granger-causes y. In this paper, Granger-causality tests will be performed with panel data, which may present an endogeneity problem due to the dynamic pattern of the data analyses. In order to deal with it, Holtz-Eakin, Newey, & Rosen (1988) proposed a panel vector autoregressive (VAR) model estimated by means of the generalized method of moments (GMM) estimators. This methodology has been further developed by, among others, Arellano & Bond (1991) and Blundell & Bond (1995).The general dynamic relationship is characterized by the presence of lagged regressors, which include apart from the causality-based variables (x and y, i.e. FDI or per capita GDP), one (or several) additional control variable(s) (z, e.g. infant mortality rate):

$$y_{it} = \sum_{j=1}^{m} \delta_j y_{i,t-j} + \sum_{l=1}^{n} \beta_l x_{i,t-l} + \sum_{k=1}^{r} \gamma_k z_{i,t-k} + u_{it} \quad (1)$$

[1] A literature survey is provided in a separate appendix available from the author upon request.

where$t$=1,...,T represents time (year) and i=1,...,N denotes the countries. The number of lags, m, n and r, will be assumed finite and shorter than the given time series (see section 2.2 for further details on the optimal lag length selection's procedure). It is assumed that u_{it} follows a one-way error component model

$$u_{it} = \mu_i + \lambda_t + \upsilon_{it} \quad (2)$$

Where $\mu_i \sim IID(0,\sigma_\mu^2)$ is the unobserved country-specific effect, $\lambda_t \sim IID(0, \sigma_\lambda^2)$ represents period-specific effects and $\upsilon_{it} \sim IID(0,\sigma_\upsilon^2)$ the error term. The dynamic panel data regressions described in (1) and (2) are characterized by two sources of persistence over time: autocorrelation due to the presence of a lagged dependent variable among the regressors and heterogeneity across individuals characterized by the individual effects. According to Granger (1969), in many economic situations, an apparent instantaneous causality would disappear if economic variables were recorded at more frequent time intervals or if the models took account of additional causal variables. So, simultaneity or instantaneous causality may be spurious (meaning instantaneous causality between variables observed at the low frequency without any causality at the high frequency). Thus, here, in order to avoid spurious instantaneous causality, the lags of all right-hand side variables in equation (1) start from 1 and not from 0.

It is important to note that, since y_{it} is a function of μ_i, it follows that $y_{i,t-1}$ is also a function of μ_i. Therefore, $y_{i,t-1}$, a right-hand regressor in (1) is correlated with the error term (problem of endogeneity), which renders the OLS estimator biased and inconsistent even if the υ_{it} are not serially correlated. In this case, it is appropriate to use the Blundell & Bond (1995) GMM estimator to perform these estimates[2] (see Huang, Hwang & Yang, 2008 for a discussion). It combines in a system the regressions in differences with the regressions in levels ("system„ GMM estimator) and use instrumental variables, which are lagged values of the dependent variable, to manage the endogeneity problem described above[3].The coefficients are robust to the presence of any pattern of heteroskedasticity and of autocorrelation within countries[4]. The test of whether x Granger-causes y consists of a test of the hypothesis that $\beta_1=\beta_2=...=\beta n$ are equal to zero (Wald test) after controlling for y's own lags and the influence of additional controls (z).

2.2 Lags Length and Control Variables Selection

Results from causality tests are highly sensitive to the order of lags in the autoregressive process. This means that an inadequate choice of the lag length would lead to inconsistent model estimates. Unfortunately, no single method for choosing the lag length is ideal in all cases. In this study, the optimal lag length of the different right-hand side variables is selected according to a specific criterion for GMM estimation, which is the minimization of the model and moment selection Bayesian information criterion (MMSC-BIC) proposed by Andrews & Lu (2001)[5]. It is able to consistently select the correct model and moments for GMM estimation from a number of different specifications[6]. The MMSC-BIC criterion selects the parameters and the instruments that minimize the following formula:

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[2] The Blundell &Bond (1995) GMM estimator and not the Arellano and Bond GMM estimator is used because the latter generally suffers from weak instruments, which yields large biases in finite samples and poor precision (lagged values of the levels of the original regressors frequently make weak instruments for the differenced values of the regressors used in the dynamic-panel equation because they may be non-stationary). This is why, to mitigate this problem, a "system„ GMM estimator (from Blundell &Bond, 1995), which also uses lagged difference instead of the level form as possible instruments in order to solve the statistical problem of unit root or near unit root, seems to be a relatively safe choice (Huang, Hwang &Yang, 2008).

[3] The number of instruments cannot be higher than the number of countries (which is equal to 54 in this study) and must be higher or equal to the number of regressors (which varies according to the number of right-hand side variables that are considered and to their respective lags length).

[4] Option "robust" in Stata.

[5] This criterion is the analogue of the widely used BIC model selection criterion in the sense that it makes the same asymptotic trade-off between the "model fit" and the "number of parameters".

[6] Andrews &Lu (2001) demonstrated that the MMSC-BIC procedure is found to work quite well in a variety of contexts. They also showed that the model and moment selection criterion Akaike information criterion (MMSC-AIC) is not consistent.

$$MMSC - BIC = J_i - \log(N)(l_i - k_i) \quad (3)$$

Where J_i refers to the Hansen test statistic used to test the validity of the over-identifying restrictions evaluated under the specification of model i, k_i to the number of parameters to be estimated, l_i to the number of moment conditions under model i and N to the sample size. This criterion includes bonus terms that reward the use of less parameters for a given number of moment conditions and thus, the use of more moment conditions for a given number of parameters. In this lags length procedure, each autoregressive process is estimated by means of the Blundell and Bond methodology described above and each combination of variables (from 2 to 8) and of lags length (from 1 to 4) is considered, which corresponds to 500'000 different specifications. The number of instrumental variables must be equal to or higher than the number of right-hand side variables and lower than the number of countries. It is possible to constrain the number of right-hand side variables by limiting the maximal number of the lags length of the regressors. For this reason, it varies between one and four. As instruments, the most recent lags of the dependent variable are used. The MMSC criterion is then calculated for each specification, allowing to select the right-hand side variables and their lag length.

2.3 Adjusting the Number of Instruments

Consistency of the GMM estimator depends on the validity of the instruments. Thus, for the selected specification, the instrumental variables selection is submitted to the following standard diagnostic tests. If the instruments do not pass one of these tests, then the specification with the second smallest value of the MMSC criterion is selected and tested in the same way. The procedure is repeated until the selected specification fulfills all the tests. First, the Hansen test of over-identifying restrictions allows testing the overall validity of the instruments[7]. A second test examines the hypothesis that the error term υ_{it} is not serially correlated. If the errors in levels are serially independent, those in first-differences will exhibit first- but not second-order serial correlation[8] (Arellano, 2003). This corresponds to the AR(1) and AR(2) tests respectively. Finally, despite the fact that system GMM is more robust to weak instruments than the difference estimator, it can also suffer from weak instrument biases[9] (Bazzi & Clemens, 2009). There is no single criterion for evaluating the joint strength of the instrument set of the dynamic panel system GMM estimator (Wintoki, Linck & Netter, 2009). Nevertheless, one possible empirical check suggested by Bond, Hoeffler & Temple (2001), which corresponds to a third diagnostic test of the instruments selection, is to compare estimated panel GMM autoregressive parameters with the empirical bounds implied by the corresponding estimates from OLS (known to be biased upwards) and from simple fixed-effects panel regression (known to be biased downwards). Although time-consuming and never used in previous studies, the above-described procedure (sections 2.2 and 2.3) provides a rigorous basis for the empirical specifications finally selected in the analysis.

3. Empirical Results

In this paper, a panel of 54 developed and developing countries is used over the period 1980-2013 (see table A1 in the Appendix A1 for the list of countries and income groups). Apart from FDI and GDP per capita, six additional control variables are used to reflect economic (inflation, openness to trade, gross fixed capital formation and domestic credit provided by the banking sector) and social conditions (infant mortality rate and primary completion rate). Basic statistics regarding those variables, along with data sources, are listed in Appendix A2 table A2. The Fisher unit root test is applied to all the series (first-differenced) in order to ensure that they are stationary[10]

[7] The null hypothesis is that there is no correlation between the instruments used and the residuals. The reason for using this statistic as opposed to the Sargan statistic, is that it is robust to heteroskedasticity and autocorrelation.

[8] The null hypothesis is that the errors of the first-difference regression do not exhibit second order serial correlation.

[9] The instrumental variables are said to be weak when there is very low correlation between the instrument and the endogenous variable being instrumented. In that case, the model is said to be weakly identified.

[10] The Fisher unit root test is used because, contrary to the other unit root tests available in the software Stata, it can be applied to series containing gaps, which is the case of several series used in this study. This test's results are listed in Table A3 in Appendix A2.

3.1 Whole Sample

3.1.1 Selection of Control Variables and Lags Length

As one may choose to include between zero and up to six different control variables, there are 64 basic specifications explaining each of the two dependent variables (FDI and GDP per capita). Taking into account the additional degrees of freedom implied by the number of lags (between one and four for each variable) leads to a total of more than 500'000 different potential specifications. The final specifications have been selected by minimizing the MMSC-BIC criterion according to the procedure described in section 2.2. The final specifications are reported in table 3.1.

Table 3.1: Selected Specifications for the Whole Sample

Dependent variable	Independent variables†		Optimal number of lags†			Min. MMSC-BIC
m	n	r	m*	n*	r*	
Log(GDP)	FDI ratio	Inflation	1	3	1	-109,9
FDI ratio	*Log(GDP)*	*Domestic credit provided by the banking sector*	*1*	*1*	*2*	*-117,1*

† control variables and lags are optimally selected through the minimisation of the MMSC-BIC criterion over the set of specifications with valid instruments.

The optimal specification explaining the GDP per capita is the one with the explanatory variable inflation and the selected specification for FDI includes domestic credit provided by the banking sector. It is also important to note that the number of lags is not identical for each right-hand side variables, which reveals that performing a lags length selection process is pertinent.

3.1.2 Global Results

Results for the bivariate and selected specifications are reported in table 3.2. There is no evidence that FDI Granger-causes GDP per capita, even in the bivariate specification. According to the results of the optimal specification, it seems that inflation in the host country has more impact on GDP than the other economic and social variables considered in this study. This suggests that price stability might be important for the economic development of a country as it creates a safer environment for the various economic actors. The results also indicate that GDP does not Granger-causes FDI. The optimal specification includes domestic credit provided by the banking sector. Even if this variable is not statistically significant, this might suggest that the quality of the financial system is an important condition for the host country in order to attract FDI inflows. As mentioned by Alfaro et al. (2004), well-developed local financial markets might be important for an economy to take advantage of potential FDI spillovers by, for example, lowering costs of conducting transactions and/or ensuring that capital is allocated to projects that yield returns.

Table 3.2: Blundell and Bond Estimates - Whole Sample

Dependent variable	Log(GDP)		FDI ratio	
Specification	Bivariate	With controls	Bivariate	With controls
Coefficients values (p-values in parentheses)				
$LogGDP_{t-1}$	0,998	0,987	-8,745	0,723
	*0.000****	*0.000****	*0,403*	*0,365*
$LogGDP_{t-2}$			8,537	
			0,487	
$FDI\ ratio_{t-1}$	0,007	0,009	0,607	0,664
	0,241	*0,575*	*0.000****	*0.007****
$FDI\ ratio_{t-2}$	-0,005	-0,010		
	0,339	*0,328*		
$FDI\ ratio_{t-3}$	0,000	0,019		
	0,950	*0,109*		
$Inflation_{t-1}$		0,000		
		0,369		
Domestic credit provided by the banking $sector_{t-1}$				0,061
				0,325
Domestic credit provided by the banking $sector_{t-2}$				-0,090
				0,177
Constant	0,036	0,073	1,070	-3,944
	0,626	*0,270*	*0,602*	*0,549*
Hansen test (p-value)	0,133	0,51	0,250	0,93
First order serial correlation test (p-value)	0,009	0,064	0,002	0,006
Second order serial correlation test (p-value)	0,838	0,157	0,116	0,119
Number of observations	1660	1600	1723	1097
Number of instruments	47	53	49	53

Coefficients of dummy variables are not reported.

*, ** and ***: statistical significance at the 10, 5 and 1 percent level respectively.

t-statistic are in italic

The fact that the estimates do not allow to conclude that there is causality between GDP per capita and FDI contradicts most of the studies on this topic. The difficulty to find Granger-causality between these two variables may be explained by the fact that there is no strong macroeconomic relationship between them and suggests that there is rather correlation than causality between FDI and GDP per capita. This result can also be due, among others, to country heterogeneity that is not appropriately captured by the empirical specification. One possible way to control for the latter is to perform the analysis by subgroups according to the level of income of the countries. This is explored in the next section.

3.2 Results by Country Groups

The objective here is to perform the same analyses as for the whole sample, but at the level of subgroups, in order to control for heterogeneity and to get some more detailed results. Two different subsamples are considered; one contains 22 upper-middle and high income countries and the other one, 32 lower-middle and low income economies[11]. Because of lack of data, it is unfortunately not possible to divide the whole sample into more detailed subgroups.

As the number of countries in the subsamples is relatively low in comparison to the number of years, the minimum number of instruments is higher than the number of countries and thus, leads to biased results. One solution to this problem is to reduce the number of time periods in the sample by calculating the arithmetic and (non) overlapping average over several years between 1980 and 2013 for each series (see Choe, 2003 for example); in this study, the series are averaged over three years (non overlapped). This allows using a number of instruments which is lower than the number of countries.

[11] The World Bank countries classification of the year 1992 is considered.

However, it must be mentioned that temporal aggregation would generate a loss of dynamic information and might induce an apparent lack of Granger-causality even if one exists (see Herzer, Klasen & Nowak-Lehmann D., 2006). However, this process has the advantage to dilute cyclical influences that can be important in some developing countries. In order to ensure that the number of instrumental variables is higher than the number of regressors, the lag length of all right-hand side variables in each framework is limited to 1 (which is equivalent to three years). The instrumental variables used in the regressions of these two subsamples are the lagged dependent variable. In order to be able to compare these additional results with the ones of the whole sample, the same estimations are also performed for the whole sample after having averaged each series over three years (designed as whole sample "averaged").

3.2.1 Selection of Control Variables

The optimal set of control variables has been identified following the procedure described above. It is different from the optimal specification for the whole sample, which shows that heterogeneity among the different countries and the cyclical variations contained in the series have an influence on the conclusions. The optimal specifications of the whole sample "averaged" and of the two subsamples are reported in table 3.3.

3.2.2 Whole Sample "Averaged" and Subsamples Results

The whole sample's results (see table 3.4) indicate that FDI positively Granger-causes GDP in the bivariate as well as in the optimal specification. Similarly to the results of section 3.1, the latter includes the variable inflation, which is, however, not statistically significant. When FDI is the dependent variables, the bivariate specification is also the optimal one and FDI is not Granger-caused by GDP. This suggests that FDI is mainly influenced by its own past values rather than by additional explanatory variables.

Table 3.3: Selected Specifications - Whole Sample "Averaged" and Subsamples

Whole sample "averaged"

Dependent variable	Independent variables†		Min. MMSC-BIC
m	n	r	
Log(GDP)	FDI ratio	Inflation	32,0
FDI ratio	*Log(GDP)*	-	-33,4

† control variables are optimally selected through the minimisation of the MMSC-BIC criterion over the set of specifications with valid instruments

Upper-middle and high income countries

Dependent variable	Independent variables†		Min. MMSC-BIC
m	n	r	
Log(GDP)	FDI ratio	Inflation	-30,1
FDI ratio	*Log(GDP)*	*Gross fixed capital formation*	-29,3

† control variables are optimally selected through the minimisation of the MMSC-BIC criterion over the set of specifications with valid instruments.

Low and lower-middle income countries

Dependent variable	Independent variables†		Min. MMSC-BIC
m	n	r	
Log(GDP)	FDI ratio	Gross fixed capital formation	-32,1
FDI ratio	*Log(GDP)*	-	-32,7

† control variables are optimally selected through the minimisation of the MMSC-BIC criterion over the set of specifications with valid instruments

Table 3.4: Blundell and Bond Estimates - Whole Sample "Averaged"

Dependent variable	Log(GDP)		FDI ratio
Specification Coefficients values (p-values in parentheses)	Bivariate	With controls	Bivariate
$LogGDP_{t-1}$	0,995	0,993	-0,342
	0.000***	0.000***	0,542
FDI $ratio_{t-1}$	0,047	0,043	0,462
	0.008***	0.074*	0.005***
$Inflation_{t-1}$		0,000	
		0,277	
Constant	-0,065	-0,027	4,603
	0,703	0,955	0,322
Hansen test (p-value)	0,278	0,453	0,154
First order serial correlation test (p-value)	0,015	0,011	0,004
Second order serial correlation test (p-value)	0,893	0,427	0,510
Number of observations	538	538	539
Number of instruments	27	19	19
Coefficients of dummy variables are not reported.			
*, ** and ***: statistical significance at the 10, 5 and 1 percent level respectively.			
t-statistic are in italic.			

Table 3.5: Blundell and Bond Estimates - Upper-Middle and High Income Countries Subsample

Dependent variable	Log(GDP)		FDI ratio	
Specification Coefficients values (p-values in parentheses)	Bivariate	With controls	Bivariate	With controls
$LogGDP_{t-1}$	0,972	0,939	-1,470	-2,915
	0.000***	0.000***	0,510	0.090*
FDI $ratio_{t-1}$	0,023	0,022	0,312	0,245
	0.041**	0.001***	0,180	0.035**
$Inflation_{t-1}$		-0,004		
		0,469		
Gross fixed capital $formation_{t-1}$				-0,746
				0.019**
Constant	0,248	0,595	18,137	44,373
	0,389	0.081*	0,341	0.051*
Hansen test (p-value)	0,355	0,898	0,543	0,800
First order serial correlation test (p-value)	0,068	0,014	0,034	0,054
Second order serial correlation test (p-value)	0,607	0,894	0,514	0,123
Number of observations	220	220	220	219
Number of instruments	19	19	15	19
Coefficients of dummy variables are not reported.				
*, ** and ***: statistical significance at the 10, 5 and 1 percent level respectively.				
t-statistic are in italic.				

In the group of high income countries (see table 3.5), the results indicate that the countries of this subgroup are able to beneficiate from FDI inflows' spillover effects; local firms are advanced enough to learn from foreigners. In the bivariate specification explaining FDI, GDP per capita does not Granger-causes FDI. In the optimal one, it can be concluded that GDP per capita Granger-causes FDI but only at the 10% level. This specification contains gross fixed capital formation, which is a proxy for domestic investment.

The fact that this variable has a negative sign and is statistically significant for this subsample might be explained by the fact that these countries are developed enough to finance investments by themselves, so that domestic investment becomes a substitute for FDI, and thus competes with it[12]. In the case of low income economies (see table 3.6), the estimates indicate that the optimal GDP per capita specification is the one including gross fixed capital formation and that, like for the subgroup of more developed countries, FDI Granger-causes GDP. This result shows that, even if the level of income of this category of countries might be low, these economies can all the same beneficiate from the spillover effects from FDI (through the creation of jobs or technology transfers for example). The variable gross fixed capital formation is statistically significant. It suggests that, in low and lower-middle income countries, domestic investment is positive for economic development, in addition to FDI. However, no Granger-causality can be observed in the bivariate specification. Similarly, there is no Granger-causality from GDP per capita to FDI. Like for the whole sample "averaged", when FDI is the dependent variable, the bivariate specification is also the optimal one.

Table 3.6: Blundell and Bond Estimates - Low and Lower-Middle Income Countries Subsample

Dependent variable	Log(GDP)		FDI ratio
Specification Coefficients values (p-values in parentheses)	Bivariate	With controls	Bivariate
$LogGDP_{t-1}$	0,978	0,956	0,235
	0.000***	0.000***	0,682
$FDI\ ratio_{t-1}$	0,032	0,046	0,645
	0,276	0.036**	0.000***
$Gross\ fixed\ capital\ formation_{t-1}$		0,012	
		0.000***	
Constant	0,124	-0,056	0,147
	0,671	0,914	0,972
Hansen test (p-value)	0,295	0,872	0,366
First order serial correlation test (p-value)	0,037	0,033	0,061
Second order serial correlation test (p-value)	0,745	0,735	0,454
Number of observations	318	316	319
Number of instruments	15	19	19
Coefficients of dummy variables are not reported.			
*, ** and ***: statistical significance at the 10, 5 and 1 percent level respectively.			
t statistic are in italic.			

Summing up, the results show that, for both subgroups of countries, there is Granger-causality from FDI to GDP per capita but that no Granger-causality can be observed from FDI to economic growth. It can also be mentioned that economic and social host country characteristics seem to play a role for the attractiveness of FDI inflows and for economic activity. In particular, the results suggest that domestic investment might displace FDI inflows in upper-middle and high income countries but that it positively influences GDP per capita in low and lower-middle income economies.

4. Summary

In this paper, the Granger-causality link between GDP per capita and FDI has been analyzed for 54 developing and developed countries over the period from 1980 to 2013, by means of a dynamic panel data model based on the Blundell and Bond methodology (system GMM estimator). This analysis provides several improvements with regard to previous studies. In particular, the control variables and the lags length of the right-hand side variables have been selected according to a specific procedure, the minimization of the MMSC-BIC criterion, and host country social and economic characteristics have been directly included in the empirical setting.

[12] According to Lucas (1993), domestic investment may have a positive impact or a negative effect on FDI depending on whether the two variables are substitutes or complements.

The results demonstrate that host country social and economic conditions might have an impact on GDP per capita and on FDI inflows. They also reveal that the optimal lag length is not identical for each explanatory variables and that FDI and GDP per capita are influenced by some local conditions. However, no Granger-causality can be observed between these two variables. If we correct for the cyclical disturbances contained in the series by averaging them over several years, the results are different. They reveal that FDI positively Granger-causes economic growth and that FDI is only influenced by its own past values. The specifications performed for the two subsamples of countries confirm that there is a positive causal link from FDI to GDP per capita whatever the income level of the countries is. However, no reverse causality can be observed. These results also show that host country local conditions, in particular domestic investment, play a role for the two variables of interest.

Finally, several possible improvements of this study should be enumerated. The link between FDI and economic development might be clarified by taking into account additional host country social and economic characteristics, such as corruption or the importance of the black market for example. The analysis of the short- and long-run relations between GDP per capita and FDI (through error correction models, for example) might also be interesting. The use of firm-level instead of or in addition to country-level data might also provide additional evidence on the channels behind the relationship between economic development and foreign investment inflows. It can also be mentioned that, due to the heterogeneity among the countries, the use of panel data models that allow heterogeneous coefficients or of time series could also improve the precision of the results obtained in this analysis. Another possibility would be to enlarge the dataset in order to be able to divide the whole sample into more detailed subgroups. All these additional analyses should improve our understanding of the complex relationship between FDI and GDP per capita.

Appendix

A.1 Countries Classification

Table A1: Countries Classification

World Bank 1992 countries classification – Income group			
Low-income economies	**Lower-middle-income economies**	**Upper-middle-income economies**	**High-income economies**
Burkina Faso	Algeria	Botswana	Denmark
China	Bolivia	Gabon	Finland
Egypt, Arab Rep.	Chile	Greece	Germany
Ghana	Congo, Rep.	Korea, Rep.	Iceland
Honduras	Cote d'Ivoire	Malaysia	Ireland
Indonesia	Costa Rica	Malta	Italy
India	Dominican Republic	Mexico	Japan
Mali	Ecuador	Portugal	Norway
Malawi	El Salvador	Saudi Arabia	New Zealand
Nicaragua	Guatemala	Trinidad and Tobago	Sweden
Rwanda	Iran, Islamic Rep.	Uruguay	United Arab Emirates
Sri Lanka	Jordan	Venezuela, RB	
Zimbabwe	Morocco		
	Paraguay		
	Peru		
	Senegal		
	Swaziland		
	Syrian Arab Republic		
	Thailand		
	Tunisia		
Income group: Economies are divided according to 1992 GNI per capita in US$, calculated using the World Bank Atlas method. The groups are: low income, $675 or less; lower middle income, $676 - $2'695; upper middle income, $2'696 - $8'355; and high income, more than $8'355.			

Source: World Bank, http://web.worldbank.org

A.2 Data Summary

In this paper, a panel of 54 developed and developing countries is used (see Appendix A1, table A1 for countries classification), over the period from 1980 to 2013. The considered variables are the FDI to GDP ratio, real GDP per capita in (constant 2005) US$ and socioeconomic indicators: openness to trade, gross fixed capital formation, inflation, domestic credit provided by the banking sector, primary completion rate and infant mortality rate. All variables are made available by the World Bank (World Bank Development Indicators (WDI) 2014) except FDI data and infant mortality rate that come from, respectively, the United Nations Conference on Trade and Development (UNCTAD) FDI database and the United Nations Population Division. Countries are selected according to the availability of the different series. Furthermore, in order to avoid FDI round-tripping effects, the off-shore centers are excluded from the analyzed economies (see European Central Bank, 2007 and Appendix A3, table A4 for the offshore centers list).

Table A2: Data Summary

Variable	Name and units of measurement	Number of observations	Mean	Standard-deviation	Minimum	Maximum	Source
Foreign direct investment ratio (FDI divided by GDP)	fdiratio rate in %	1834	2,245602	3,503697	-22,54435	33,40671	UNCTAD
Real GDP per capita (constant 2005 US$)	gdp_pcap05 millions of US$	1830	9610,375	13636,98	140,2539	67804,55	The World Bank
Openness to trade (exports plus imports divided by GDP)	ott rate in %	1800	0,7106977	0,3469767	0,0632034	2,204072	The World Bank
Inflation (GDP deflator growth rate in %)	infl growth rate in %	1830	38,6519	493,7472	-29,17266	13611,63	The World Bank
Gross fixed capital formation (% of GDP)	gfcf rate in %	1798	21,88315	6,25276	2,000441	59,7324	The World Bank
Domestic credit provided by banking sector (% of GDP)	dcbs rate in %	1799	62,0776	54,20662	-79,09235	368,0342	The World Bank
Primary completion rate, total (% of relevant age group)	prim_rate rate in %	1801	83,8206	29,16118	9,32447	353,131	The World Bank
Infant mortality rate per 1000 live births	inf_mor rate in ‰	1836	37,22887	32,48576	1,6	160,5	UN

Table A3: Fisher Unit Root Test

Variable (first differenced)	χ^2-statistics	p-value
Foreign direct investment ratio (FDI divided by GDP)	2545.242	0.000
Real GDP per capita (constant 2005 US$)	866.889	0.000
Openness to trade (exports plus imports divided by GDP)	1654.933	0.000
Inflation (GDP deflator growth rate in %)	2640.243	0.000
Gross fixed capital formation (% of GDP)	1292.515	0.000
Domestic credit provided by banking sector (% of GDP)	1167.487	0.000
Primary completion rate, total (% of relevant age group)	1301.158	0.000
Infant mortality rate per 1000 live births	337.118	0.000
***H0**: all time series are non-stationary*		
***H1**: at least one series in the panel is stationary*		

A.3 Off-shore Centers

Table A4: List of Off-shore Financial Centers

Off-shore financial centres[1]
Andorra
Antigua and Barbuda
Anguilla
Netherlands Antilles
Barbados
Bahrain
Bermuda
Bahamas
Belize
Cook Islands
Dominica
Grenada
Guernsey
Gibraltar
Hong Kong
Isle of Man
Jersey
Jamaica
Saint Kitts and Nevis
Cayman Islands
Lebanon
Saint Lucia
Liechtenstein
Liberia
Marshall Islands
Montserrat
Maldives
Nauru
Niue
Panama
Philippines
Singapore
Turks and Caicos Islands
Saint Vincent and the Grenadines
Virgin Islands, British
Virgin Islands, U.S.
Vanuatu
Samoa

[1] *Based on Eurostat and OECD list of off-shore financial centres.*

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