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## Forecasting global FDI: a panel data approach\*

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### Abstract

The future patterns of foreign direct investment (FDI) are important inputs for policymakers, even more so during severe economic downturns, such as the one caused by the COVID-19 pandemic. Yet, there is neither empirical consensus nor significant ongoing empirical research on the most appropriate tool for forecasting FDI inflows. This paper aims to fill this gap by proposing an approach to forecasting global FDI inflows based on panel econometric techniques – namely the generalized method of moments – accounting for the heterogeneous nature of FDI across countries and for FDI dependence across time. The empirical comparison with alternative time-series methods confirms the greater predictive power of the proposed approach.

**Keywords:** FDI, forecast, panel econometrics, time-series econometrics, underlying FDI trend, generalized method of moments

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## 1. Introduction

Foreign direct investment (FDI) is an important contributor to economic growth. The FDI-growth linkage operates through direct and indirect channels. Directly, multinational enterprises (MNEs) expand host countries' production capacities and employ local workers (Dunning and Lundan, 2008), resulting in higher employment and increased income. Indirectly, MNE activity can produce positive spillovers to domestic economies, improving the productivity of local firms through the transfer of advanced production technologies, managerial knowledge and working practices (Segerstrom, 1991; Grossman and Helpman, 1994). Foreign direct investments have been instrumental in the expansion of global value chains (GVCs), with MNEs coordinating GVCs through their networks of foreign affiliates and non-equity mode partners (UNCTAD, 2013; Farole and Winkler, 2014).

Future FDI trends are pivotal information for policymakers, in particular in developing economies, where development prospects are often tied to inflows of foreign productive capital. Sustainable and sustained external financing, including FDI, is key to achieving the United Nations Sustainable Development Goals (SDGs; UNCTAD, 2014). In the midst of an unprecedented health and economic crisis, with potentially dramatic consequences for cross-border capital flows (UNCTAD, 2020), and with less than a decade left to the deadline for the SDGs, it is all the more important to have reliable tools for predicting future trends in FDI.

Yet, although the forecasting of macroeconomic variables such as gross domestic product (GDP) and inflation has a long history, the forecasting of FDI remains empirically relatively unexplored. Some studies perform FDI forecasting for a single country or for a limited set of countries through the application of country-specific univariate time-series, disregarding countries' heterogeneity and interdependence (Al-Rawashdeh, Nsour and Salameh, 2011; Shi et al., 2012; Perera, 2015; Nyoni, 2018; George and Rupashree, 2019; Sharma and Philli, 2020). To our knowledge, Speller, Thwaites and Wright (2011) is the only effort to simulate future international capital flows at the aggregate level – i.e. including not only FDI. The paper proposes a simulation approach based on simple ordinary least square (OLS), which is potentially prone to problems of endogeneity and reverse causality between the covariates and the dependent variable. UNCTAD has included forward projections of FDI at the global and regional level in its annual World Investment Report for many years, integrating econometric forecasting employing the estimated generalized least square approach (EGLS) with survey data and perspectives based on project announcements. This study formally presents an improvement to UNCTAD long-standing forecasting approach, employing the generalized method of moments (GMM) instead of EGLS to address some key issues related to FDI forecasting.

Two issues make FDI forecasting particularly challenging, explaining to some extent the very limited methodological advances in this area: (i) the highly volatile nature of FDI data and (ii) the complexity of properly capturing the many determinants that affect FDI and their interactions.

- (i) Although FDI is the most stable source of external financing (*World Investment Report*, various editions), in the last 20 years its dynamics have exhibited significant variations (figure 1). These are typically generated by one-off transactions such as large cross-border mergers and acquisitions (M&As) and by financial flows, mainly involving developed economies. A useful step for forecasting is to mitigate the strong volatility in the data while retaining the most structural and productive component of FDI.
- (ii) Longitudinal and cross-sectional factors interact in complex ways to determine the level of FDI in a country, as investment depends both on the behaviour of past investors (longitudinal dimension) and on the macroeconomic and institutional conditions prevailing across countries (cross-sectional dimension).

The purpose of this paper is to suggest an econometric approach to forecasting FDI that properly addresses these two issues. For the first problem (volatility of FDI) we introduce an *underlying FDI trend*, smoothing the FDI time series by taking into account the differing nature of the key FDI components, such as greenfield investment, cross-border M&As, financial flows and intracompany loans (ICLs) (section 2).<sup>1</sup> For the second problem (heterogeneity across countries and time dependence), we suggest a dynamic panel econometric approach (section 3). The resulting model is a GMM model such as that proposed by Arellano and Bover (1995), accounting for cross-country heterogeneity and time dependence (section 4). The GMM model is then used to forecast FDI (section 5) and the results are compared with alternative time-series methods, confirming the higher predictive power of the proposed approach (section 6). This paper is a step in investigating methods for forecasting global FDI flows within a panel data econometric framework; possible alternative directions for future research, including beyond panel data econometrics, are briefly discussed in the final section (section 7).

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<sup>1</sup> The UNCTAD underlying trend used in this paper is a composite construct combining different sets of data. For ease of interpretation, we use the term “FDI components” – which in the balance-of-payments construct of FDI denotes equity, reinvested earnings and ICLs (i.e. sources of finance) – in a different sense here to distinguish greenfield projects (i.e. new investments) and M&As (i.e. ownership changes).

## 2. Addressing the first issue (volatility of FDI): the underlying FDI trend

FDI inflows exhibit a strong volatility, particularly from the 2000s onwards. The highly volatile pattern results mostly from inflows to developed economies, while FDI to developing economies displays far more stable dynamics (figure 1).

Large fluctuations and cyclical movements in total FDI flows are mostly caused by (i) investment flows to (or rather through) large financial centres and conduit countries (offshore financial centres, or OFCs); (ii) global trends in M&As, which correlate closely with financial markets; and (iii) large swings in the volume of ICLs.

Letting global  $FDI_t$  denote global FDI inflows at time  $t$  and  $OFC_t$ , the subset including inflows to OFCs, we define:

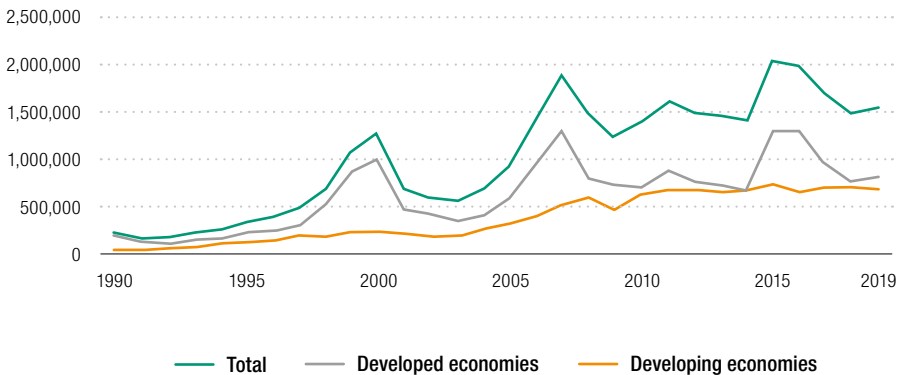
$$FDI_t^* = FDI_t - OFC_t \quad (1)$$

Decomposing  $FDI_t^*$  into its ICL component ( $ICL$ ), its M&A component ( $M\&A$ ), and its greenfield component ( $GI$ ) then yields:

$$FDI_t^* = ICL_t^* + M\&A_t^{**} + GI_t^{**} \quad (2)$$

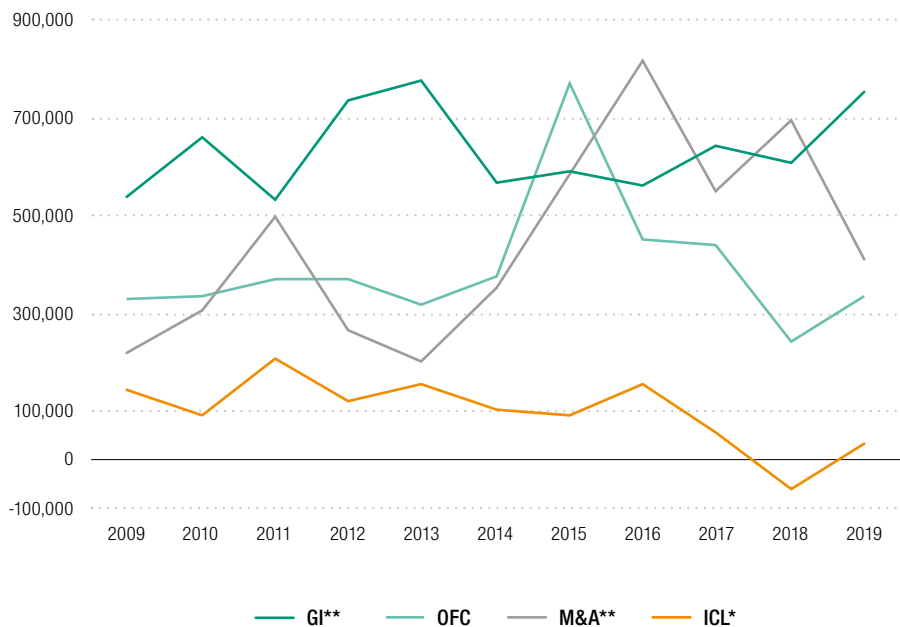
where  $ICL_t^*$  are ICLs excluding OFCs and  $M\&A_t^{**}$  are cross-border M&As, after excluding flows to OFCs and ICLs, with the residual component  $GI_t^{**}$  interpreted as the greenfield, non-financial component of FDI.

**Figure 1. FDI inflows, 1990–2019** (Millions of dollars)



Decomposition (2) can be concretely obtained in two steps. First, FDI inflows to the set of OFCs are subtracted from total FDI inflows to derive  $FDI_t^*$ ; second, ICLs ( $ICL_t^*$ ) and cross-border M&As ( $M\&A_t^{**}$ ), sourced from national accounts data and commercial project databases (such as Refinitiv) respectively, are subtracted from  $FDI_t^*$  to compute an approximation of the greenfield component  $GI_t^{**}$ .<sup>2</sup> Figure 2 shows the historical pattern of the components in decomposition (2).

**Figure 2. FDI components, 2009–2019** (Millions of dollars)



Source: Based on UNCTAD FDI data.

Note: OFC: FDI inflows to offshore financial centres; M&A\*\*: cross-border mergers and acquisitions in all countries, excluding OFCs; ICL\*: intracompany loans to all countries, excluding OFCs; GI\*\*: residual component.

<sup>2</sup> Notice that although exclusion of OFCs from ICLs and cross-border M&As is straightforward, there is no clear way to break down ICLs by mode of entry, making exclusion of ICLs from cross-border M&As not feasible from the perspective of data availability. As a consequence, for computational purposes in decomposition (2) we assign to  $M\&A_t^{**}$  (i.e. cross-border M&As excluding OFCs and ICLs) the value of  $M\&A_t^*$  (i.e. cross-border M&As excluding only OFCs), assuming that the ICL component of M&As is sufficiently small not to alter the dynamics and interpretation of the components in decomposition (2). This assumption appears safe, because cross-border M&As tend to translate into the equity component of FDI.

The main driver of the large fluctuations in global FDI inflows is the value of cross-border M&As, which in some years of frothy financial markets can account for more than half of global FDI values. For example, the peaks in 2000, 2007 and 2015 (figure 1) were driven to a large extent by M&A booms (compare with figure 2 for 2015). In some years, global FDI statistics are skewed by a very few extremely large transactions, such as the SAB Miller deal in 2016 (6 per cent of global flows in that year), or the Verizon deal in 2014 (10 per cent of total flows). Although the volatility of ICLs is greater, their impact on global FDI flows is significantly less due to their limited absolute size. Nonetheless, they can cause very significant upward or downward swings in individual countries.

All components of FDI are relevant indicators of global investment trends, from the perspectives of both macroeconomics (e.g. the health of a country's balance of payments) and international production (which expands as much through M&As as through greenfield investments). Yet, it can be hard for policymakers to draw sound conclusions – say, on progress in building a conducive investment climate – on the basis of trends that show wild fluctuations, often driven by exogenous cyclical dynamics in financial markets or by anomalous outliers (such as one-off M&A transactions). It is therefore helpful to study the underlying directional trend, net of the oscillations caused by the most volatile elements in FDI flows. Not only is the construction of an underlying trend a useful descriptive monitoring and analytical tool in itself (*UNCTAD, 2019 and 2020*), it is also instrumental in addressing the issue of volatility in the forecasting exercise.

The main challenge is to define the underlying trend in such a way as to remove the most disturbing part of the volatility while retaining the fundamental long-term dynamics of FDI. To do so, we rely on decomposition (2), leveraging our prior knowledge of the economic interpretation and statistical behaviour of the elements involved:

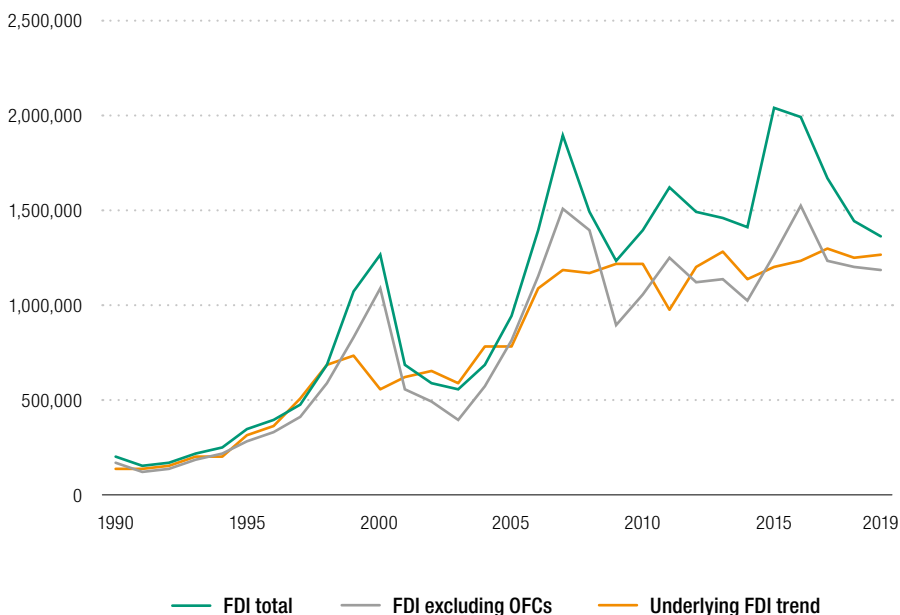
- FDI to OFCs is excluded from the calculation of the trend, as it is largely conduit flows and driven by financial and tax motives.
- The moving average technique is applied to smooth the dynamics of M&A\*\* and ICL\*, to mitigate large swings generated by one-off transactions.
- The remaining component, GI\*\*, is retained as is to recognize the more productive nature of greenfield investment, which is empirically supported by the evidence of a more stable historical pattern relative to the other components (figure 2).

The underlying FDI trend  $FDI\_trend_t^*$  is then calculated as:

$$FDI\_trend_t^* = GI_t^{**} + MA_5(M\&A_t^{**} + ICL_t^*) \quad (3)$$

where  $GI_t^{**}$ ,  $M\&A_t^{**}$  and  $ICL_t^*$  are defined as in (2) and  $MA_5(\dots)$  is the five-year moving average function. Consistent with the notation introduced, the asterisk superimposed on the variable  $FDI\_trend$  indicates the exclusion of flows to OFCs. Figure 3 shows the dynamics of the underlying FDI trend,  $FDI\_trend_t^*$ , relative to total FDI and to total FDI without OFCs ( $FDI_t$  and  $FDI_t^*$ , respectively).

**Figure 3. FDI inflow, with and without OFCs, and underlying FDI trend, 1990–2019** (Millions of dollars)

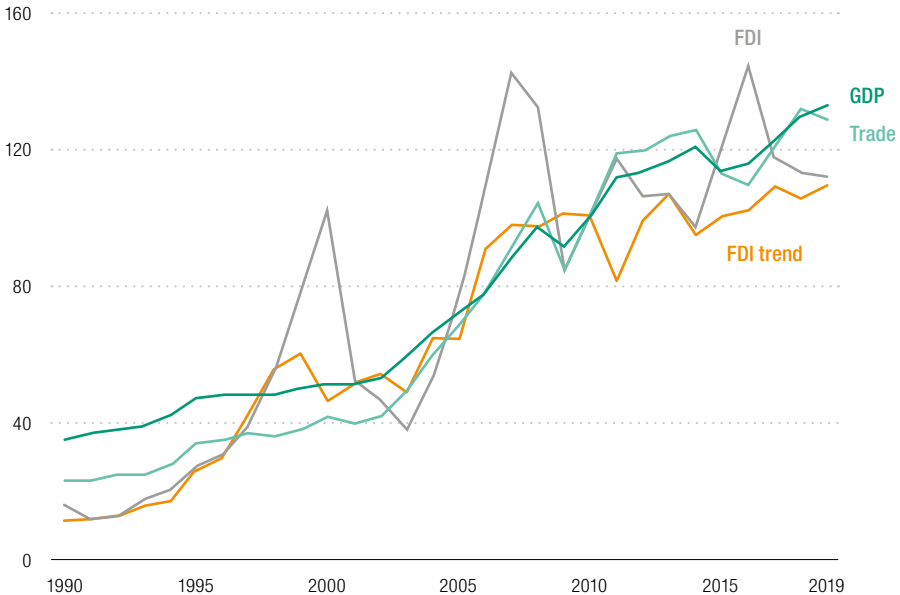


Source: Based on UNCTAD FDI data.

The underlying investment trend line does not show the drops in FDI after the dotcom boom and during the global financial crisis. This suggests that FDI is, at its core, quite stable: investment projects have long gestation periods and investment decisions are not easily reversed on the basis of developments in financial markets. Also, a large part of FDI flows is generated by existing FDI stocks, particularly the non-M&A component – including, for example, reinvested earnings. This time-dependent feature makes the underlying FDI trend less prone to external shocks and inherently more stable.

The underlying trend line follows global macroeconomic indicators, such as GDP and trade, more closely than total FDI (figure 4).

**Figure 4. FDI and other macroeconomic indicators, 1990–2019** (Indexed, 100 = 2010)



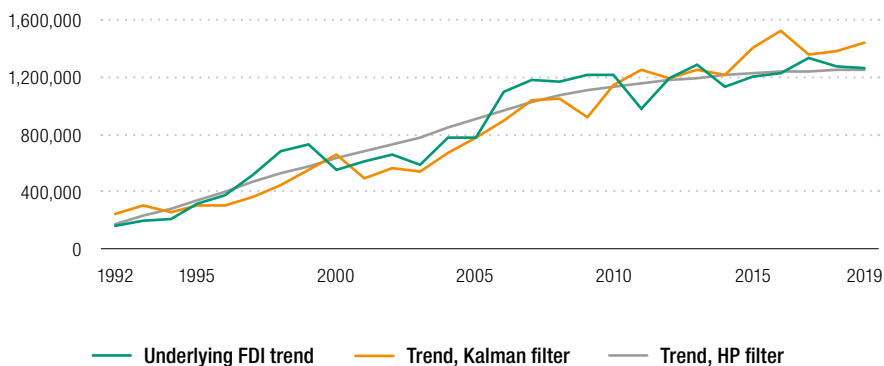
Source: Based on UNCTAD FDI data.

UNCTAD's underlying trend can be seen as an *informed* approach to smoothening the FDI time series. It has the big advantage of offering a very natural economic interpretation of the trend in terms of the underlying components of FDI, as opposed to smoothing techniques, such as filtering techniques, that rely on algorithmic solutions. Figure 5 compares UNCTAD's underlying trend with two alternative well-established filtering techniques applied to FDI time series, that of Hodrick and Prescott (1997) and the state-space model of the Kalman (1960) filter.

The graph suggests that the underlying FDI trend has a pattern similar to the trends calculated with alternative techniques, as also confirmed by high correlation among the three series (see the correlation matrix in table 1A in the appendix). This suggests the robustness of the methodological approach in (3) for the extraction of the FDI trend and provides reassurance about its application for forecasting purposes.



**Figure 5. Comparison between the underlying FDI trends and the trends generated by Kalman filtering and HP filtering, 1992–2019** (Millions of dollars)



Source: Estimation based on UNCTAD FDI data.

### 3. Addressing the second issue (time dependence and cross-country heterogeneity): dynamic panel model

Besides the volatile nature of FDI, intrinsic features of the investment process such as its time dependence and cross-country heterogeneity make FDI forecasting particularly challenging and prone to issues such as endogeneity and reverse causality.

FDI is a dynamic process in which past investment experience serves as a predictor of future investment paths. Investors take time to become familiar with the culture, institutional framework and preferences prevailing in a market. As they learn, they adapt their cross-border investment decisions. Time dependence of investments is also generated “automatically” by the reinvestment of foreign earnings, a component of FDI in national accounts. This inherent time structure requires explicit inclusion of the past (lagged) value into any econometric and forecasting model attempting to explain or predict the behaviour of FDI.

In addition to time dependence, a rich empirical literature has identified various country-level macroeconomic and institutional factors influencing FDI inflows, such as market size, openness, taxes, labour costs, trade costs and exchange rate, among others (for a complete review of FDI determinants and relevant literature, see the *UNCTAD 1998*, and Vujanović (2018)). These factors cause cross-sectional (or spatial) heterogeneity of FDI across countries, which needs to be addressed by the forecasting model directly.

Combining a time-dependent (autoregressive) component and a cross-sectional component in the standard linear model leads to the following formulation of the econometric problem, for the general case with  $T$  periods,  $N$  observations for each period and  $M$  covariates:

$$Y_t = a_1 Y_{t-1} + a_2' X_t + u_t; \quad t = 1, 2, \dots, T \quad (4)$$

$$u_t = \eta + \varepsilon_t \quad (5)$$

where  $Y_t$  is a  $(N \times 1)$  vector of dependent variables,  $X$  is the  $(N \times M)$  matrix of the explanatory variables and  $u_t$  is the  $(N \times 1)$  vector of the composite error term consisting of two components (5). The first component  $\eta$  is fixed over time and represents unobserved time-invariant fixed effects, such as the culture or the institutional framework. The second dynamic component,  $\varepsilon_t$ , is the idiosyncratic error term, independent from the explanatory variables.

Two endogeneity issues – conditions in which an explanatory variable is correlated with the error term – prevent us from estimating eq. (4) with simple OLS regression:

- (i) The first issue (simultaneity bias) arises from the fact that the unobservable time-invariant component of the error term ( $\eta$  in 5) is correlated with the (lagged) dependent variable  $Y_{t-1}$  ( $E[Y_{t-1}, u_t] \neq 0$ ) appearing in the right-hand side of the econometric equation (4).
- (ii) The second issue (reverse causality) arises as explanatory variables in the covariate matrix  $X_t$  are potentially influenced by the dependent variable. Specifically, multinational firms can contribute to host countries' income through production, labour creation and technology transfers (Findlay, 1978), causing reverse causality between GDP and FDI and (upward) bias estimate of GDP coefficient.

Simple cross-sectional methods, such as OLS, are not equipped to deal with endogeneity issues. *Static panel econometric techniques* offer some partial solutions. For example, fixed-effect models attenuate simultaneity bias by demeaning each variable but do not deal with reverse causality.

*Dynamic panel models*, such as the *generalized method of moments* (GMM), instead allow for the appropriate consideration of the FDI dynamics while also addressing reverse causality and other potential endogeneities. Broadly, GMM models apply an instrumental variable approach that offers a wide set of internal instruments (available within the data set) to deal with endogenous variables. Their main advantage is to allow for the inclusion of the dynamic component, while solving resulting endogeneity issues with internal – easy to construct – instruments whose validity can be tested. Testing can be performed with the first- and second-order autocorrelation tests as well as the Sargan and Hansen tests of overidentifying restriction.

Finally, adding to their empirical appeal, GMM models do not require distributional assumptions such as the condition of normality and allow for heteroscedasticity (for details on GMM and instrumental variables, see for example Pesaran and Smith (1995) and Greene (2008)).

In the alternative between *differenced GMM* (Arellano and Bond, 1991) and *system GMM* (Arellano and Bover, 1995; Blundell and Bond, 1998), the preference here is given to the latter, which offers a wider choice of instruments (exploiting simultaneously levels and differences) and is more suitable when the panel data show some persistence (this is particularly the case for the underlying FDI trend) (Blundell and Bond, 1998; Roodman, 2009).

#### 4. Model selection and results

We therefore apply system GMM to equation (4) in the following form, including time and regional fixed effects:

$$FDI_{it} = a_1 FDI_{it-1} + a_2' X_{it} + a_3' Z_{it} + \partial_t + \rho_k + u_{it} \quad (6)$$

$$u_{it} = \eta + \varepsilon_t \quad (i = 1, 2, \dots, N; t = 1, 2, \dots, T)$$

The dependent variable  $FDI_{it}$  is FDI inflows to country  $i$  at time  $t$ ,  $X_{it}$  is a vector of  $M$  explanatory variables,  $Z_{it}$  is a vector of  $H$  control variables, and  $\partial_t$  and  $\rho_k$  are the variables representing time and regional fixed effects, respectively. The error term is the sum of country-specific unobservable fixed effect  $\eta$  and the idiosyncratic error term  $\varepsilon_t$ . Logarithmic transformation is applied to  $FDI_{it}$  as well as to other continuous variables in the vectors  $X_{it}$  and  $Z_{it}$  (see table 2A in the appendix).<sup>3</sup> The time horizon is 2003–2019 ( $T = 17$ ). The number of countries  $N$  changes according to the year (making an unbalanced panel) because some observations of covariates in the vector  $Z_{it}$  are missing for some countries in some years.

A second specification is introduced using the underlying FDI trend as the dependent variable to capture the more structural dynamics of FDI and to mitigate volatility, in line with the discussion in section 2:

$$FDI\_trend_{it} = b_1 FDI\_trend_{it-1} + b_2' X_{it} + b_3' Z_{it} + \partial_t + \rho_k + v_{it} \quad (7)$$

where  $FDI\_trend_{it}$  is defined by decomposition (3) for each country  $i$ , individually, after suppressing the superscript\* for notational convenience.

<sup>3</sup> Logarithmic transformation makes the variable's distribution closer to the "normal" bell-shaped one, while allowing the interpretation of the effects in terms of percentage changes.

For FDI forecasting purposes, it is critical to select a set of predictors  $X_{it}$  (i) that is significant in explaining the behaviour of FDI and (ii) for which there exist solid forecasts to feed into the forward-looking estimation. The natural choice falls then on the two variables, GDP and trade openness, which are not only the most (theoretically and empirically) established determinants of FDI,<sup>4</sup> but are also supported by long-standing forecasting practice by international institutions. The model is then complemented by a vector of controls  $Z_{it}$  that includes other relevant variables such as taxation, income group, tariffs and exchange rate – all theoretically important drivers of FDI (Overesch and Wamser, 2010; Bevan and Estrin, 2004; Carstensen and Toubal, 2004; Martínez-San Román, Bengoa and Sánchez-Robles, 2016; Dixit and Pindyck, 1994; Aliber, 1970). Lacking established sources of their future values, the controls do not enter the forecasting exercise, but they are important to test the robustness of the predictors (the autoregressive term and the explanatory variables). Details on the definition, construction and sources of the dependent and independent variables are provided in the appendix (table 2A).

The results of model (6) and (7) are presented in table 1. The diagnostics tests confirm the model's validity. First- and second-order autocorrelation tests indicate that the instruments are correlated with the endogenous variables but not with the error term. Sargan and Hansen tests also confirm that the instruments, as a group, appear exogenous.

In both models (columns I and II), the lagged dependent variable, GDP and trade openness are significant with the expected positive sign, after controlling for other relevant factors  $Z_{it}$ , and for time and regional fixed effects. The coefficient of the lagged dependent variable indicates that the past is a good predictor of the future behaviour of both FDI inflows (column I) and the FDI trend (column II). The positive effect of GDP confirms the importance of market size for FDI inflows. Likewise, trade openness has the expected positive impact on FDI, although much smaller than the impact of GDP. Control variables  $Z_{it}$  – taxes, tariffs, exchange rate and the income group – are not statistically significant in either of the models, which is reassuring in regard to the choice – imposed by data constraints – to limit the set of predictors to only GDP and trade.

Comparing the estimates between the two GMM models (column I and column II) provides further insights. The lagged dependent variable affects FDI inflows more strongly than FDI trend. Market size and trade openness, by contrast, have a greater effect on FDI trend, confirming the conceptual intuition (and empirical observation – see figure 4) that the underlying FDI trend can track economic fundamentals more closely.

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<sup>4</sup> The theoretical and empirical literature on market size (GDP) and trade openness (trade) as FDI determinants is vast. On the theoretical side, see for example Rodrik (1999) and Keller and Yeaple (2013) for GDP; and Caves (2007) for trade. On the empirical side, useful references for GDP include Resmini (2000); Hilber and Voicu (2010); Estrin and Uvalic (2014); and Blonigen and Piger (2014); and for trade include Janicki and Wunnava (2004); Clausing and Dorobantu (2005); and Du et al. (2014).

**Table 1. System GMM estimation results, equation (6) and (7)**

	Ln (FDI inflows)	Ln (FDI trend)
$\text{Ln}(\text{FDI}_{it-1}) / \text{Ln}(\text{FDI\_trend}_{it-1})$	0.665*** (0.132)	0.168* (0.160)
$\text{Ln}(\text{GDP}_{it})$	0.369*** (0.147)	0.825*** (0.223)
$\text{Openness}_{it}$	0.0042** (0.00147)	0.00894** (0.00397)
$\text{Tariffs}_{it}$	0.0523 (0.0276)	0.0700 (0.0492)
$\text{Ln}(\text{exchange rate}_{it})$	-0.0419 (0.0686)	0.0385 (0.0847)
$\text{Corporate taxes}_{it}$	0.00243 (0.00633)	-0.0158 (0.0125)
<b>Income group</b>		
Low income	-0.0181 (0.294)	-0.577 (0.463)
Lower middle income	-0.117 (0.198)	-0.246 (0.382)
Upper middle income	0.0327 (0.156)	-0.105 (0.284)
<b>Regional dummies</b>		
Asia and Oceania	-0.292 (0.168)	-0.477 (0.323)
Europe	-0.00268 (0.188)	-0.163 (0.352)
Latin America and the Caribbean	0.102 (0.145)	0.105 (0.299)
North America	-0.192 (0.309)	-1.045 (0.544)
Other developed countries	0.240 (0.168)	0.0196 (0.238)
South-East Europe and the new CIS	0.183 (0.175)	0.0898 (0.355)
Cons	-1.977* (0.874)	-3.821* (1.859)
<b>Number of observations</b>	866	686
<b>Number of countries</b>	70	61
<b>Period</b>	2003–2019	2003–2019
<b>Model diagnostics (p-values)</b>		
<b>1st order autocorrelation</b>	0.000	0.000
<b>2nd order autocorrelation</b>	0.690	0.601
<b>Sargan test</b>	0.117	0.100
<b>Hansen test</b>	0.377	0.973

Source: Estimation based on multiple sources (see table 2a in the appendix).

Note: Year dummies are excluded from the model results. Africa is a base region (to which other regions are compared) and is omitted from the table results. High-income countries are also the base income group. Standard errors are in parentheses. \*\*\* 1% significance level, \*\* 5% significance level, \* 10% significance level.

## 5. Forecasting FDI with GMM

Panel data econometrics are gaining interest as forecasting tools (Baltagi and Griffin, 1997; Stock and Watson, 2004; Longhi and Nijkamp, 2007; Arkadieievich et al., 2008; Girardin and Kholodilin 2011; Wenzel 2013). Yet, their application is still limited relative to time-series econometrics. Their main value added is the ability to control for heterogeneity of FDI across countries (Baltagi, 2013), in addition to the usual dynamic structure. Micro (country) unit contains important information for the dynamics of the aggregate series, and hence, pooling the country data into a panel, can add to the forecasting precision, under the assumption of homogeneity across slope parameters (Fok, Van Dijk and Franses, 2005; Baltagi, 2008; Hsiao, 2014; Dees and Güntner, 2014). The individual countries' forecast errors can also partially cancel out upon aggregation (Theil, 1957; Baltagi, 2013).

The final GMM specifications used in forecasting are derived from (6) and (7) after excluding the control variables  $Z_{it}$ :

$$FDI_{it} = a_1 FDI_{it-1} + a_2' X_{it} + \partial_t + \rho_k + u_{it} \quad (8)$$

$$FDI\_trend_{it} = b_1 FDI\_trend_{it-1} + b_2' X_{it} + \partial_t + \rho_k + v_{it} \quad (9)$$

The GMM regressions results for decompositions (8) and (9) (table 3A in the appendix) are fully consistent with the estimates from equations (6) and (7) reported in table 1.

This model has been used to provide the latest 2020-2021 forecasting of FDI inflows and the FDI trend, reported by UNCTAD 2020 (as of June 2020). UNCTAD forecasting has been relying on the past values of FDI up to 2019 (autoregressive term) and the projections of GDP and trade for 2020 and 2021. GDP and trade projections for 2020 and 2021 are sourced from the International Monetary Fund (IMF) World Economic Outlook of April 2020 and from the World Trade Organization (April 2020),<sup>5</sup> respectively.

Table 2 reports the forecasted growth rates of global FDI inflows and the FDI trend for 2020 and 2021, on the basis of the GMM estimation of model (8) and (9) (see table 3A in the appendix) and the IMF and WTO projections for GDP and trade.

The projection indicates a sharp decline of global FDI in 2020, to about a third lower than its value in 2019 (-35 per cent) because of the impact of COVID-19 and pre-existing challenging conditions. COVID-19 is exerting a dramatic impact on FDI

<sup>5</sup> World Trade Organization (2020). Trade set to plunge as COVID-19 pandemic upends global economy, press release, [https://www.wto.org/english/news\\_e/pres20\\_e/pr855\\_e.htm](https://www.wto.org/english/news_e/pres20_e/pr855_e.htm).

**Table 2. FDI inflows and underlying FDI trend 2020–2021 forecasts, annual growth rate (Per cent)**

	2020	2021
<b>FDI inflows</b>	-35	-9
<b>Underlying FDI trend</b>	-12	4

*Source:* Forecast based on multiple sources: UNCTAD FDI database for FDI data; IMF World Economic Outlook (April 2020) for GDP and WTO (April 2020) for trade. Forecast obtained with Stata statistical software, aggregating country-level forecasts.

*Note:* UNCTAD projections for FDI inflows in *UNCTAD, 2020* are presented as ranges. For 2020, the reported expected decline of global FDI inflows is between 30 per cent and 40 per cent, including the GMM forecast in the table (-35 per cent) as the middle point (see *WIR 2020*, table I.3, page 8).

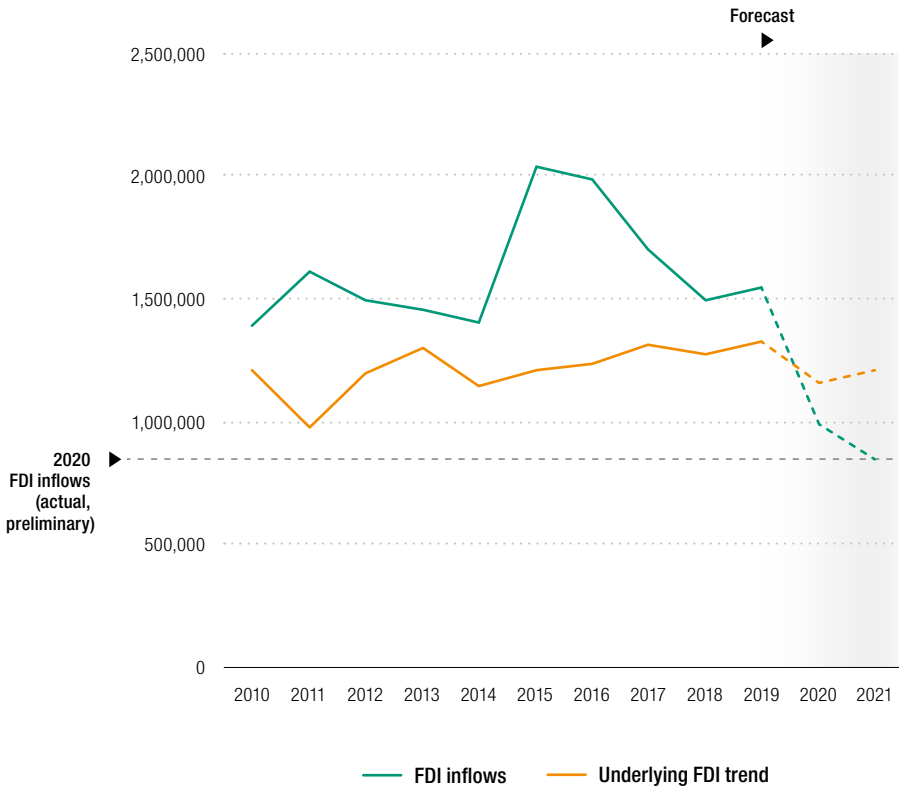
through different channels of transmission: the lockdown measures (supply-side), the automatic effect of reinvested earnings, the recessionary spiral (demand-side) and the policy context (see *UNCTAD, 2020*).

This projection is subject to significant uncertainty. The COVID-19 exogenous shock adds to the high volatility of the FDI trend over the last two decades. Accounting for this uncertainty, the decline in FDI in 2020 was reported in UNCTAD, 2020 as ranging between -30 per cent and -40 per cent. In 2021 the value of FDI was forecasted to further deteriorate, with an expected decrease of 9 per cent relative to 2020.

As expected, the forecast for the underlying trend – designed to capture the long-term dynamics of FDI, netting out fluctuations driven by one-off factors such as megadeals and volatile financial flows – indicate milder, but still substantial, decline in 2020 (-12 per cent in 2020 relative to the value of the underlying trend in 2019) and the first rebound in 2021 (+4 per cent relative to 2020). The prospects for the underlying trend can be seen as the more systematic effect of the economic crisis, after removing the effect of the temporary shock (mainly related to the lockdown measures). However, by limiting the impact of the highly variable components in FDI, the underlying trend is particularly suitable for the analysis of “normal” times, when the trend and the economic fundamentals drive the dynamics of FDI and the variation is residual. When there are big discontinuities and very large swings, the indication of the underlying trend should be taken carefully (and loosely interpreted as the long-run level to which FDI will eventually revert when the shock is over).

The most recent figures from UNCTAD’s *Global Investment Trend Monitor* (January 2021), although preliminary, confirm our most pessimistic forecasts, with a 42 per cent decline in global FDI inflows to a level of \$850 billion (figure 6).

**Figure 6. FDI inflows and underlying FDI trend, 2010–2019 and 2020–2021 forecasts** (Millions of dollars)



Source: Forecast based on multiple sources: UNCTAD FDI database for FDI data; IMF World Economic Outlook (April 2020) for GDP and WTO (April 2020) for trade. Forecast obtained with Stata statistical software, aggregating country-level forecasts. Preliminary figures for FDI inflows 2020 from UNCTAD's *Global Investment Trend Monitor* (January 2021).

Beyond a good forecasting performance in the current year – particularly in capturing the massive discontinuity due to COVID-19 – FDI inflows and the underlying FDI trend are relatively well forecast also for the previous years (table 3). In general, the forecasts for the FDI inflows perform well in capturing the direction of the change – in table 3, the expected sign is in line with the actual sign in 10 out of 12 years – but it allows for potentially very large gaps. The forecast of the FDI trend instead helps mitigate the differences, producing a forecast that is generally closer to the actual values than the FDI inflows, and for some years very close. Yet, large discrepancies persist in some specific years (for example, 2014 and 2015 for FDI inflows, and 2016 and 2009 for the FDI underlying trend).



**Table 3. FDI inflows and underlying FDI trend: realized and forecast 2008–2019, annual growth rates (Per cent)**

Year	FDI inflows	FDI inflows forecast	FDI trend	FDI trend forecast
2019	3	-2	4	1
2018	-12	-2	-3	-3
2017	-14	-21	7	-4
2016	-3	-12	2	-11
2015	45	2	6	-8
2014	-4	13	-12	-9
2013	-3	-1	8	2
2012	-8	-8	22	6
2011	16	15	-19	-16
2010	13	27	-1	0
2009	-17	-25	4	-11
2008	-21	-9	0	1

Source: UNCTAD FDI data for realised values. Forecasts with Stata statistical software.

## 6. GMM vs time series: an empirical comparison

Panel data econometric techniques have proved to be quite reliable FDI forecasting tools even in the very challenging context of the current pandemic. Yet, their applications to forecasting, within and beyond FDI, are growing but still quite limited. A lack of general forecasting practice suggests some additional caution, relative to more established forecasting techniques such as in the time-series domain. To this purpose, in this section, we run a complete comparison between GMM forecasting and two time-series forecasting methods: the univariate autoregressive integrated moving average (ARIMA) model, popularly known as the Box-Jenkins (1970) methodology, and the multivariate autoregressive integrated moving average with explanatory variable (ARIMAX) model. The ARIMA model explains the outcome variable – FDI inflow (trend) – as the linear function of its past values and the unknown stochastic error process. The ARIMAX model allows for the inclusion of explanatory covariates, such as GDP. To preserve important country-level information, we apply the time-series forecasting to each of 195 UN-recognized countries individually, and then aggregate them at the global level.

The country-by-country ARIMA models have the following specification:

$$FDI_t = \alpha_o + \sum_{i=1}^p \alpha_i FDI_{it-i} + \sum_{i=0}^q \beta_i \varepsilon_{t-i} \quad (10)$$

$$FDI\_trend_t = \gamma_o + \sum_{i=1}^s \gamma_i FDI\_trend_{it-i} + \sum_{i=0}^m \zeta_i \varepsilon_{t-i} \quad (11)$$

where  $FDI_t$  ( $FDI\_trend_t$ ) is a function of the autoregressive terms of the order  $p$  ( $s$ ) and the noise is presented as a moving average process of the order  $q$  ( $m$ ), and  $\alpha_o$  and  $\gamma_o$  are the two constants of equations (10) and (11), respectively. To allow for the inclusion of GDP as an explanatory variable, we also include an ARIMAX model in the comparison:

$$FDI_t = \alpha_o + \sum_{i=1}^p \alpha_i FDI_{it-i} + \lambda_0 GDP_t + \sum_{i=0}^q \beta_i \varepsilon_{t-i} \quad (12)$$

$$FDI\_trend_t = \gamma_o + \sum_{i=1}^s \gamma_i FDI_{it-i} + \varpi_0 GDP_t + \sum_{i=0}^m \zeta_i \varepsilon_{t-i} \quad (13)$$

The appropriate number of  $p$  and  $q$  ( $s$  and  $m$ ) autoregressive terms are assessed with the use of the autocorrelation function and partial autocorrelation function and their corresponding correlograms. The best model choice is decided with the Durbin and Watson test (for serial correlation) as well as the Akaike and Bayesian information criteria of the model fit (Lütkepohl, 1984; Enders, 2008). The appropriate model choice (10-13), parameters estimation and forecasts are automatized with an automatic forecasting algorithm produced in R software (Hyndman and Khandakar, 2007). Once country-level forecasts of FDI inflows and trend are obtained, they are aggregated at the global level.

To summarize the results of the comparison over the 2008–2019 period, two measures of forecast errors are calculated: mean absolute deviation (MAD) and mean square error (MSE) (table 4). MAD is the absolute difference between the actual value and the forecasted values divided by the number of observations forecasted. MSE is the sum of the squared errors divided by the number of observations forecasted.

The GMM forecasting performance is superior to the two time-series techniques based on both MAD and MSE. Time-series techniques, even when applied to each country, produce less precise forecasts than panel econometric techniques, supporting the relevant theory and empirical evidence (Baltagi et al., 2000; Baltagi, Bresson and Piroette, 2002; Brücker and Siliverstovs, 2006; see discussion in section 3). Applying the FDI trend improves the precision of forecasting for both the GMM and ARIMA techniques, confirming its validity as a tool to mitigate large variations and smooth the forecasting exercise. The poor forecasting performance of ARIMAX may be caused by the inclusion of endogenous GDP (see discussion in section 3), generating biased estimates at the country level and inflating the forecasts. Although the ARIMA model has better forecasting

performance than the ARIMAX model, it performs less well than the GMM model. The reason could be that ARIMA is a simple univariate technique that only account for the time dynamics of FDI, disregarding external macroeconomic factors that affect investors' preferences.

**Table 4. FDI inflows and underlying FDI trend: forecast errors by GMM, ARIMA and ARIMAX**

Model	Forecast error	FDI inflow (6)	FDI trend (7)
GMM	MAD	11	7
	MSE	236	87
ARIMA	MAD	14	9
	MSE	354	147
ARIMAX	MAD	18	38
	MSE	360	1541

Source: Authors' calculation based on GMM, ARIMA and ARIMAX forecasts over the 2008-2019 period, obtained in Stata (GMM) and R (ARIMA and ARIMAX).

## 7. Conclusions

One look at the pattern of global FDI inflows in the last 20 years (figure 1) suffices to appreciate why forecasting global FDI has become a very challenging task. Yet, FDI remains one of the most relevant economic targets for countries, especially developing ones, and a key indicator of global economic trends. This paper is a step forward in the development of reliable forecasting tools to predict global FDI.

The methodology presented in this paper was the basis of the UNCTAD forecast of global FDI 2020–2021 reported by *UNCTAD 2020*, produced in the midst of the outbreak of the COVID-19 pandemic. The model has proved to be effective in capturing the observed collapse of global FDI in 2020.

The proposed methodology is based on dynamic panel econometric techniques, particularly the system generalized method of moments (system GMM) of Arellano and Bover (1995) (Blundell and Bond, 1998). Dynamic panel econometric techniques directly address the heterogeneous nature of FDI

across countries and FDI dynamics across time. System GMM is suited to deal with endogeneity issues caused by the inclusion of lagged FDI and GDP among the regressors.

The forecast is applied not only to the FDI inflows but also to the underlying FDI trend. The underlying FDI trend is an alternative representation of FDI inflows, more in line with the economic fundamentals as it reduces noise in the data caused by one-off transactions and financial flows. The forecast of the underlying trend complements the standard FDI forecast by providing an indication of the long-term future dynamics of FDI.

Compared with two alternative time-series techniques (ARIMA and ARIMAX), the GMM models show better predictive performance, supporting the case for the use of panel data techniques (rather than time-series), pooling countries' individual information for forecasting FDI at the aggregate level.

Although highly encouraging, the results presented in this paper should not lead to any general claim about the superiority of this approach. This study aims at providing a step forward stimulating more systematic analysis of different methods in forecasting FDI.

Beyond GMM, other econometric tools deserve investigation. The panel vector autoregression (PVAR) accounts well for the static and dynamic interdependence between variables and between countries, as well as the contemporaneous and lagged effects of exogenous variables (Canova and Ciccarelli, 2004). This could be an important aspect in modeling FDI dynamics, where investors usually take time to react to changed macroeconomic circumstances. Spatial econometric techniques is another interesting option (Baltagi, 2013; Baltagi, Fingleton and Pirotte, 2014). In addition to the heterogenous nature of FDI across counties (and possibly across time) spatial econometric tools account for the spatial (geographical) dependence of FDI and its determinants.

\* \* \*

Improving methods to forecast international investment flows, while seemingly an impossible task due to their lumpy and volatile nature, is important for the policy community. At the national level, it is helpful for policymakers to understand the expected direction of investment trends in processes ranging from designing industrial policies to setting performance targets for investment promotion agencies and special economic zones. At the international level, ongoing efforts to boost investment facilitation and to negotiate investment chapters in regional economic cooperation agreements benefit from greater awareness of the tides against which they are rowing and the currents they can exploit.

A huge push for new investment in infrastructure, renewable energy and Industry 4.0 is expected from the recovery stimulus packages that are being adopted in the more affluent regions of the world. It will be interesting to see how this big push affects investment trends going forward and to what extent the model presented in this paper will be able to capture those effects.

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## Appendix

**Table 1A. Pearson correlation coefficient matrix, underlying FDI trend, trend - Kalman filter, trend - HP filter**

	Trend Kalman filter	Trend HP filter	Underlying FDI trend
Trend Kalman filter	1.0000		
Trend HP filter	0.9702	1.0000	
Underlying FDI trend	0.9496	0.9746	1.0000

Source: Authors' elaboration.

**Table 2A. Variables definition, data sources and supporting literature**

Variable	Definition	Sources	Literature review
<b>Dependent variable</b>			
FDI	Log (FDI inflows, millions of dollars, current prices)	UNCTAD (national statistical sources and central banks)	
FDI trend	Log (FDI underlying trend (equation1))	UNCTAD	
<b>Main explanatory variables (<math>X_{it}</math>)</b>			
Market size	Log (GDP, million of dollars, current prices)	UNCTAD; IMF World Economic Outlook	Resmini, 2000 Bevan and Estrin, 2004 Janicki and Wunnava, 2004 Carstensen and Toubal, 2004 Clausing and Dorobantu, 2005 Hilber and Voicu, 2010 Estrin and Uvalic, 2014
Openness	(Export + Import) / GDP *100	UNCTAD; IMF World Economic Outlook; WTO	Garibaldi et al., 2001 Janicki and Wunnava, 2004 Clausing and Dorobantu, 2005 Du, Harrison and Jefferson, 2014
<b>Controls (<math>Z_{it}</math>)</b>			
Tax levels	Log (Corporate tax)	Tax Foundation	Carstensen and Toubal, 2004 Clausing and Dorobantu, 2005 Overesch and Wamser, 2010
Labour cost/ Income	Dummy variable for different income groups	World Bank	Holland and Pain, 1998 Resmini, 2000 Janicki and Wunnava, 2004 Bevan and Estrin, 2004 Carstensen and Toubal, 2004
Tariffs	Log (Import tariffs on manufacturing goods, ores and metal)	UNCTAD	Cardamone and Scoppola, 2012 Carstensen and Toubal, 2004 Du, Harrison and Jefferson, 2014 Hijzen, Görg and Manchin, 2008
Exchange rate	Log (Exchange rate – compared to dollar)	International Financial Statistics, central banks	Blonigen, 1997 Abbott, Cushman and De Vita, 2012 Cavallari and d'Addona, 2013 Jeanneret, 2016

Source: Authors' elaboration.

**Table 3A. System GMM estimation results, specification (8) and (9)**

	FDI inflows Model (8)	FDI trend Model (9)
<b>Autoregressive term</b>		
Log (FDI <sub>t-1</sub> )	0.485*** (0.0977)	
Log (FDI trend <sub>t-1</sub> )		0.328*** (0.0736)
<b>Macroeconomic factors</b>		
Log (GDP)	0.340** (0.153)	0.643*** (0.109)
Trade openness	0.00356** (0.00175)	0.00538*** (0.00111)
<b>Regional dummies</b>		
Asia and Oceania	0.210 (0.251)	-0.135 (0.166)
Europe	0.447 (0.328)	0.125 (0.281)
Latin America and the Caribbean	0.363* (0.195)	0.143 (0.166)
North America	1.042 (0.655)	-0.0263 (0.489)
Other developed countries	0.735** (0.293)	0.336 (0.216)
South East and the new CIS	0.308** (0.130)	0.245* (0.130)
<b>Time dummies</b>		
2004	0 (.)	0.197** (0.0861)
2005	0 (.)	0.0437 (0.111)
2006	0.328*** (0.0979)	0.378*** (0.0947)
2007	0.341*** (0.0927)	0.248* (0.137)
2008	0.315*** (0.107)	0.287*** (0.109)
2009	-0.0287 (0.111)	0.222* (0.131)
2010	0.150 (0.115)	0.241** (0.108)
2011	0.261** (0.113)	0.0890 (0.138)
2012	0.198* (0.103)	0.161 (0.133)

.../...

**Table 3A. System GMM estimation results, specification (8) and (9) (Concluded)**

	FDI inflows Model (8)	FDI trend Model (9)
<b>Time dummies</b>		
2013	0.0870 (0.107)	0.0870 (0.126)
2014	0.130 (0.115)	0.166 (0.126)
2015	0.0252 (0.117)	0.0690 (0.141)
2016	0.181 (0.115)	0.194 (0.125)
2017	0.141 (0.119)	0.123 (0.127)
2018	0.159 (0.109)	0.00881 (0.127)
2019	0.0497 (0.108)	0.0787 (0.133)
_cons	-0.554 (1.107)	-2.645*** (0.721)
<b>Number of observations</b>	1662	1829
<b>Number of countries</b>	111	111
<b>Diagnostics (p-value)</b>		
<b>Autocorrelation tests</b>		
<b>1st order</b>	0.000	0.000
<b>2nd order</b>	0.106	0.108
<b>Hansen test</b>	0.099	0.732

Source: Estimation based on multiple sources (see table 2a).

Note: Africa is a base region (that other regions are compared to) and is omitted. Standard errors in parentheses. \*\*\* 1% significance level, \*\* 5% significance level, \* 10% significance level.