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FOREIGN DIRECT INVESTMENT AND INDUSTRIALIZATION IN SUB-SAHARAN AFRICA: IS THERE A SPATIAL EFFECT?

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Abstract: This paper analyzes the effect of Foreign Direct Investment (FDI) on industrialization in Sub-Saharan Africa. Using panel data on 30 countries over the period 1996-2019, we apply a dynamic spatial panel regression. The results show that FDI contributes positively to industrialization. Moreover, there is a spatial effect that improves the estimations. Thus, a country whose neighbors have received more FDI is more likely to industrialize than a country that does not have these assets.

Keywords: Foreign Direct Investment, Industrialization, Spatial effects, sub-Saharan Africa.

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1. INTRODUCTION

Most development theories present industrialization as a key factor for an economy's emergence (James A. Robinson, 2010; African Development Bank, 2018). To make it happen, investment is essential. Due to the lack of capital observed since independence, many countries are seeking the support of foreign investors and creating a wide range of incentives to attract Foreign Direct Investment (FDI).

FDI can be understood as the establishment of a company from a given country (whose parent company is in that home country) in a foreign territory (host country), or as the investment by foreigners (shareholding) in a local company or a foreign company (usually a Multi-National Firm) established in the host country. Over the past three decades, investors from most countries have significantly increased their participation in global investments due to the reduction of trade barriers and the subsequent growth of capital flows.

In this context, FDI has become the largest source of external finance for developing countries (Aitken and Harrison, 1999) and has replaced international trade as the main driver of global market integration (Raff, Ryan, and Stähler, 2012). In Africa, FDI inflows have increased significantly from US$20 billion in 2001 to US$54 billion in 2014 (UNECA, 2015). Given this trend, a key question to analyze is whether the growth of FDI in Sub-Saharan Africa has contributed to its industrialization. This question is all the more credible given that most Sub-Saharan African countries have a medium-term industrialization agenda, with the goal of achieving emerging country status.

In the literature, the relationship between FDI and industrialization is analyzed on both the theoretical and empirical aspects. On the theoretical aspect, most authors agree on the fact that the effect of FDI on the host country's industry occurs at several levels. On the one hand, by integration into the global value chain dominated by transnational corporations, and on the other hand, the entry of FDI can also lead to a positive enhancement effect or a negative crowding-out effect by technological spillover (learning time, abandonment of national entrepreneurs who do not have the means to acquire this technology).

As empirical studies on our topic are scarce, most support the idea that FDI does not exert an independent and robust exogenous influence on industrialization (Megbowon *et al.*, 2019; Ongo, 2016; Gui-Diby *et al.*, 2015 and Okafor *et al.*, 2015). Other papers show that FDI has a positive and significant effects on industrialization (Jie and Shamshedin, 2019; Patrick Müller, 2021).

Among all the studies that have preceded us, none has attempted to capture the spatial effects of FDI on industrialization, yet in a context of growing integration and trade liberalization between states, taking these effects into account would contribute to the analysis of the different channels through which FDI can improve industrialization in Sub-Saharan Africa.

The issues of regional integration and the free movement of goods and services are signs of a neighborhood effect. Considering these observations: is there a neighborhood effect between FDI and industrialization? If so, do these effects improve the effect of FDI on industrialization?

Our main contribution is to introduce spatial effects in the modeling of the relationship between FDI and industrialization, by using a weight matrix based on the distances between 30 Sub-Saharan African countries over the period 1996-2019.

This paper, therefore, analyzes the effect of FDI on industrialization in Sub-Saharan Africa. Results show a non-significant effect of FDI on industrialization if we do not take into account the possibility of spillover in a given country from the effects of FDI installed in its neighboring countries. Moreover, an analysis with a spatial lag also on FDI has shown that although FDI has a positive effect on industrialization in sub-Saharan Africa, most of this effect for a country comes from the externalities of FDI invested in its neighbors. There is thus a spillover effect.

Referring to the work of Blonigen *et al* (2007 and Regelink & Elhorst (2015), there is a possibility of FDI's endogeneity in our work. We hope to correct it by adopting dynamic spatial econometric modeling.

The rest of this paper is structured as follow: section 2 presents the literature review of the relation between Foreign direct investment and industrialization; section 3 presents the methodological framework; the results of our analysis are presented in section 4, followed by a conclusion.

2. FOREIGN DIRECT INVESTMENT AND INDUSTRIALIZATION

In the literature, the relationship between Foreign Direct Investment and industrialization is analyzed on both a theoretical and empirical level.

On the theoretical level, it has been shown that the degree of foreign capital inflow will have a significant impact on the host country's industrial modernization (Kee *et al.*, 2016). The effect of FDI on the host country's industry occurs in several degrees. On the one hand, after the entry of foreign capital, the domestic industry is integrated into the global value chain dominated by transnational companies. Because of the monopoly and competition motivation of multinational firms, combined with the weak technology and talent of developing countries, the international division of labor dominated by multinational firms is easily locked into the lower end of the value chain.

On the other hand, according to the literature on the spillover effect of FDI, the entry of FDI can also lead to a positive upgrading effect or a negative crowding out effect through technological spillover. Moreover, the development of international trade will promote the allocation of domestic resources and the adjustment of the industrial structure, which will affect economic growth and fluctuations through the adjustment of the price of domestic resources (Lipsey,2000). There is a spillover effect from domestic firms to multinational firms in the use of local inputs. Multinational firms using more local inputs than domestic firms reduce the latter's level of production of intermediate goods (Markusen *et al*, 1999). Competition in product and factor markets tends to reduce the profits of domestic firms, but linkage effects with supplier industries can reduce input costs and increase profits.

The spread of FDI means high-end technology brought in by multinational firms, which will help to emulate technological innovation for developing countries (Balaine, 2009). On the other hand, FDI can have adverse effects on the domestic economy, such as decreasing employment and wages and international trade deficit (Davis and Huston, 1992; Barrell *et al*., 1997; Blomstrom *et al*., 1997).

Empirically, the ideas of Brasseul (1993) and Rodriguez-Clare (1996) converge on the fact that FDI influences industrialization through two mechanisms. A direct mechanism marked by the volume of jobs created in the manufacturing sector, and an indirect mechanism based on the transfer of technology by multinational firms to domestic firms. For example, it has been shown that in the United States the technology provided by foreign firms contributes to a 10% increase in the productivity of local firms (Haskel *et al*, 2007).

As regards the volume of jobs, the quality of human capital remains a strong condition for ensuring a better impact of FDI on industrialization in the medium and long term in developing countries. The increase in academic and professional training allows for a better absorption of tacit knowledge in new technologies and is therefore a factor in the attractiveness of FDI and therefore industrialization (Bruno *et al*, 2013; Majeed *et al*, 2008). Furthermore, Gorg *et al* (2005), by examining data from several Ghanaian firms between 1991 and 1997, show that capital mobility reinforces the contribution of human capital.

On the whole, in empirical evidence, foreign direct investment has been recognized as one of the main tools that can lead the host country to achieve industrialization because of the multiple roles of providing capital investment, technology and skills, which are vital to the industrialization process. However, the indirect spillovers (human capital enhancement, improved country attractiveness, etc.) of foreign direct investment on host country industrialization have mostly been observed in South and East Asia. Di Maio (2009) and Dahlman (2009) show in particular that the role of the state in supporting the industrial process is crucial. Technological progress and investment in human capital and infrastructure should reassure foreign investors that a real industrial process is being set up.

In Africa, to our knowledge, very few studies have looked at the industrial spillovers of FDI, however, as recent studies we can cite those of: Mamba *et al* (2020), Megbowon *et al* (2019), Shamshedin *et al* (2019), Ongo (2016), Loris *et al* (2015), Gui-Diby *et al* (2015), and Okafor *et al* (2015). Indeed, Mamba *et al*. (2020) analyze the effects of FDI on structural transformation in West African Economic and Monetary Union

(WAEMU) countries by considering the industry, manufacturing, agriculture, and services sectors from 1990 to 2017. Using a panel error correction model, they show the neutrality of FDI flows on industrial, manufacturing and agricultural productivity in the WAEMU region. However, the results showed a positive effect of FDI inflows on service sector productivity and imply that the low quality of WAEMU institutions may lead to the failure to design and implement sound agricultural policies in the region that may not attract FDI, resulting in a negative effect of FDI on the structural transformation of the region.

Megbowon *et al* (2019) analyze the effects of FDI from China on the industrialization of African countries. Using a standard error correction model on a panel of 26 sub-Saharan African economies over the period 2003-2016, the authors show that FDI from China into sub-Saharan Africa has a positive and insignificant effect on industrialization in sub-Saharan Africa. This result can be explained by weak energy infrastructure. Shamshedin *et al* (2019) test the effect of FDI flows to Ethiopia on industrialization using a vector autoregression model (VECM) over the period 1992 to 2017. The result of the Johansen cointegration test showed that there is a long-run equilibrium relationship between the variables. Moreover, the result of VECM for the long-run analysis showed that FDI has a positive and significant impact on industrialization while the result of the short-run analysis showed that FDI has a positive and insignificant effect on industrialization.

Ongo (2016) uses data from 53 African countries from 1974 to 2014 to discuss the contribution of FDI to the continent industrialization. The estimation technique is based on the system generalized method of moments on dynamic panel. The results show that: FDI contributes significantly to industrial value added relative to GDP but does not contribute to industrial employment; the positive and significant effect was observed in four subregions except East Africa; using a composite index of industrialization, the contribution of FDI is very high.

Loris *et al.* (2015) examine the relationship between FDI and the industrialization process in Africa. They use panel data from 49 countries over the period 1980-2009. The results indicate that FDI did not significantly affect industrialization in these countries, while other variables, such as market size, financial sector, and international trade, were important. This study concludes that the role of FDI in the transformation agenda currently under discussion in Africa should be carefully analyzed to maximize the impact of these capital inflows. Specifically, Gui-Diby *et al* (2015) show that FDI has not positively and significantly influenced Africa's industrialization process. The paper looks at 49 countries between 1980 and 2009. The generalized least squares method is used. The insignificance of the results is explained by the low contribution of the industrial sector to GDP and inappropriate industrial policies. Okafor *et al*

(2015) look at 36 south african countries between 1996 and 2010. According to this study, factors related to market size (economic weight of the countries, trade openness among others) tend to justify the massive entry of FDI in Sub-Saharan Africa. However, long-term growth is less influenced by these factors.

These studies, although analytically relevant, do not cover all the contours of the FDI-industrialization relationship in Africa. For example, the failure to consider spatial effects and the possibility of a dynamic relationship in the estimates could reduce or even mask the expected impact of FDI on the industrialization of African countries. Indeed, none of these studies has attempted to capture the spatial effects of FDI on industrialization, yet in a context of growing integration and trade liberalization between States, taking these effects into account would contribute to the analysis of the different channels through which FDI can improve industrialization on the continent. This last observation remains valid outside the continent. Spatiality is too important to be ignored.

Anselin (1988) already shows that some economic behavior in one region can be influenced by neighboring regions, so they tend to show spatial dependence or spatial correlation. Spatiality influences FDI and also affects industrial structure. For Davis *et al.* (2001) and Fujita *et al.* (1996), since ancient times, geographic layout has significantly determined population density and transportation cost even with rapid improved technologies. For example, the regional labor market depends on the geographical arrangements of the countries in the region, which affects the cost of industrial firms and thus influences the growth of the industrial sector. For Puga *et al.* (2010), once a metropolis has been formed, labor and firms would cluster, due to a productivity offset and a large market.

To our knowledge, only two studies have attempted to capture the spatial effects of FDI on industrialization. Ni *et al.* (2017) used firm-level data to study the spillover effects of FDI in Vietnam, controlling for the origin of foreign investors. Zhou *et al.* (2019) studied the role of industrial structure in the evolution of ecological efficiency, focusing on the spillover effect of industrial structure upgrading. Spatial interactions justify accelerating economic integration among Association of South East Asian Nations (ASEAN) countries to continuously attract FDI.

3. METHODOLOGICAL FRAMEWORK

3.1. Analysis of spatial effects

3.1.1. Weight matrices and spatial effects analysis

The methods of spatial econometrics aim to deal with the two main characteristics of spatial data: spatial autocorrelation, which measures the influence of one observation on another that is geographically close to it, and spatial heterogeneity, which is linked to the spatial differentiation of variables and behaviours, and measures whether the effect of a phenomenon on an observation depends on its geographical location. Cliff and Ord (1973) wrote a book presenting the state of knowledge in spatial econometrics in a synthetic way. Then, at the end of the 1970s and the beginning of the 1980s, we witnessed the refinement of Cliff and Ord's original analytical framework and, more particularly, the development of the theory of estimation and the related tests (Ord, 1975; Haining, 1978; Anselin, 1988).

The definition of the spatial neighborhood necessary for the verification of the existence of a spatial phenomenon and the consideration of the phenomenon in case of existence are prerequisites for a modeling with spatial effect. Concerning the spatial neighborhood, Le Gallo (2000) divides the locations in space into three categories. For the author, these can be points representing, for example, the locations of stores, urban areas, etc. These points are often measured by their size, which is the same as the size of a city. These points are often measured by their latitude and longitude. Second, these locations can be lines, such as a road or river network. Finally, data are sometimes provided for geographic areas such as regions or countries. In all cases, the number of these points, lines or areas is finite.

For Cressie (1993), this characteristic makes it possible to distinguish between the techniques of spatial econometrics and those of geostatistics. Spatial econometrics is mainly used when one is in the presence of a finite set (regular or not) of points or areas linked together by neighborhood relations. The definition of the spatial neighborhood requires the specification of the topology of the spatial system and for this, we use weight matrices.

Since the spatial units are generally interdependent, the relative positions of the observations with respect to each other must be considered in addition to their dimensions and structures. Therefore, these matrices are exogenous, they are defined a priori by the modeler based on his knowledge of the relationships and interactions between spatial units. Weight matrices fall into two main categories: adjacency matrices and generalized weight matrices. For more information on adjacency matrices, the reader may refer to the work of Anselin and Smimov (1996).

Following Blonigen *et al* (2006), we adopt a generalized weight matrix. However, unlike the latter, we choose an exponential specification.

Indeed, in the case of general weight matrices, each element represents the intensity of the interaction between the two countries, an intensity that is no longer necessarily related to contiguity. A first possibility is to use distance matrices. In this case, it is assumed that the intensity of the interaction between two countries i and j depends on the distance between the centers of these countries or between the capitals of these countries. Several indicators can be used depending on the definition of the distance:

distance as the crow flies, distance by road, etc. One can of course generalize to travel times or more general accessibility indices. Various functional forms are also available, the most commonly used being the inverse exponential function or a function of the inverse of the distance, as used by Blonigen *et al* (2006). If d_{ij} denotes the distance between country i and country j, the elements of the distance matrix for these two different cases are respectively defined by :

$$W_{ij} = e^{-\alpha d_{ij})} \tag{1}$$

And

$$W_{ij} = \begin{cases} \frac{1}{d_{ij}^{\beta}} si\ d_{ij} < \bar{d} \\ 0\ sinon \end{cases} \tag{2}$$

α et β are parameters determined a priori, $\bar{d}$ is the threshold value beyond which it is assumed that there is no direct interaction between region i and region j.

As mentioned above, in this work we use the inverse exponential function with $\alpha = 1$. The formula we use to find the haversine distance (distance with spherical approximation of the earth) between two points on the globe according to Sinnott (1984) is the following:

$$a = \sin^2(\Delta\phi/2) + \cos\left(\phi_A * \frac{\pi}{180}\right) * \cos\left(\phi_B * \frac{\pi}{180}\right) * \sin^2\left(\frac{\Delta\lambda}{2}\right) \tag{3}$$

$$\Delta\phi = (\phi_B - \phi_A) * \frac{\pi}{180} \tag{4}$$

$$\Delta\lambda = (\lambda_B - \lambda_B) * \frac{\pi}{180} \tag{5}$$

$$c = 2 * atan2\left(\sqrt{a}, \sqrt{1-a}\right) \tag{6}$$

$$d_{AB} = R.c \tag{7}$$

Where d_{AB} is the distance in kilometers between two points A and B on the globe. R=6 371 km the radius of the earth. ϕ_i is the latitude of the point i and λ_i the longitude of the point $i, (i \epsilon \{A, B\})$.

Adjacency matrices or generalized weight matrices are often standardized so that the sum of each row is equals to 1. The weights are then between 0 and 1 and this operation makes the spatial parameters in the spatial processes comparable between models.

Once the spatial neighborhood has been defined, we analyze the existence of spatial effects, namely spatial autocorrelation and spatial heterogeneity. With respect to spatial autocorrelation, there are several statistics available to measure it in quantitative variables: Geyry's index, Moran's index. The most widely used global statistic is the one of Moran (1948). It is formally written as follows:

$$I = \frac{\frac{\Sigma_{ij} w_{ij} (x_i - \overline{x})(x_j - \overline{x})}{s_o}}{\frac{\Sigma_i (x_i - \overline{x})^2}{N}} \tag{8}$$

With $S_0 = \Sigma_{ij} W_{ij} \; et \; \overline{x} = \frac{1}{N} \Sigma_i x_i$. The numerator is interpreted as the covariance between contiguous units, each contiguity being weighted by $\frac{W_{ij}}{S_o}$. It is normalized by the denominator which is the total observed variance. The reader can find analytical expressions for the mean and variance of this statistic under various assumptions including normality (Cliff and Ord, 1973, 1981). The centered and reduced Moran statistic asymptotically follows a normal distribution of zero mean and unit variance and thus serves as the basis for testing spatial autocorrelation in a series. The Moran test was developed as a two-dimensional extension of the test for temporal correlation in univariate time series. Under the null hypothesis of spatial independence, the Moran test is a locally best invariant test (King, 1981) and is asymptotically a likelihood ratio test. Once identified, spatial autocorrelation must be taken into account in the model specification and as an example, see the work of Case *et al* (1993) and Brueckner (1998) to model strategic interactions and tax competition between municipalities by fitting a spatial autoregressive model and many other works.

Spatial heterogeneity in econometric specifications can be expressed in two ways: by different coefficients or by different variances of the error terms according to location (Le Gallo, 2004). In the first case, we speak of spatial instability of the regression parameters, which vary systematically with location. In the second case, we are confronted with a problem of heteroscedasticity, which is a frequent problem in cross sections. These two cases, structural instability and heteroscedasticity, can appear together. The last one is identified and treated by the same methods as those developed in general econometrics without explicitly taking into account the spatial nature of the data, even if their adaptation in a spatial framework allows to highlight interesting interpretations. For example, dummy variables and regimes are typically used to model discrete variations of the function in a regression model. For Greene (2000), these variations can be of any nature, such as temporal variations, variations by age, by income level, etc. See for example Le Gallo (2004) for applications.

In this study, we will verify the existence of spatial effects of FDI on the industrialization of Sub-Saharan African countries and to do so, we will use a dynamic panel model to take these effects into account. This being said, in the following subsection, we propose an overview of the Generalized Method of Moments (GMM) on spatial dynamics panel and its use in the analysis of the effects of FDI on industrialization.

3.1.2. The GMM estimation method in Spatial Dynamic Panel

The work of Cliff and Ord (1981), Anselin (2001), and Elhorst (2014) provide extensive studies of different spatial patterns and suggest econometric strategies for estimating them. More generally, spatial data are characterized by the spatial arrangement of observations. As Monteiro and Kukenova (2009) point out, the idea behind modeling by GMM approach in spatial dynamic panel is the risk of having in simple panel: (i) a bias due to the autocorrelation of errors, because each country being observed over all the years, there is a possibility of autocorrelation of errors for the same country and if the countries are interdependent, this autocorrelation is generalized to all the countries and therefore to the model; (ii) an omitted variable bias (endogeneity bias), corresponding to the failure to take into account the spatial lags of the variables and in the errors; (iii) multicollinearity between certain analysis variables; (iv) an influence of the past value of the dependent variable on its present realization.

The spatial links of the observations are measured by defining the weight matrix. In the dynamic framework, since the distances are time invariant (this will generally be the case), we have $W_t = (W_{ij})_t = W_{t+1}$). However, when dealing with unbalanced panel data, this is no longer true (Egger *et al*, 2005). By stacking the data first by time and then by country, the full weighting matrix, W, is given by :

$$W = \begin{pmatrix} W_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & W_T \end{pmatrix} \tag{9}$$

In general, a spatial dynamic panel model can be defined as follows (Elhorst J. P. , 2014):

$$MANUFVA_t = \alpha MANUFVA_{t-1} + \rho(W\,MANUFVA)_t + \mu_1\, FDI_t + \mu_2\,(W\,FDI)_t + X_t\beta_1 + (WX)_t\beta_2 + \varepsilon_t \tag{10}$$

$$\varepsilon_t = \eta + \phi W \varepsilon_t + \upsilon_t,\ t = 1 \ldots T \qquad (11)$$

where $MANUFVA_t$ is a vector $N \times 1$ of the countries' manufacturing value added divided by their GDP. FDI_t is the $N \times 1$ vector of FDI of each country. W is the spatial weighting matrix of size $N \times N$, non-stochastic and exogenous to the model, η is the vector of the country effect, X_t is a matrix $N \times p$ matrix of p explanatory variables other than FDI ($p \geq 0$). μ_1 (respectively μ_2) is a constant, measuring the direct effect of FDI on industrialization (respectively the indirect effect of FDI on industrialization). β_1 and β_2 are vectors of size $P\times1$ measuring the direct and indirect effects of the other explanatory variables. Finally, υ_t follows a Gaussian distribution ($N(0, \Omega)$).

By adding some restrictions to the parameters, two popular spatial model specifications can be derived from this general spatial model, namely the dynamic spatial offset model ($\phi = 0$) and the dynamic spatial error model ($\rho = 0$).

The spatial autoregressive coefficient (ρ) associated to $W_t MANUFVA_t$ represents the effect of the weighted neighborhood average. The spatial lag term determines whether the dependent variable $MANUFVA_t$ is affected by $MANUFVA_t$ from other nearby locations weighted by a given criterion. Let w_{min} and w_{max} be the smallest and highest eigenvalue of the spatial matrix W, then this spatial effect is assumed to be between $\frac{1}{w_{\min}}$ and $\frac{1}{w_{\max}}$.

Despite the fact that dynamic panel models have been the subject of relatively important recent developments (see Baltagi and Kao, 2000 or Phillips and Moon, 2000), econometric analysis of spatial dynamic panel models is scarce. In fact, there are only a limited number of estimators available that deal with spatial and temporal dependence in a panel setting. For our model presented above, the System-GMM method seems to be the most appropriate (Arellano & Bover, 1995; Blundell & Bond, 1998).

Specifically with respect to the GMM approach, empirical papers dealing with a dynamic spatial panel model with several endogenous variables generally apply the GMM method in a system. Haining (1978) has already proposed to instrument a first-order spatial autoregressive model using lagged dependent variables. While this method is not effective in a cross-sectional setting because it does not efficiently use all available information (Anselin, 1988), this is no longer necessarily the case in a panel setting. The bias-corrected LSDV-IV estimator proposed by Korniotis (2007) is consistent with this approach and considers the lagged spatial lag and the dependent variable as instruments. As a result, the use of the GMM system could be justified in this trade-off situation, since the spatial lag would be instrumented by lagged values of the dependent variable and the spatial autoregressive variable. In particular, the extended GMM can correct for the endogeneity of the spatial lag and the lagged dependent variable as well as other potentially endogenous explanatory variables. It also allows for some econometric problems such as measurement error and instrument weakness. In addition, it also controls for time-invariant individual-specific effects such as distance, culture and political structure. From a practical point of view, it also avoids the inversion of the high-dimensional spatial weights matrix W and the computation of its eigenvalues, which may sometimes be computationally infeasible to estimate the model with N and/or T large enough.

For simplicity, the model is reformulated for a given country i ($i = 1, ..., N$) at time t ($t = 1, ..., T$) :

$$MANUFVA_{it} = \alpha MANUFVA_{it-1} + \rho(WMANUFVA_t) + \mu_1 FDI_{it} + \mu_2(W\,FDI_t)_i + X_{it}\beta_1 + (W\,X_t)_i\,\beta_2 + \eta_i + \upsilon_{it} \qquad (12)$$

According to the GMM procedure, we need to get rid of the individual effects (η_i) correlated to the covariates and the lagged dependent variable, by rewriting the equation in first order difference for country i at time t :

$$\Delta MANUFVA_{it} = \alpha\Delta MANUFVA_{it-1} + \rho\Delta(WMANUFVA_t)_i + \mu_1\Delta FDI_{it} + \mu_2\Delta(W\,FDI_t)_i + \Delta X_{it}\beta_1 + \Delta(WX_t)_i\,\beta_2 + \upsilon_{it} \qquad (13)$$

Although the within fixed effects estimator cancels the country effect (η_i), the lagged endogenous variable ($\Delta MANUFVA_{it-1}$)) is still correlated with the idiosyncratic error terms (υ_{it}). Anderson and Hsiao (1981) showed that the within estimator has a measured bias of the order of O (1/T) and is consistent only for large T. Since this condition is generally not satisfied, the GMM estimator is also biased and inconsistent. Arellano and Bond (1991) propose the following moment conditions associated with the above equation:

$$E(MANUFVA_{i,t-\tau}\ \Delta\upsilon_{it})=0; \text{ for } t = 3,\ldots, T \text{ et } 2 \leq \tau \leq t-1 \qquad (14)$$

But estimation based solely on these moment conditions is insufficient if the assumption of strict exogeneity of the covariates (X_{it} and FDI_{it}) has not been verified. The explanatory variables are valid instruments to improve the efficiency of the estimator, only when the strict exogeneity hypothesis is satisfied:

$$E(X_{i\tau}\ \Delta\upsilon_{it}) = 0; \text{ for } t = 3,\ldots, T \text{ et } 2 \leq \tau \leq T \qquad (15)$$

$$\text{and } E(FDI_{i\tau}\ \Delta\upsilon_{it}) = 0; \text{ for } t = 3,\ldots, T \text{ et } 2 \leq \tau \leq T \qquad (16)$$

However, the GMM estimator based on the above moment conditions may still be inconsistent when $\tau < 2$ and in the presence of reverse causality (Kukenova *et al.* 2009), i.e. $E(X_{i\tau}\ \Delta\upsilon_{it}) \neq 0$ and $E(FDI_{i\tau}\ \Delta\upsilon_{it}) \neq 0$. To overcome this problem, one can assume that the covariates are weakly exogenous for $\tau < t$, which means that the moment condition can be rewritten :

$$E(X_{i,t-\tau})\ \Delta\upsilon_{it}) = 0;\ pour\ t = 3,\ldots, T\ et\ 1 \leq \tau \leq t\text{-}1 \quad (17)$$

For the different endogenous variables and taking into account the imprecision due to the sample size, the valid moment conditions are :

$$E(\Delta MANUFVA_{i,t-1}\ \upsilon_{it}) = 0;\ \text{for } t = 3,\ldots, T \quad (18)$$

$$E(\Delta EX_{i,t}\ \upsilon_{it}) = 0;\ \text{for } t = 2,\ldots, T \quad (19)$$

$$E(\Delta EN_{i,t-1}\ \upsilon_{it}) = 0;\ \text{for } t = 3,\ldots, T \quad (20)$$

$$E(\Delta[W_{t-1}\ MANUFVA_{t-1})]\ \upsilon_{it}) = 0;\ \text{for } t = 3,\ldots, T \quad (21)$$

Where $EX_{i,t}$ is the part of exogenous covariates and $EN_{i,t}$ the part of the endogenous covariates. The consistency of the SYSTEM-GMM estimator relies on the validity of these moment conditions, which depend on the assumption of uncorrelated residuals and the exogeneity of the explanatory variables. Therefore, it is necessary to apply specification tests to ensure that these assumptions are justified.

More generally, it should be kept in mind that the estimate of the spatial autoregressive coefficient, while "potentially" consistent, is generally not the most efficient. Efficiency relies on the "appropriate" choice of instruments, which is not an easy task to determine. Arellano and Bond propose two specification tests to check the consistency of the GMM estimator. First, the overall validity of the moment conditions is checked by the Sargan-Hansen (1955, 1982) test. The null hypothesis is that the instruments are uncorrelated with the residuals. Recognizing that too many instrumental variables tend to validate invalid results by the Hansen J (1958) test for joint validity of these instruments, as well as Sargan-Hansen difference tests for subsets of instruments, it is advisable to limit the number of instruments by defining the maximum number of lags or by grouping the instruments together (Roodman, 2006). Second, the Arellano-Bond test examines the correlation property of residuals in level.

3.2. Data and Descriptive statistics

3.2.1. Data Sources

The data used in this work comes mainly from the World Bank's World Development Indicators (WDI) database for 30 Sub-Saharan African countries over the period 1996-2019. On the basis of the literature review and the current economic situation in Sub-Saharan Africa, 16 variables were selected for this analysis (Table 2 in the Appendix).

3.2.2. Descriptive Statistics

Figure 1 in appendix shows an association between changes in the share of manufacturing value added in GDP and the share of resource rents in GDP. For most countries, an increase in resource rents stimulates industrialization.

In the correlation analysis, the variables of interest and their log-transformed versions were included (see Table 3 in the Appendix). The correlation analyses between variables suggest a positive correlation between FDI and industrialization (whether measured by the share of industrial value added in GDP or manufacturing value added in GDP). The best correlations are observed for variables transformed into logarithmic form. This is therefore the version we keep. We also use the share of manufacturing value added in GDP as a proxy for industrialization.

4. FDI AND INDUSTRIALIZATION: RESULTS

4.1. Estimation Results

Since we have several variables that can capture other potential sources of spatial linkage such as trade, we will use a weight matrix based on the distances between countries (d_{ij}), calculated on the basis of the geographical coordinates of the countries (latitude and longitude), with spherical approximation of the globe:

$$W_{ij} = e^{-d_{ij}};\ i, j = 1\ldots30 \tag{22}$$

The spatial non-autocorrelation test on the errors (H0) gives for Moran's statistic the value -0.024 with a p-value of 0.18> 0.05. We can therefore conclude that the form of the model with diffusion effect is not to be considered. We will therefore estimate models without spatial effect on the errors.

We therefore make three estimates. Our results are presented in table 1 :

(i) The first considers the possibility of an effect of FDI from neighboring countries on the industrialization of a given country and a dynamic effect of the dependent variable (dynamic SLX)

Column 1 of table 1 gives the result of the Arellano-Bond (1991) estimation of the Durbin spatial model, with neighborhood effect only on the explanatory variables (the same explanatory variables being taken as additional instruments for the model). We find that the lagged value of industrialization has no significant effect on it. However, FDI entering a country has a positive effect on its industrialization. This is reflected in an elasticity of 0.014 for this variable. An increase of 1% in FDI will therefore lead to an increase in the share of manufacturing value added in GDP of 0.014%.

However, there is a Dutch disease effect due to the negative relationship between the increase in the exploitation of natural resources and the growth of the manufacturing sector. This is shown by the elasticity coefficient of -0.064. This may be the result of a flight of unskilled labor from manufacturing to the extractive sector, which would be more profitable in Sub-Saharan Africa.

A surprising result is the sign of the terms of trade index. Indeed, considering its direct effect and its indirect effect (spatial lag term) we find that an increase of one unit in the terms of trade directly reduces the industrialization of a country by 0.002%. But such an improvement in a country's neighborhood also increases industrialization by 0.002%. This paradoxical result could indicate an endogeneity bias linked to the collinearity of the terms of trade index with that of neighboring countries.

As the other spatial lags of the explanatory variables were not significant, we estimated a SAR (Spatial AutoRegressive) model in column 2 and a model with spatial lag only on the explanatory variables (SLX) excluding potentially endogenous variables with respect to the first model, in order to ensure the robustness of our results. In view of the magnitude of the coefficient on FDI, which remains stable for both models, these models are alternative, depending on what the reader might be looking for.

Table 1: Modeling the FDI-industrialization relationship

		Coef(tstat)signif	
lmanufacturingVA_GDP	*(1: Dynamic SLX)*	*(2: SAR)*	*(3: SLX)*
lmanufacturingVA_GDPL1.	0.031(0.87)		
w1y_lmanufacturingVA_GDP		0.371(3.25)***	
lFDI_net_inflow	0.014(8.4)***	0.013(2.21)**	0.013(2.41)**
lnatural_resources_GDP	-0.064(-5.79)***	-0.158(-4.5)***	
Terms_of_trade_index	-0.002(-5.96)***	0.002(2.32)**	
Mobile_cel	0.001(4.78)***	0.004(2.9)***	0.008(6.26)***
Urban_chareof_pop	-0.004(-7.03)***	-0.006(-2.96)***	-0.005(-2.3)**
School_tertiary	-0.052(-2.18)**	-0.013(-0.17)	
Trend		0.074(1)	
w1x_lFDI_net_inflow	-0.006(-1.09)		0.029(1.79)*
w1x_lnatural_resources_GDP	-0.032(-1.02)		
w1x_Terms_of_trade_index	0.002(2.29)**		
w1x_Mobile_cel	-0.0004(-0.63)		-0.004(-1.13)
w1x_Urban_chareof_pop	-0.002(-0.91)		-0.009(-1.83) *
w1x_School_tertiary	-0.078(-1)		
Constant	6.875(24.37)***	3.303(2.68)***	6.413(19.38)***

Source: authors calculations using the World Development Indicators, 2020

Note: lmanufacturingVA_GDP (resp. lmanufacturingVA_GDPL1) refers to manufacturing value added in share of GDP(Resp. the lag 1 of the same variable). W1y_lmanufacturingVA_GDP represents the first order spatial lag of the manufacturing value added in share of GDP. The w1x_variables are the first order spatial lag of the explanatory variables.

Coeff=Coefficient; tstat=t-Statistic; Signif=significance level: *** 1%; **5%; *10%; " ">>10%.

(2) The second considers only a spatial effect on the variable of interest (SAR): From this estimate, a 1% increase in the industrialization of a third country's neighbors increases its industrialization by 0.37%. Moreover, increasing the inflow of FDI into a country by 1% increases its share of manufacturing value added in GDP by 0.013%. Thus, the inflow of FDI into a country has a positive effect on its industrialization (all other things being equal). Combining this result with the spillover effect on the industrialization of neighboring countries, we can say that FDI has an indirect spatial effect which is also positive (we demonstrate this below by means of matrix calculations). Indeed, if we consider that there is an increase in the inflow of FDI in the neighborhood of a country, then this increases the industrialization of its neighboring countries, which together by a spatial average also increase the industrialization of this country. This is what the positive effect shows directly and indirectly in the model estimated in the 3th column (0.013 and 0.029 respectively).

In this model, all signs seem reasonable. The Dutch disease effect due to the exploitation of natural resources remains. The improvement in the terms of trade also improves industrialization. An increase in the terms of trade index of one unit increases industrialization by 0.002%. The effect is twofold for technological development, as measured by the number of cell phone subscribers per 1,000 inhabitants. However, the share of the urban population in the total reduces industrialization. An increase in this share of 1% slightly reduces industrialization by 0.006%. This can be explained by the fact that the urban population is generally concentrated in the service sector. And since the service sector appears to be more profitable, some employees in the manufacturing sector would generally migrate to jobs in private services or in public administration work. Another explanation for this sign would be the level of education in the urban population. Also, university-educated individuals often have difficulty finding suitable employment in Sub-Saharan Africa and are engaged in business activities or influential occupations, for those who are not employed in the public service or in business.

(3) The third one considers a model with spatial effect only at the level of the explanatory variables (SLX): The coefficients on the direct effects of the explanatory variables remain the same in terms of sign. As regards indirect effects, FDI has the highest coefficient, so that a 1% increase in the average FDI received by a given country's neighbors increases the industrialization of that country by 0.029%. On the other hand, an increase in the average share of urban populations in the total of neighboring countries marginally decreases the industrialization of a country (a decrease of 0.009%).

4.2. Demonstration of Direct and Indirect Effects Analysis

The calculations of direct and indirect effects below have been made for each explanatory variable with a spatial effect. The one for FDI is presented for illustrative purposes only. We draw on Jean Paul Elhorst (2014, pages 20-21).

4.2.1. Analysis of direct and indirect effects of FDI in model 2

The effects of FDI on industrialization in this model are given by the following formula:

$$\left[\frac{\partial E(ImanufacturingVA_{GDP}}{\partial FDI_1}\cdots\frac{\partial E(ImanufacturingVA_{GDP}}{\partial FDI_{30}}\right]=$$

$$\begin{bmatrix} \dfrac{\partial E\left(\boldsymbol{lmanufacturingVA_{GDP_1}}\right)}{\partial FDI_1} & \cdots & \dfrac{\partial E\left(\boldsymbol{lmanufacturingVA_{GDP_1}}\right)}{\partial FDI_{30}} \\ \vdots & \ddots & \vdots \\ \dfrac{\partial E\left(\boldsymbol{lmanufacturingVA_{GDP_{30}}}\right)}{\partial FDI_{30}} & \cdots & \dfrac{\partial E\left(\boldsymbol{lmanufacturingVA_{GDP_{30}}}\right)}{\partial FDI_{30}} \end{bmatrix}$$

$$= (I_{30} - 0.371W)^{-1}[0.013\mathrm{I}_{30}]$$

$$\approx 0.013\mathrm{I}_{30} \qquad (23)$$

The coefficient 0.371 in this model is well below 1, showing that the stationarity condition is verified. In this model, the indirect effects that represent the non-diagonal elements are zero. The only significant effect is therefore the direct effect of FDI on industrialization, whose value is 0.013 on average. Thus, a 1% increase in FDI inflows to a given country in Sub-Saharan Africa increases the share of its manufacturing value added in GDP by 0.013%. Moreover, this effect is almost the same in all countries according to our model 2.

4.2.2. Analysis of direct and indirect effects of FDI in Model 3

The effects of FDI on industrialization in this model are given by the following formula:

$$\left[\frac{\partial E\,(\textbf{lmanufacturingVA\_GDP})}{\partial FDI_1}\cdots\frac{\partial E\,(\textbf{lmanufacturingVA\_GDP})}{\partial FDI_{30}}\right] = [0.0131_{30} + 0.029W] \quad (24)$$

In this model, the direct effect of FDI on industrialization is the average of the diagonal elements of the matrix above. All calculated, they are worth 0.13, so, as above, a 1% increase in FDI in a given country increases the share of its manufacturing value added in GDP by 0.013%.

As for the indirect effect, it is the average of the vector of the sum of the non-diagonal elements per column and is worth 0.02, corresponding to a local effect. Thus, a 1% increase in FDI in the neighborhood of a given country increases its industrialization by 0.029%.

5. CONCLUSION

This study was designed to analyze the effect of FDI on industrialization in Sub-Saharan Africa. In order to do it, we used the dynamic spatial econometric method on panel data. We find that not considering spatial effects in the modeling of such a relationship leads to lower estimates. Second, modeling with a spatial effect on FDI inflows has shown that there is a spatial effect in the FDI-industrialization relationship. Moreover, this spatial effect improves the estimates and shows that the inflow of FDI in the neighborhood of a country is beneficial, because it contributes to improve its industrialization, but in a smaller proportion than the direct entry of FDI in the same country. Our results thus coincide with those of Jie and Shamshedin (2019) and Patrick Müller (2021) with the difference that we show the contribution of the spatial arrangement of countries, which is important.

CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data for this study comes from the World Bank's World Development Indicators (WDI) database and covers the period 1996-2019.

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APPENDIX

Table 2: Presentation of variables used

N°	*Variable*	*Description*
	Dependent variables	
1	lindustVA_GDP	Industrial value added (in % GDP)
2	lmanufacturingVA_GDP	Manufacturing value added (% GDP)
	Causal (explanatory) variable	
3	lFDI_net_inflow	Net value of inward FDI at current prices
	Control variables	
4	Business_extent_disclosure_index	Index of protection of property and confidential information of companies
5	Terms_of_trade_index	Terms of Trade Quality Index
6	School_enrollment_tertiary	Literacy rate in higher education
7	School_enrollment_primary	Primary school literacy rate
8	Women_Business_Law_Index1_100	Index of women's involvement in business
9	Net_foreign_assets	Net foreign assets
10	Mobile_cellular_subscriptions_pe	Percentage of people using cell phones
11	Individuals_usingInternet_shareo	Proportion of individuals using the Internet per 1000 inhabitants
12	Openess	Degree of openness
13	Gross_capital_formation_curr	Gross fixed capital formation (investment)
14	Gov_final_consumption_exp_curren	Government final consumption expenditure
15	Natural_resources_rents_chareGDP	Revenues from natural resources
16	Urbanpopulation_chareof_total	Share of urban population in total

Source: World Development Indicators (WDI), 2020

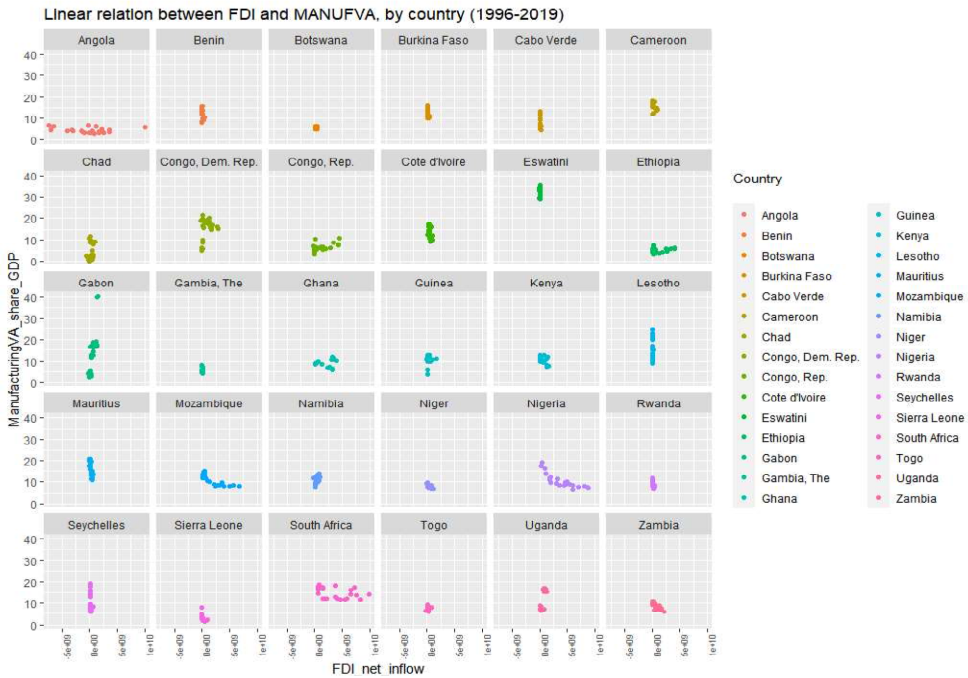

Figure 1: Scatterplot showing the relationship between FDI and industrialization by country

Source: authors calculations using the World Development Indicators, 2020

Table 3: Correlation matrix of variables

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1	lindustVA_GDP	1.0000																								
2	industVA_GDP	0.9516*	1.0000																							
3	Manufactur_GDP	0.1909*	0.3148*	1.0000																						
4	lmanufactu_GDP	0.1438*	0.3185*	0.8905*	1.0000																					
5	FDI_net_inflow	0.0423	0.0841*	0.0007	0.0586	1.0000																				
6	lFDI_net_inflow	0.2295*	0.2269*	-0.0264	0.0100	0.6858*	1.0000																			
7	Business_extent_disclosure_index	0.0465	0.0417	-0.1594*	-0.1057*	0.1330*	0.1680*	1.0000																		
8	Terms_of_trade_index	0.2613*	0.2558*	-0.0577	-0.0525	0.2378*	0.4381*	0.2162*	1.0000																	
9	School_enrollment_tertiary	-0.1157*	-0.0303	0.0578	0.1722*	0.0035	0.0107	-0.0573	-0.1416*	1.0000																
10	School_enrollment_primary	-0.3773*	-0.2597*	0.0634	0.0991*	0.0676	-0.0958*	-0.1459*	-0.2052*	0.2012*	1.0000															
11	Women_Business_Law_Index1_100	-0.2536*	-0.2038*	-0.1349*	-0.0019	0.1528*	0.2995*	0.0586	0.0870*	0.3469*	0.1476*	1.0000														
12	Net_foreign_assets	0.0725	0.0894*	0.0046	0.0384	0.2419*	0.3135*	0.0896*	0.2394*	-0.0371	0.0041	0.0431	1.0000													
13	Mobile_cellular_subscriptions_pe	0.0267	0.0356	0.0230	0.0556	0.2207*	0.3543*	0.2965*	0.2520*	0.3043*	-0.0454	0.5276*	0.1361*	1.0000												
14	Individuals_usingInternet_shareo	-0.0550	-0.0268	0.0748*	0.1008*	0.1713*	0.2616*	0.1445*	0.1230*	0.4089*	0.0070	0.5203*	0.1061*	0.8487*	1.0000											
15	Openess	0.3061*	0.2195*	-0.0165	-0.0775*	-0.0567	0.0646	-0.2240*	-0.1445*	0.1858*	-0.1441*	0.1075*	-0.1772*	0.1296*	0.1489*	1.0000										
16	Gross_capital_formation_curr	0.0963*	0.1425*	-0.0109	0.0470	0.6301*	0.5290*	0.1438*	0.3269*	-0.0803*	-0.0111	0.1982*	0.4213*	0.2398*	0.2219*	-0.1426*	1.0000									
17	Gov_final_consumption_exp_curren	0.0702	0.1114*	0.0276	0.0771*	0.5428*	0.4286*	0.1373*	0.2366*	-0.0508	-0.0105	0.2617*	0.1978*	0.2749*	0.2756*	-0.0844*	0.5616*	1.0000								
18	Natural_resources_rents_shareGDP	0.5651*	0.4147*	-0.2854*	-0.3641*	0.0793*	0.2791*	0.1485*	0.3712*	-0.3957*	-0.3486*	-0.2994*	0.1320*	-0.1322*	-0.2599*	0.1875*	0.0426	-0.0222	1.0000							
19	Urbanpopulation_shareof_total	0.4670*	0.4115*	-0.0943*	-0.0645	0.1462*	0.2708*	0.1341*	0.1759*	0.0747*	-0.2807*	0.1610*	0.0091	0.4707*	0.3771*	0.2190*	0.2282*	0.2578*	0.1816*	1.0000						
20	VA	-0.1605*	-0.0778*	-0.0128	0.1135*	0.0984*	0.0752	-0.0574	-0.1458*	0.4315*	0.2298*	0.5168*	-0.1164*	0.3292*	0.3731*	0.0491	0.1048*	0.2107*	-0.4910*	0.2804*	1.0000					
21	PS	-0.0369	-0.0106	0.0802*	0.1192*	-0.1653*	-0.1552*	-0.1220*	-0.1311*	0.3410*	0.0862*	0.3435*	-0.2846*	0.2934*	0.3007*	0.1324*	-0.2039*	-0.0697	-0.4189*	0.3459*	0.6806*	1.0000				
22	GE	-0.0976*	-0.0118	0.1103*	0.2145*	0.0457	0.0089	-0.1403*	-0.1513*	0.5140*	0.2083*	0.4486*	-0.2001*	0.2893*	0.3874*	0.1218*	0.0560	0.1993*	-0.5668*	0.1854*	0.7714*	0.6688*	1.0000			
23	RQ	-0.1484*	-0.0406	0.1330*	0.2248*	0.0407	0.0225	-0.0187	-0.1040*	0.3747*	0.2565*	0.4373*	-0.1245*	0.2784*	0.3143*	-0.0566	0.0582	0.1997*	-0.5779*	0.1366*	0.7515*	0.6652*	0.8561*	1.0000		
24	RL	-0.1417*	-0.0557	0.0934*	0.1757*	-0.0187	-0.0705	-0.1874*	-0.1231*	0.4868*	0.2587*	0.4595*	-0.1804*	0.3300*	0.4047*	0.0710	-0.0349	0.0814*	-0.5755*	0.1988*	0.8154*	0.8013*	0.8744*	0.8401*	1.0000	
25	CC	-0.1489*	-0.0694	0.0971*	0.1575*	-0.0413	-0.1365*	-0.1960*	-0.1882*	0.5173*	0.2681*	0.4341*	-0.2988*	0.3041*	0.3808*	0.1506*	-0.0804*	0.0640	-0.5793*	0.1478*	0.7422*	0.7336*	0.8531*	0.7465*	0.8845*	1.0000

Source: authors calculations using the World Development Indicators, 2020