The Impact of Political Instability and Trade Openness on FDI in Africa:

A Proposed Structural Equation Model

Dr. Douar Brahim
Maitre de conférences à UMMTO

Hammache Souria
Maitre assistante à UMMTO

Abstract:

This study examined the impact of political instability and trade openness on FDI in Africa. we applied a Sructural Equation Model basing on the path analysis. The results suggest that the market size and trade openness are both directly impacting FDI in Africa. In adition, FDI inflows seem to be also driven by political stability, voice and accountability and property right. Oil production is an other determinant of FDI in Africa. In the other hand, we had confirmed that trade openness is determined and explained by population, GDP per capita, surface area and state policy. Our results highlited that population impact GDP and trade openness at the same time.

Key words: Political instability –FDI- Trade openness – Africa countries – Path analysis – Structural Equation Model (SEM).

Introduction:

Africa has become the interests of many economies around the world. In the past, the African continent was viewed as the continent of instability, violence, poverty, corruption and slow economic growth. However, development strategies leaded by severel countries in the continent has changed the economic landscape of the Africa. Today, seven of the top 10 fastest growing economies are on the African continent; trade with the rest of the world increased, foreign debt are declining and productivity growing. Africa is slowly emerging as the continent of opportunities. (Idsardi, E.F and all 2016).

Consider the reality: Africa's population since 2010 has officially been more than one billion. It is projected to be more than two billion in about 30 years, the growing domestic demand in Africa, highly interests multinational compagnies. So the continent seems to be an opportunity for international firms to increase their rentability. In this context Africa countries should take advantage by openning their market and ensuring an environment conducive to inward FDI.

Africa has increased dramatically its FDI over the years. The total amount of FDI in Africa was 19.1 billions US $ in 2005 ; but in 2013, FDI inward in the continent had increased to 40.6 billions US$. This huge and significant increase in FDI inflows is due to the new discoveries of natural ressources in Africa. However, it is importance to note, that the FDI net inflows in the region is differs from region to another. While, FDI net flows has significantly declined, in North Africa (Algeria,Egypt, libya,Tunisia) by around 31%, FDI in Sub-Saharan Africa has increased by around 4.8%. (Abdelbagi E, and all).

Foreign direct investment flows are expected to be influenced by political instability. Africa is still suffering from the risk of violence and political instability. In some regions of the continent, FDI seem to be severely impacted due to the high political risk. Indeed, political stability is an extremely important aspect to attract FDI. Some regions in Africa, East Africa in particular, is becoming ever more attractive to foreign companies, but investors still weigh up risks before making their decision.

Political instability on the continent remains their main concern. The biggest deterrents to FDI inflows, regardless of the quality of environment in a countries are armed conflict, political uncertainty and security threats, as can be seen from the reduced FDI inflows to North and West Africa in recent years.

We aim in this article to analyse the impact of political stability and trade openness on FDI in Africa. We aim also to investigate the principal determinants of FDI in the continent. We will carry on a Structural Equation Model, based on Path Analysis approach. It is important to note that studies applying this type of method and approach are not abundant. Our analysis is taking into account 11 Africans countries from the period starting from 2000 to 2014.

1- Literature review:

The most popular conceptualization of the theoretical framework for FDI determinants is the “eclectic paradigm” proposed by Dunning (1977, 1993). It provides a pattern that groups of determinants that help to understand why and where multinational companies invest abroad. According to his stadies the firms invest abroad to seek for three types of advantages: Ownership (O), Location (L), and Internalization (I) advantages. This is called the OLI framework.

As well as, Dunning (1993) identified four categories of motives for FDI: resource seeking (The firm aim to acces to labor force, natural ressources and physical infrastructure resources), market seeking (the aim here is to access to the host-country domestic market), efficiency seeking (Firm seek to exploit the lower labor costs, especially in developing countries), and strategic-asset seeking (here firms want to have access to research and development, innovation, and advanced technology) (Cleeve, 2008).

The literature on determinants of FDI has identified also both policy and non-policy factors as drivers of FDI (Fedderke and Romm, 2006). Policy factors include : product-market openness, corporate tax rates regulation, labor, direct FDI restrictions, and infrastructure. Non-policy factors include market size of the host country (often measured by the GDP), political and economic stability or factor endowment and distance/transport costs, (Mateev, 2009).

Anyanwu and Erhijakpor (2004) indicate that telecommunications infrastructures economic growth, openness and significantly increase FDI inflows to Africa while credit to the private sector, export processing zones, and capital gains tax have significantly negative effect.

In 2007 Daude and Steinby using bilateral FDI stocks around the world, explore the importance of a wide range of institutional variables as determinants of the location of FDI and find that better institutions have a positive and economically significant effect on FDI. The series of variables that seem to be significantly associate with FDI are : laws, regulations and policies, excessive regulatory burden, government instability and lack of impact negatively FDI in Africa.

Campos and Kinoshita (2003), using panel data set for 25 transitions economies between 1990 and 1998, find that the main determinants of inward FDI are quality of institutions, and trade openness.

Ali et al (2006) examine the role of institutions in determining FDI inflows using a panel of 69 countries during 1981 and 2005 and find that institutions are important of overall FDI and that the most significant institutional variables that impact FDI are : propriety rights, the rule of law and expropriation risk. Corruption and low transparency are found to deter FDI inflows.

Al-Sadig (2009) who uses panel data from 117 host countries over the period 1984-2004 found similare results. He shows that higher corruption levels decrease FDI inflows. Thus, secure property rights, political stability, and lack of corruption allow markets to properly function, and therefore attracting FDI (Disdier and Mayer, 2004; Kinda, 2010).

In addition to this, Dupasquier and Osakwe (2006); Aseidu, 2002; and Deichmann and al, 2003), report that the availability of natural resources has a positive and significant effect on FDI inflows.

Mohamed and Sidiropoulos (2010), using a panel of 36 countries (12 Middel East and North Africa countries and other 24 developing countries), conclude that the important determinants of FDI inflows in MENA countries are the natural resources, the size of the host economy, the government size, and institutional variables.

Asiedu (2006), using panel data for 22 countries in Sub-Saharan Africa over the period 1984–2000, find that countries that are well endowed with natural resources or have large size markets attract more FDI. As well as, good infrastructure, an educated labor force, macroeconomic stability, openness to FDI, an efficient legal system, less corruption and political stability promote inward FDI.

Hailu (2010) conducts an empirical analysi of FDI to African countries and found that natural resources, labor quality, trade openness, market size and infrastructure condition positively and significantly affect FDI inflows.

Abdelbagi E,and al (2016) studied , the determinant of FDI in Africa, the study covered 50 African countries in the time period from 1974 to 2013, using GMM methode, the empirical results suggest that FDI inwards, in Africa and all income levels, are determined by economic growth, trade openness, domestic investment, human capital and infrastructure during the period of interest.

So according to the prior studies the main drivers of FDI inwards in Africa, seem to be : The market size of the host country- political stabily- quality of institution particularly controled corruption, and available property right and trade openness.

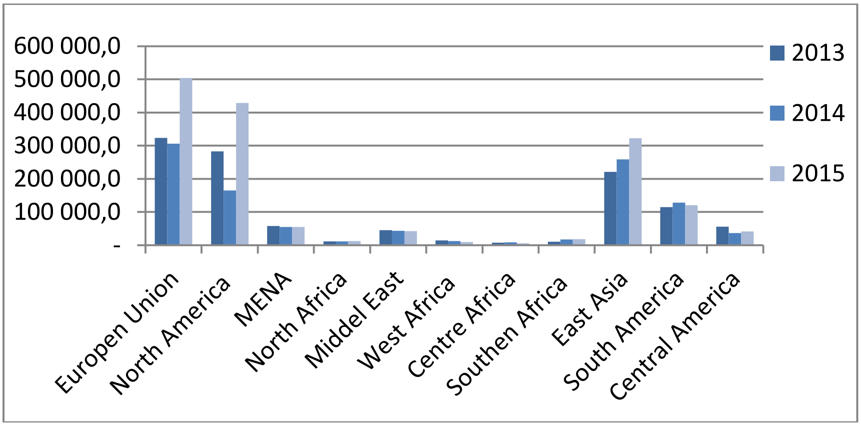
Concerning the determinant of trade openness, the researchers agree on three main variables. Indeed, Guttmann and Richards, (2006) concluded that the variables explaining trade openness are the economic, geographic and policy related characteristics. Consequently, the study considers such variables as economic characteristics (GDP per capita), institutional characteristics (trade policy), and natural characteristics (geographical distance, surface area, and population size).

Rose and Wincoop, (2001), find that the level of trade between countries is a negative function of the distance between trading countries. Large geographical area as well as higher population tend to provide countries with more opportunities within their countries and therefore reducing their levels of external trade volumes (Rao and Kumar, 2009; Zannou, 2010).

2- Overview of FDI in Africa:

Comparing North Africa region and other Africa regions with the other regions of the world we notice the poor attractivness of Africa in terme of FDI inward flows. As we can see, in the figure 1, Europe and North America are the pioneers in term of the attractiveness of FDI in the world. East Asia seems also achieve a good performance, by attracting more FDI in 2015 comparing to 2013 and 2014.

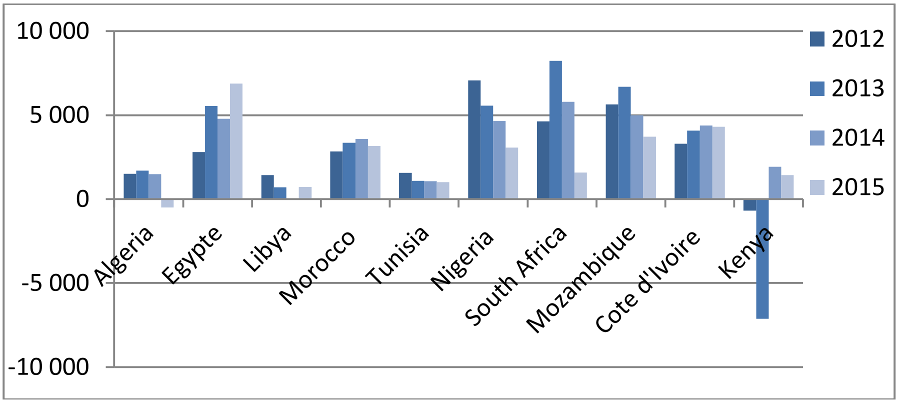
Figure 1: FDI inflows in the world from 2013 till 2015



Source: Adapted by authors using UNCTAD data (http://unctadstat.unctad.org/wds/TableViewer/tableView.aspx?ReportId=96740) Consulted on 15 th Novembre 2016)

The figure 2 illustrates the evolution of FDI in some countries in Africa, we note that South Africa remains by far the country that attracts the most foreign investment in 2014, followed by Nigeria and Mozambique. In North Africa, Egypt and Morocco seem to be the two most successful countries in attracting FDI flows. But it is interesting to note that in 2014, the inward FDI dropped in the majority of African countries.

Figure 2: Evolution of FDI in Africa in billion US $



Source: Adapted by authors using UNCTAD data. (http://unctadstat.unctad.org/wds/TableViewer/tableView.aspx?ReportId=96740) Consulted on 15 th Novembre 2016)

We note also, the fast rise of FDI for Kenya. Indeed, according to the Africa investment 2016 report of FDI Intelligence, Kenya recorded one of the biggest increases in FDI, with project numbers rising 49 percent to 85, totalling $2.4bn in investments. In the othe hand FDI inflows to South Africa slumped to a ten-year low of only $1.8-billion in 2015, a 69% decline. South Africa continue to suffer from a number of legislative uncertainties that discourage foreign investors.

2- Model specification:

In this article, we aim to determine the impact of trade openness and the political instability on FDI in Africa. After an in-depth and a state of the existing literature while considering the availability of data, the following variables were defined for 11 African countries :

Algeria- Egypte- Libya- Tunisia- Morocco- Nigeria- South Africa- Mozambique- Cote d'Ivoire- Kenya- Angola. In the period between 2000-2014. Table 1 summarize the variables, their description and the source of data.

Table n°1: Variables description and sources of data

Variables	**Description of variables**	**Source**
FDI	Foreign Direct Investment (Depended variable)	UNCTAD
GDP	Gross Domestic Product is often presented as an important variable that determines FDI	World Bank
OPEN	Trade openness : Measures aggregate trade (sum of exports and imports of goods and services) as a ratio of GDP.	World Bank
GDPPC	GDP per Capita : Used as a proxy for economic development level of a country. The data are in constant US$2010	World Bank
Population	Used as a measure of total population of a country	World Bank development indicators
Surface area	Used as a measure of a country's total area, including areas under inland bodies of water and some coastal waterways	World Bank development indicators
policy	Trade policy : Measures the degree of	Heritage

	the liberalization of countries trade regimes. We take the variable trade freedom.	Foundation and Wall Street Journal
Inflation	A high inflation rate reflects macroeconomic instability, increasing uncertainty and makes it less attractive location for FDI.	World Bank development indicators
VA	Voice and Accountability measure political, civil and human rights	World Bank development indicators
PSAV	political stability and absence of violence measures the likelihood of violent threat or change in the government including terrorism	World Bank development indicators
CC	measures the level of control of corruption in country.	World Bank development indicators
OILPRD	This variable is rarely taken into account in the model that address the determinants of FDI in Africa. In the current context of falling oil prices, it would be interesting to check the impact of the oil price drop on the inward FDI flows. : Countries that are endowed with natural resources would receive more resource-seeking FDI.	BP data base

Source: Adapted by authors.

In our research model we suppose that FDI may be impacted by two direct variables *GDP* and OPEN. We suppose that FDI flows are largely explained by the size of the market (countries with large GDP are more likely to attract foreign investment) and trade openness (countries with no barriers on trade such tariffs barriers attract more inward FDI).

In the other hand GDP and OPEN are determined by a series of other variables:

- For GDP we suppose that it is explained by inflation, voice and accountability, political stability, control of corruption and oil production.
- OPEN is supposed to be determined by population, trade policy, GDP per capita, and surface area (see figure 3).

4- Methodology and results:

The path analysis is used to describe directed dependencies among a set of variables. These models are equivalent to any form of multiple regression analysis, factor analysis, canonical correlation analysis, discriminate analysis, and more general model families in the multivariate variance and covariance analysis. In addition to being considered as a form of multiple causal regression, path analysis can be considered as a particular case of Structural Equation Modeling (SEM) - a method in which only unique indicators are used for each of the causal model variables. Other terms used to describe path analysis are causal modeling, analysis of covariance structures, and latent variable models. As well as, path analysis is considered as a powerful technique for testing multivariate regression models with direct and indirect effects.

In the structural equation modeling, it is essential for the researcher to solve the identification problem before parameter estimation, this identification allows to assign a single solution for each of the parameters to be estimated (Schumacker and Lomax (2010). A model leads to express the variance / covariance matrix of the manifest variables Σ as a function of a set of parameters θ. This model is identified if $\Sigma(\theta) = \Sigma(\theta')$ implies $\theta = \theta'$. In practice, the identification of a model implies satisfying two conditions, the condition of order (necessary condition) and the condition of rank (Najjar and Najjar, 2007). The rank condition requires an algebraic determination of whether each parameter in the model can be estimated from the covariance matrix S. Unfortunately; proof of this rank condition is often problematic in practice, particularly for the applied research. However, there are certain procedures that the applied researcher can use. For a more detailed discussion of rank condition, we refer to Bollen (1989) or Jöreskog and Sörbom (1988). The order condition depends imperatively on the degree of freedom and refers to the correspondence between the parameters to be estimated and the number of variances / covariances of the variables observed (Hoyle, 2012). Based on the work of Schumacker and Lomax 2010), the degree of freedom is expressed as follows:

$$ddl = (P (P + 1) / 2) - N$$

With :

P : The number of indicators of the model

N : The number of coefficients to be estimated from the model.

ddl : The degree of freedom.

The order condition is verified when the model is identified (over-identified), in other words, when the degree of freedom is greater than zero (ddl > 0), but if the ddl <0, at this level the model is under - identified (or not identified), this situation occurs if one or more parameters may not be determined uniquely because there is not enough information in the matrix S. A third situation can be included when the ddl = 0, in this situation this model can be just identified if additional constraints are imposed, that is, degrees of freedom equal to 0 or greater than 0 (positive value).

In structural equation methods, it is possible to adjust a model in a specific context. It is important then to evaluate the quality of the fit of the model to the data. This analysis is carried out using several indices classified into three categories: absolute indices, incremental indices and parsimony indices. The following table summarizes the key values of some of the most widely used indices.

Table n°2: The adjustment indices

Absolute indices		Incremental indices		Parsimony indices	
indice	Threshold	indice	Threshold	indice	Threshold
Khi deux GFI AGFI SRMR RMSE	No threshold >0.9 >0.9 <0.08 <0.08	NFI TLI CFI	>0.9 >0.9 >0.9	CMIN AIC ECVI	< 5 Lowest possible No threshold

Source : Adapted from Roussel P, Durrieu F, Campoy Eet El Akremi, A, (2002) Méthodes d'équations structurelles: recherche et applications en gestion, Economica, page ….

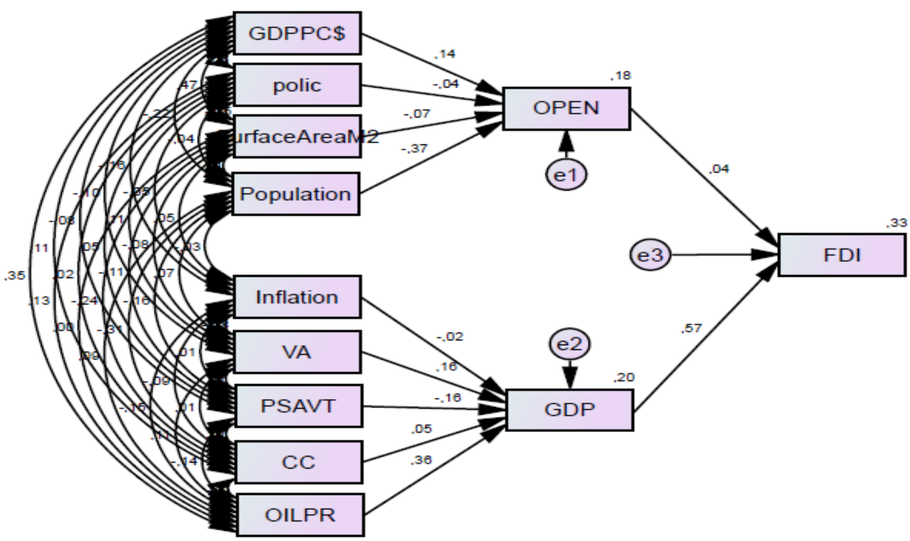
According to this table, we distinguish three types of indices of model's adjustments, the absolute indices of measurement, which evaluate in what extent the theoretical model reproduces correctly the collected data (Roussel et al, 2002). The most common absolute indices are chi-square. Nevertheless, the chi-square test of the fit of the pattern can lead to erroneous conclusions regarding the results of analysis. The criterion of the chi- square fit adjustment model is sensitive to the sample size, as if the sample size increases (usually greater than 200), the chi-square statistic tends to indicate a significant probability.On the other hand, if the sample size decreases (usually less than 100), the chi-square statistic indicates non-significant probability levels. The chi-square statistic is therefore affected by the size of the sample

(Schumacher and Lomax, 2010). The GFI (Goodness of Fit Index) and AGFI (Adjusted Goodness of Fit Index) are indices that measure the relative share of the variance covariance explained by the GFI model, adjusted by the number of variables compared to the degree of freedom number AGFI (Roussel and al., 2002). Like a squared multiple correlation, it varies from 0-1 with 1 being a perfect fit. A variant of this statistic is the Adjusted Goodness of Fit index (AGFI), which includes an adjustment for model complexity. This is done because the more parameters included in any model, the greater the amount of variance explained. The AGFI takes this into account by correcting downward the value of the GFI as the number of parameters increases. The AGFI has not performed well in some computer simulations and is less popular than the GFI. Values greater than 0.9 are considered well fitting. (Jeffrey L. Jackson, and al 2005)

The SRMR, standardized version of the RMR (Root Mean Square Error), is interpretable even if the initial data matrix is the variance matrix covariances. The RMSEA((Root Mean Square Error of Approximation) is one of the most relevant absolute indices, it is independent of the sample size and represents the average difference per degree of freedom expected in the total population and not in the sample. As the average discrepancy between the observed and predicted covariances increases, so does the value of the RMSEA. A value of the RMSEA of about .05 or less would indicate a close fit of the model in relation to the degrees of freedom.

The incremental indices measure the improvement of the fit by comparing the model tested with a more respective model, among these indices we find the NFI (Normed Fit Index) which represents the proportion of the total covariance between variable explained by the model tested when the zero model is taken as a reference. The NFI indicates the proportion in the improvement of the overall fit of the researcher's model relative to a null model, typically the "independence" model. The independence model is one in which all variables are assumed to be uncorrelated. An NFI of .80 means that the overall fit of the tested model is 80% better than that of an independence model, based on the sample data. (Jeffrey L. Jackson, and al 2005). The TLI compares the lack of fit of the model to be tested to the basic model. The IFC measures the relative decrease in the lack of adjustment. The parsimony indices allow overestimating a given model and detecting if the poor degree of adjustment of a model does not come or originate from the opposite of an underestimation (Roussel et al., 2002). The most common parsimony indices are the CMIN, which is an index for detecting over-adjusted and under-adjusted models. The AIC test (Akaike's Information Criterion) is used to compare models with different numbers of latent variables (Akaike 1987). The ECVI (Expected Cross-validation Index) tests the consistency of model performance when moving a sample to other samples so that these samples belong to the same community as the model parameter estimates can be reproduced.

Figure n°3 : The research model.



Source : Established from the use of the survey data using AMOS software

Table n°3: Measurement model adjustment indicators

absolute indices		Incremental indices		Parsimony indices	
indice	Threshold	indice	Threshold	indice	Threshold
Khi-square GFI AGFI SRMR RMSEA	**233, 287** **0 ,875** **0,486** **0, 109** **0,262**	NFI TLI CFI	**0,568** **0,569** **0,548**	CMIN AIC ECVI	**12,278** **351,287** **22,142**

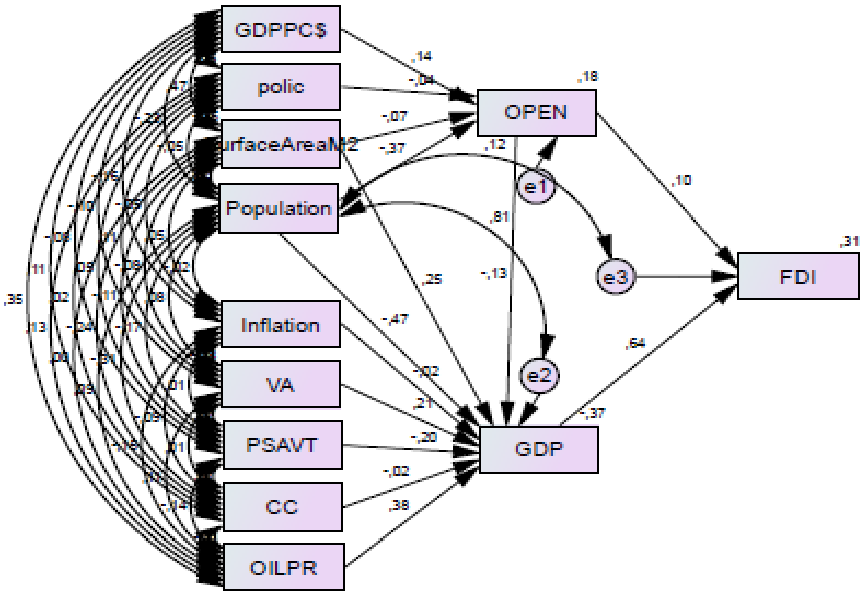
Source : Calculed by authors using AMOS software

Through the table 3 we note that all the indices are not close to the norms of a good fit, indeed for a khi-square = 233, 287, DDL = 19 and P = 0.000, the GFI and the AGFI (0.875, 0.486) these results do not approach the standard (0.9), the SRMR (0.109) are also far from the standard of a good fit, the RMSEA with a coefficient of 0.262. Regarding the incremental indices, the NFI, TLI and CFI (0.568, 0.569 and 0.548), these values did not reach the threshold of 0.9, which means that the incremental criteria do not support the acceptance of the proposed theoretical model.

For indices of parsimony we note that the CMIN is not acceptable with a value greater than 5 (12.278) however it should be noted that the AIC and the ECVI their values are very high which means that the parsimony indices reject the Validation of the conceptual model of our research.

We will proceed to a second-order path analysis by referring to some modifications reported by the AMOS software, in order to improve the theoretical model of the research.

Figure n°4: The adjusted research model



Source : Established from the use of the survey data using AMOS software

Table n°4: Measurement Model Adjustment Indicators

Absolute indices		Incremental indices		Parsimony indices	
indice	Threshold	indice	Threshold	indice	Threshold
Khi-square	**21, 097**	NFI	**0,961**	CMIN	**1,507**
GFI	**0 ,980**	TLI	**0,929**	AIC	**543,919**
AGFI	**0,889**	CFI	**0,985**	ECVI	**13,266**
SRMR	**0,035**				
RMSEA	**0,056**				

Source : Calculed by authors using AMOS software

After carrying out a second-order path analysis, we note that all the indices have reached the standards of a good fit after the modifications that have been made. The khi-square is estimated at 21.097 with a DDL of 14 and P = 0.091, for absolute indices: The GFI and the AGFI (0.980, 0.880) these results approximate the norm (0.9), the SRMR (0.035) has the standard of a good adjustment, the RMSEA also reached the critical threshold (0.056) after The changes that have been made which means that the absolute criteria support the acceptance of the proposed theoretical model. Concerning the incremental indices, the NFI, TLI and CFI (0.961, 0.929 and 0.985), we notice a marked improvement in these values, which means that the incremental indices validate the proposed conceptual model.

Conclusion :

This study examined the impact of political instability and trade openness on FDI in Africa. we applied a Sructural Equation Model basing on the path analysis. The results suggest that the market size and trade openness are both directly impacting FDI in Africa. In adition, FDI inflows seem to be also driven by political stability, voice and accountability and property right. Oil production is an other determinant of FDI in Africa. This confirming the prior empirical studies which argue that countries with natural ressources attract more FDI flows in African countries. In the other hand, we had confirmed that trade openness is determined and explained by population, GDP per capita, surface area and state policy. We note, the results highlited that population impact GDP and trade openness at the same time.

References :

- Abdelbagi E, Azali M, Azman H, Md Nor N (2016,) What Factors Determines the FDI Net Flows in Africa? GMM and PMG Techniques. Journal of Global Economics 4: 170.

- Ali, F., Fiess, N and MacDonald, R. (2006), “Do Institutions Matter for Foreign Direct Investment?”, *Open Economies Review*, Volume 21, Number 2, April, 201-219.

- Al-Sadig, A. (2009), “The Effects of Corruption on FDI Inflows”, *Cato Journal*, Vol. 29, No. 2, Spring/Sumner.

- Anyanwu, J. C. (1998), "An Econometric Investigation of the Determinants of Foreign Investment in Nigeria", in Nigerian Economic Society (1998), Rekindling Investment for Economic Development in Nigeria, Ibadan, 219 - 241.

- Anyanwu, J. C. (2006), “Promoting of Investment in Africa”, African Development Review, Volume. 18, No.1, April 2006, 42-71.

- Asiedu, E., (2006), “Foreign Direct Investment in Africa: The Role of Natural Resources, Market Size,Government Policy, Institutions and Political Instability”, *World Economy*, 29, pp. 63-77.

- Cleeve, E. (2008), “How Effective Are Fiscal Incentives to Attract FDI to Sub-Saharan Africa?”, The Journal of Developing Areas, Volume 42, Number 1, Fall, 135-153.

- Campos, N. F and Kinoshita, Y. (2003), Why Does FDI Go Where it Goes? New Evidence from the Transition Economies, IMF Working Paper, working paper /03/228, November.

- Dunning, J.H. (1977), Trade, location of economic activity and the MNE: a search for an eclectic approach in B. Ohlin and P.O. Hesselborn: The International Allocation of Economic Activity, London, Macmillan, 395-418.

- Dunning, J. H. (1980), “Toward an Eclectic Theory of International Production: Some Empirical Tests”, Journal of International Business Studies, Volume. 11, Spring/Summer, No. 1, 9-31.

- Dunning, J.H. (1993), Multinational Enterprises and the Global Economy, Addison-Wesley

- Guttmann, S. & Richards, A. (2006), "Trade openness: an Australian perspective." Australian Economic Papers, Volume. 45, No.3: pp. 188-203.

- Hailu, Z. A. (2010), “Demand Side Factors Affecting the Inflow of Foreign Direct Investment to African Countries: Does Capital Market Matter?”, International Journal of Business and Management, Vol. 5, No. 5, May, 104-116.

- Idsardi, Cloete, and Bezuidenhout, Trends and Determinants of Foreign Direct Investment in Africa’s Agro-food Sector, IFAMA 2016 SYMPOSIUM

- Jeffrey L. Jackson, Introduction to Structural Equation Modeling (Path Analysis) SGIM Precourse PA08 May 2005.

- John C. Anyanwu, Determinants of Foreign Direct Investment Inflows to Africa, 1980-2007, working paper N° 136- September 2011, Africain Development Bank Group

- Jöreskog, K. G, & Sörbom D, (1974–2012), LISREL for Windows [Computer software]. Lincolnwood, IL: Scientific Software International.

- Mateev, M (2009), “Determinants of Foreign Direct Investment in Central and Southeastern Europe: New Empirical Tests”, Oxford Journal, Fall, Volume. 8, N. 1, 133-149.

- Mohamed, S. E. and Sidiropoulos, M. G. (2010), “Another Look at the Determinants of Foreign Direct Investment in MENA Countries: An Empirical Investigation”, Journal of Economic Development, June, Vol. 35, Issue 2, 75-96.

- Najjar H, & Najar C, (2013), La méthode des équations structurelles : Principes fondamentaux et applications en marketing, Int.Conference on Business, Economics, Marketing & Management Research, 3.

- Rodić I, (2007), Responsabilité sociale des entreprises – le développement d’un cadre européen, Mémoire présenté pour l’obtention du Diplôme d’études approfondies en études européennes, Université de Genève.
- Bollen K. A, (1989), Structural equations with latent variables, New York,Wiley
- Hoyle R. H, (2012). Handbook of structural equation modeling, New York, Guilford Press
- Rao, B. B. & Kumar, S. (2009), "A panel data approach to the demand for money and the effects of financial reforms in the Asian countries." Economic Modelling, Vol. 26, No.5: pp. 1012-1017.
- Roussel P, Durrieu F, Campoy Eet El Akremi, A, (2002) Méthodes d'équations structurelles: recherche et applications en gestion, Economica.
- Rose, A. K. (2000), "One money, one market: the effect of common currencies on trade." Economic policy, Volume. 15, No.30: pp. 7-46.
- Schumacker, R. E, & Lomax R. G, (2010), A beginner’s guide to structural equation modeling (3rd ed.), New York, Routledge.