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A Spatio - Temporal Analysis of FDI-Conflict Nexus in MENA Region

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Abstract

In this study we use a spatial methodology to explore the greenfield FDI in the aftermath of conflicts in the MENA region. Empirical results show that country risk is crucial for this type of FDI. In addition, we found that greenfield FDI and political stability in the MENA region benefit from a feedback loop effect. Furthermore, the spatial econometric regressions reveal the occurrence of spillovers (indirect effects) across the MENA countries. These spillovers do not only affect neighbors in close vicinity (neighbors of first order or contiguous neighbors), but also spread to neighbors of higher order, and might affect the whole region.

Keywords: spillover effects; spatial regression estimates; greenfield FDI; conflict.
JEL Classifications: C23, F21, D74.

ملخص

في هذه الدراسة نستخدم منهجية مكانية لاستكشاف الاستثمار الأجنبي المباشر في المجالات الجديدة في أعقاب النزاعات في منطقة الشرق الأوسط وشمال أفريقيا. وتبين النتائج التجريبية أن المخاطر القطرية حاسمة بالنسبة لهذا النوع من الاستثمار الأجنبي المباشر. وبالإضافة إلى ذلك، وجدنا أن الاستثمار الأجنبي المباشر والاستقرار السياسي في منطقة الشرق الأوسط وشمال أفريقيا يستفيدان من أثر حلقة التغذية المرتدة. علاوة على ذلك، تكشف الانحدارات الاقتصادية القياسية المكانية عن حدوث تداعيات (آثار غير مباشرة) عبر بلدان الشرق الأوسط وشمال أفريقيا. لا تؤثر هذه التداعيات على الجيران القريبين (الجيران من الدرجة الأولى أو الجيران المتجاورين) فحسب، بل تنتشر أيضًا إلى الجيران من الدرجة الأولى، وقد تؤثر على المنطقة بأكملها.

1. Introduction

Generally, transnational firms when they plan to invest abroad consider the long-term perspective. As a result, when they relocate abroad, they often want to invest in an environment with less risk and uncertainty about the future. This requirement for consistency is critical given the large funds mobilized for the initial investment and the relatively long period to reach the targeted profitability level. The analysis of the greenfield FDI-political instability includes complicated feedback loops with complex, multi-causal phenomena involving multiple operating players. Therefore, including the neighbors' effect by adopting a spatial approach is relevant for the apprehension of the dynamic relationship between greenfield FDI and conflict. To the best of our knowledge, this is the first attempt to study the impact of internal and external conflicts on greenfield FDI in the context of spatial econometric approach.

The emphasis on greenfield FDI is motivated by the fact that it is a homogeneous mode entry and is destined to create projects starting from scratch. Hence, this is useful to mitigate concerns about FDI heterogeneity. Moreover, the bulk of international investment in the MENA region is explained by this kind of FDI. Indeed, roughly 80% of the inbound FDI is explained by greenfield FDI. Greenfield foreign direct investment is considered as a prominent tool for economic growth and development. Unfortunately, the MENA region is considered as a conflict hotspot zone. Conflict repercussions cast a shadow of uncertainty over the FDI flows in the MENA region. Historically, conflict events have been associated with high risk, economic instability and social disorder.

This study aims to explore the impact of conflicts on greenfield FDI by adopting a spatial approach[1]; find the spatial model with the best of fit to specify the nature and scope of spatial dependence in the MENA region (substantive or residual); and check the presence of spillovers, evaluate their intensity and detecting their transmission channels.

2.Stylized facts

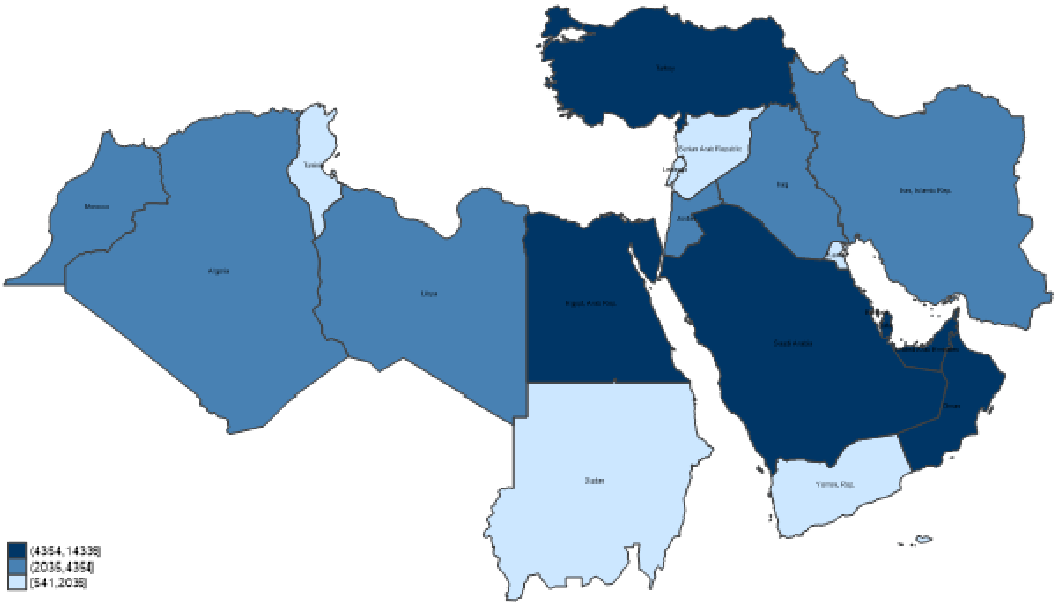
2.1. Data visualization: "A picture is worth a thousand words"

To disclose the main feature(s) of greenfield FDI investment and conflicts in MENA countries, data visualization is a treasured first step to have a glimpse of a reality that is much more complex than it seems to be. At first glance, we can observe the existence of mainly two groups represented by countries in light blue (relatively low values of greenfield FDI) and dark blue (relatively high values of greenfield FDI) exhibiting similar values of greenfield FDI investment when they are contiguous or relatively close to each other. This could be an

[1] "Spatial econometrics is a field whose analytical techniques are designed to incorporate dependence among observations (regions or points in space) that are in close geographical proximity. Extending the standard linear regression model, spatial methods identify cohorts of « nearest neighbors » and allow for dependence between these regions/observations" (Lesage, 2010, p.20).

indication of clustering phenomena. However, in order to further investigate the cluster phenomena, we must focus on local spatial autocorrelation to determine whether it is formed randomly (spatial randomness or the absence of any pattern) or if there is some rationale behind it (evidence of spatial structure).

Figure 1. Average of greenfield FDI in MENA region (Million US $, Period:2003-2021)



Source: Author's calculation using The UNCTAD Data

2.2. Evidence of spatial dependence in MENA region

The spatial econometric framework would be a promising approach to deal with the importance of territorial interferences in the context of conflict and greenfield FDI. Actually, the entire independence of a country (absolute autarky) from what happens in the World and/or in its proximate neighbors is by far an unrealistic hypothesis. Undeniably, in a conflictual context what occurs in one country may affect directly or indirectly, immediately or with a time lag, the condition prevailing in the surrounding countries. This is especially true when a conflictual and an extremely tense situation prevailing in one or more close countries are considered. The refugee crisis that affected Turkey, Tunisia (and even certain European countries) due the civil war in Syria and Libya along the Arab spring, is a spatial spillover concrete example. "The spatial effect can be in the form of a global overflow over time, which is called a spatial spillover. Spillover occurs when changes in one area cause changes in another", (Atikah and Rahardjo, 2021, p.1). The Arab Spring itself can be considered as good evidence of clustering due to spatial interaction (true contagion, mimicking, etc.).

For more than decade, the MENA region experienced severe conflicts. However, this period was marked by a major and emblematic event, namely the Arab Spring. Unfortunately, this spring which was supposed to lead to a new era with a new social contract and new ambitions, has been deviated from popular claims by: resistance forces (internal and external), foreign interferences, corrupted politicians, and geopolitical issues, etc. The aftermath of this lose-lose game was a social and political disorder combined with the occurrence of multiple events with high-intensity (but short-lived like a disillusion).

Figure 2. Internal conflict evolution in MENA19 - Period:2003-2021

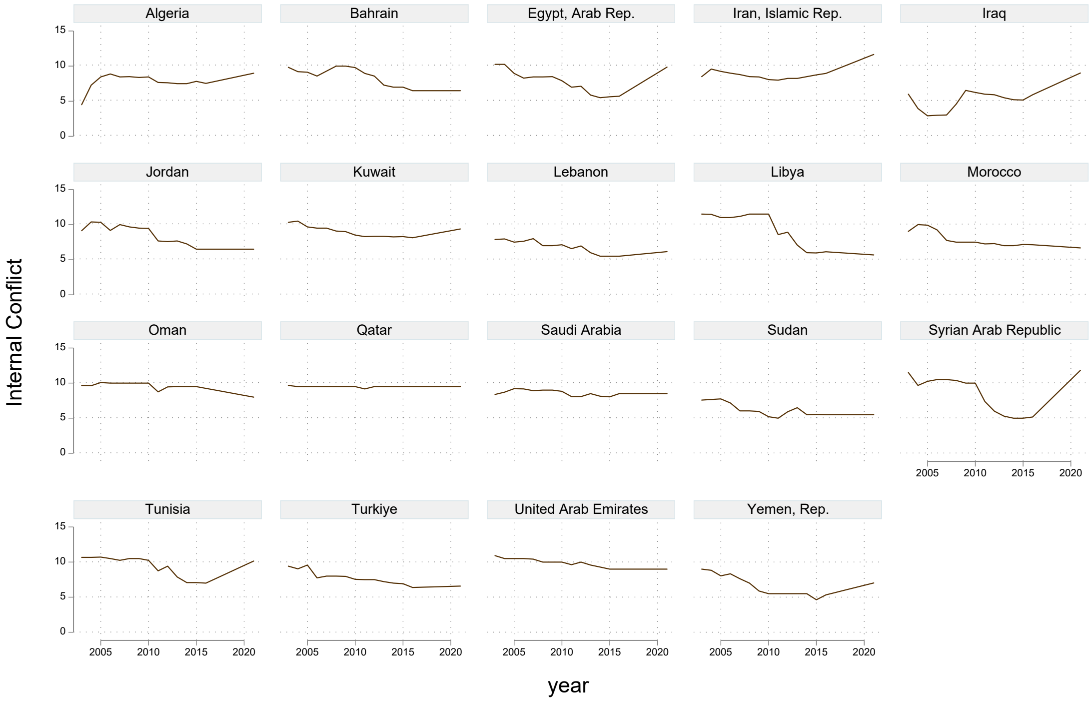
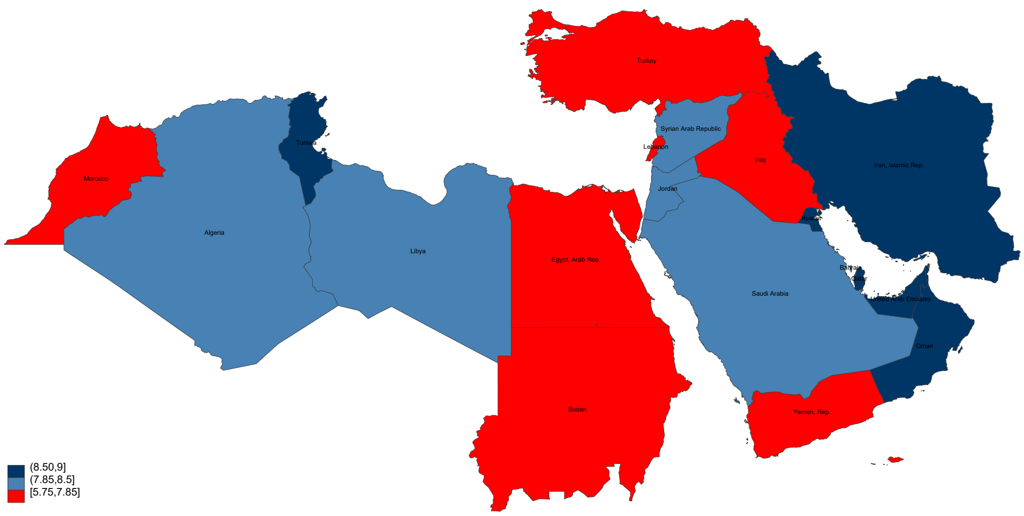


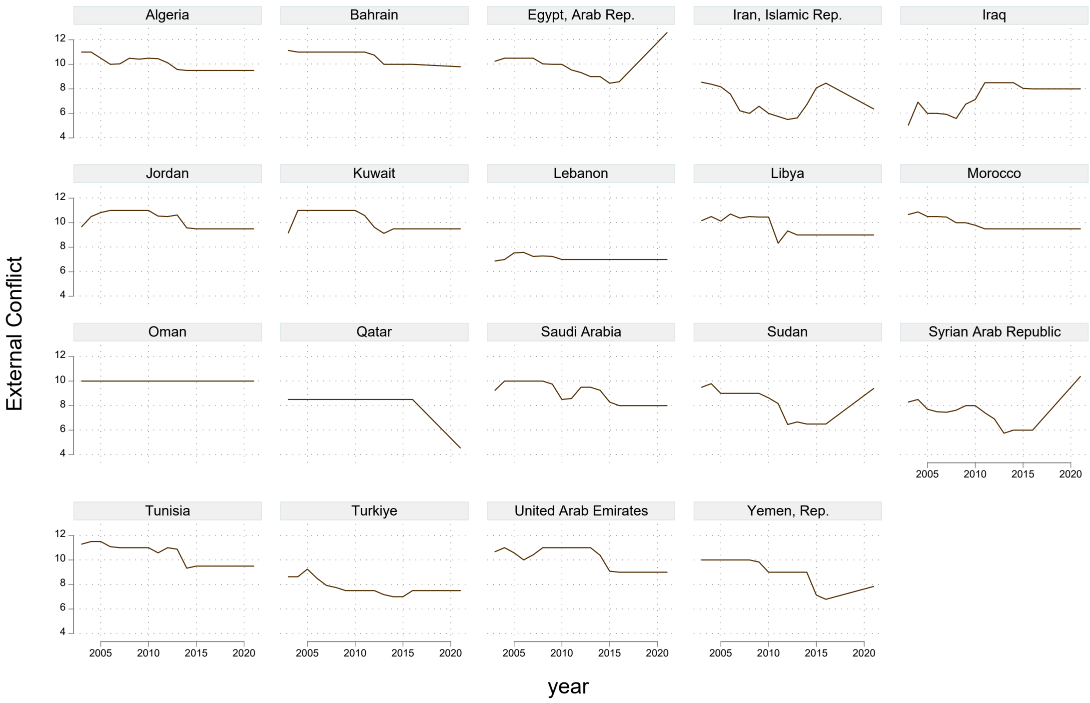
Figure 3. Internal conflict Index in MENA19 - Average Period: 2003-2021



Source: Author's calculation using ICRG data

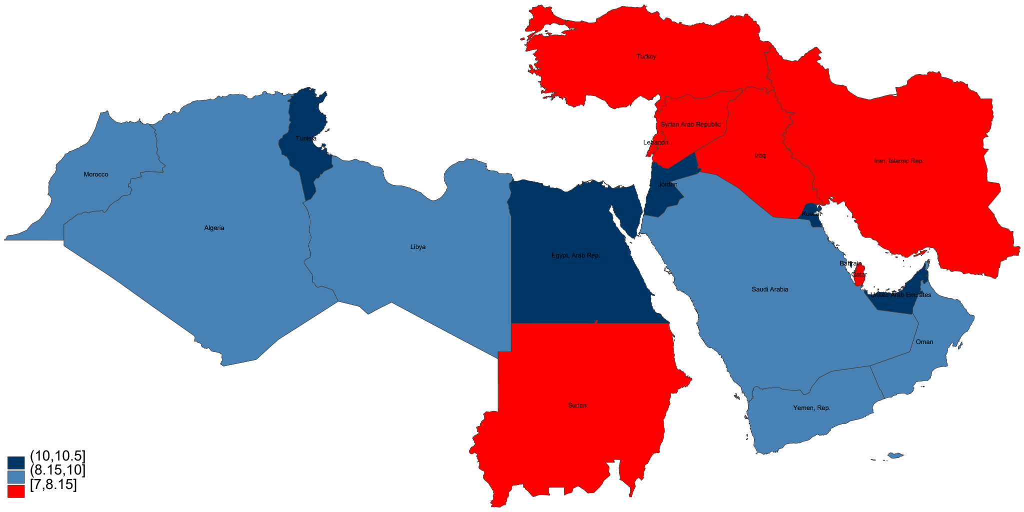
As indicated in Figure 2, a sharp decline in internal conflict score indicators (i.e., a higher risk) (ICRG) has been observed for many MENA countries since 2011, particularly Tunisia, Turkey, Egypt, Syria and Yemen. Despite not being heavily involved in the Arab Spring, Jordan and Lebanon had a considerable fall in their internal conflict score. This statement could be supported by the neighboring effect. The evolution of the external score indicator is similar to internal conflict with the exception of Qatar which had experienced a dramatic drop in its score following the political conflict with certain GCC countries. The two maps describing respectively the internal conflict and the external conflict indicate that on average Tunisia, Oman, Kuwait, Qatar, The United Arab Emirates and Iran are the most stable country in term of internal conflict index, however the less stable countries in term of external conflict are Sudan, Iraq, Syria, Iran, Qatar, Turkey and Lebanon. In addition, we observe (with few exceptions) that countries sharing similar scores tend to cluster, and it would be interesting to check whether these features occurred randomly (spatial randomness) or following a logic (evidence of spatial structure). The answer is given by further investigation via local correlation.

Figure 4. External conflict evolution in MENA19 - Period: 2003-2021



Source: Author's calculation using ICRG data

Figure 5. External conflict Index in MENA19 - Average Period: 2003-2021



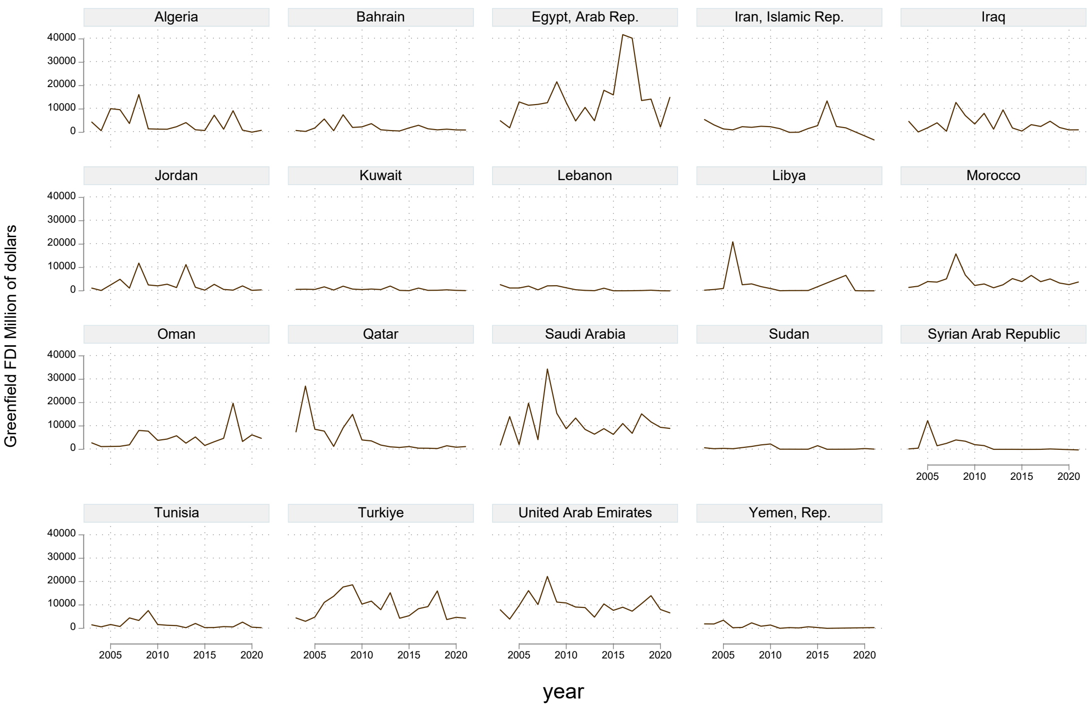
Source: Author's calculation using ICRG data.

The social disorder, economic instability and political turmoil increased the risk for business and investment for both local and foreign people. Whatever their resilience, multinational firms and foreign investors are not insensitive to the conflict risk and the associated potential economic turmoil. Political instability affects economic conditions, which in turn affects projected rates of return and risk perceptions. In addition, the act of investing abroad implies sunk costs. This is particularly true for greenfield investment (investment from scratch) where the initial costs are important in certain sectors like extraction activities, infrastructures, heavy industry, etc. Several studies (Busse and Hefeker 2007; Daude and Stein 2007; Alfaro et al. 2008) find a substantial detrimental effect of political instability on FDI. Also, the studies of Chan and Gemayel 2004; Me´on and Sekkat 2004; Mina 2012 pinpoint a negative relationship between political instability and international investment in MENA region.

In their empirical analysis, Burger et al. (2015), find that detrimental shocks to political stability affect strongly and negatively the greenfield FDI flows in the MENA region over the period 2003-2012. Nevertheless, the authors observe a differential sectoral sensitivity to political instability: the negative effect is particularly important for the flows of greenfield FDI in the non-resource tradable sectors. On the other hand, these flows toward natural resource and non-tradables industries are not significantly impacted by political instability. By running a gravity model on panel data of bilateral greenfield FDI in MENA countries for the period 2003-2018, Ben Jelili (2016) finds that perceived political risk has a negative, large, and robust influence on MENA host countries. In addition, the author empirically proves the existence of large disparate responses of foreign investors to political risk due to sectoral features.

Shocks to political stability affect economic conditions and thereby impact expected rates of return as well as risk perceptions. Whatever the resilience of FDI, multinational firms and foreign investors are not insensitive to the conflict risk and the associated potential economic turmoil. Indeed, often there are sunk costs when investing abroad. This is particularly true for greenfield investment (investment from scratch) where the initial costs are important in certain sectors like extraction activities, infrastructures, heavy industry, etc. The high volatility of greenfield investment (see Figure 6) is probably attributed (all things being equal) to the high economic and conflict risk variability in the MENA region during the last decade.

Figure 6. Evolution of greenfield FDI in MENA 19 - Period:2003-2021



Source: Author's calculation from UNCTAD Dataset.

What happens in one spatial unit will spread to others, especially nearby spatial units or those in immediate proximity. "Space, in fact, is not composed of units isolated from each other. What happens in each of them can influence others: there is spatial interaction", (Jayet, 1993, p.7). The mechanisms that should be indicated to support such an argument include spillovers, externalities, and shocks. "A (spatial) spillover arises when a causal relationship between the rth characteristic/action of the ith entity/agent (X_i^r) located at position i in located at position i in space exerts a significant influence on the outcomes/decisions/actions (y_j) of an agent/entity located at position j…..A formal definition would be: $\partial y_j / \partial x_i^r \neq 0$ which implies a spillover/impact from the rth characteristic/action of region/agent/entity i that impacts the outcome/decision/action in region j", (LeSage (2014), p.14).

2.3. The local correlation

Spatial autocorrelation is built on the idea of homogeneity of a given variable having similar values or characteristics across spatial units or showing structural or distributional similarities. Dubé and Legros (2014) stipulate that the autocorrelation measurement looks for the existence (or not) of any sort of spatial dependence between the spatial realizations of a given variable. The authors underline that "spatial autocorrelation describes the average resemblance of the values of a series in relation to the values located", (p.60). Likewise, they define spatial autocorrelation as the average resemblance of the values of a series in relation to the values located in the neighborhood. In other words, a variable's value in one spot may be related to the values the same variable has in nearby locations. The spatial phenomenon under study in a given location have an impact on surrounding phenomenon, which in turn interact with other phenomenon that are also nearby in the geographic space. All these interconnections divulge a certain level of organization of the values of the variable of concern in the geographic space. To wrap-up a spatial dependence or autocorrelation occur when a chock in one country affects bordering countries.

To detect the specific areas on the map where particular values exist and scrutinize the local spatial autocorrelation, we need to calculate a local version of Moran's I according to the following formula:

$$I_i = \frac{(x_i - \bar{x})}{\frac{1}{n}\sum_{i=1}^{N}(x_i - x_j)^2} \sum_{j=1, j\neq 1}^{n} w_{ij}(d)\,(x_i - \bar{x}) \qquad \text{Eq. 1}$$

Where w_{ij} is the weight matrix and N the sample size and $\bar{x}$ is the mean of the variable x .

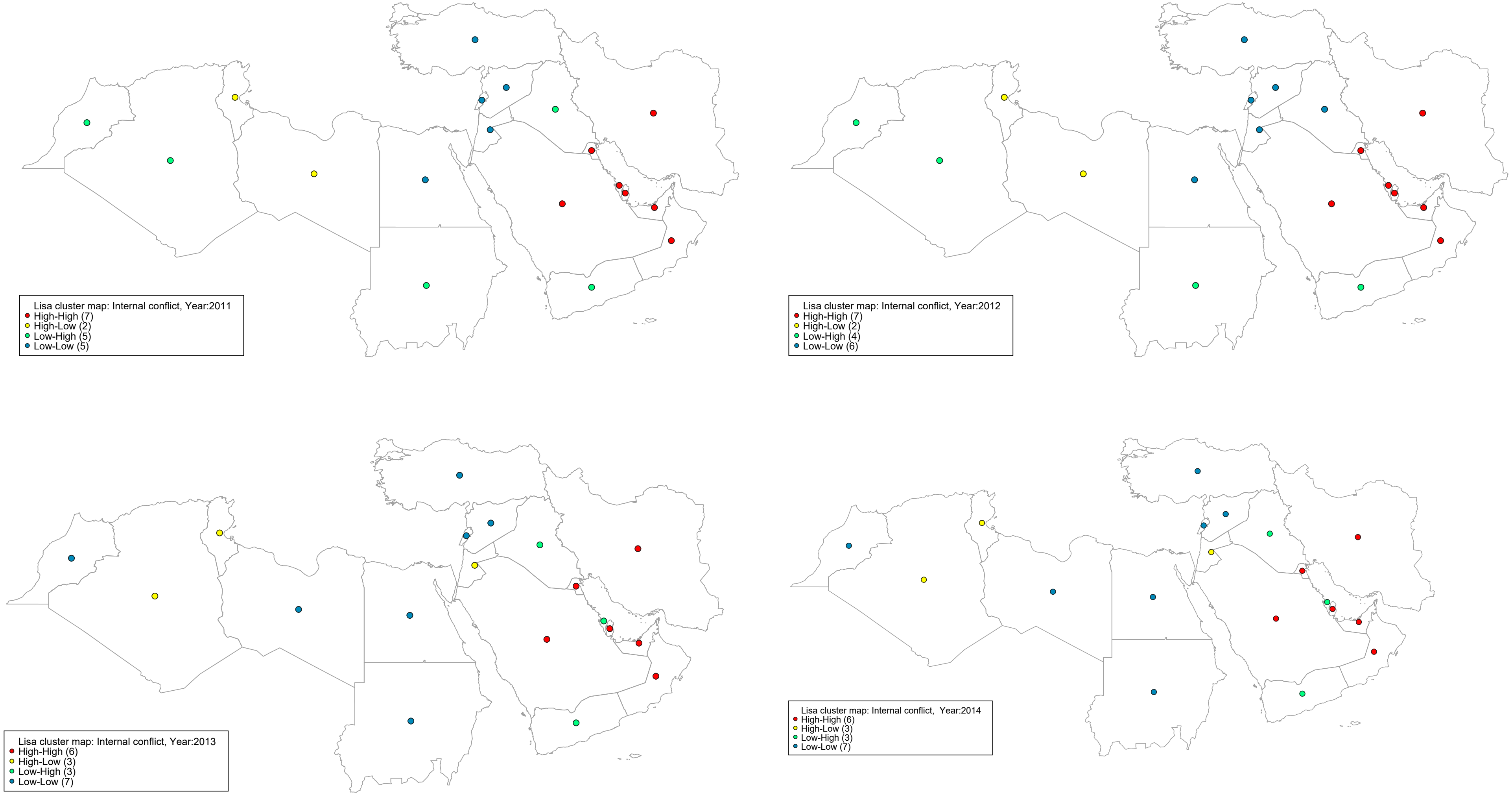
The test is useful for detecting the presence of spatial clusters. These clusters can be grouped under 4 categories namely: High-High, Low-Low, Low-High and High-Low. The results are represented by the Lisa-Cluster map (Figure 7a and 7b). The local spatial autocorrelation reveals information especially about the frequency of each category and the clustering of high values (hot spots) or low values (cold spots).

The map transposes the local spatial autocorrelation features to inspect whether a given observation i (let say the conflict score of a given country at time t) is surrounded by comparable data in other countries, or (in the reverse scenario) is being surrounded by extremely disparate observations in the other countries. Unfortunately, this technique is not applicable on panel data, so we proceed in cross-section without considering the time factor. We select the years for which the global Moran's I is significant before applying the local spatial autocorrelation method. For the internal conflict score we found that the Moran's I is significant for the years between 2011 and 2017. For the external conflict score the Moan's I is only significant for 2003, 2014, 2015 and 2016. Consequently, for each selected year we look for the presence of clusters for both indicators (see Figure 8).

The internal conflict maps reveal the presence of hot spots (High-High values group or most stable (or less risky) countries in terms of internal conflict) in the GCC and Iran. The cold spots or blue spots (Low-Low group i.e., the riskiest countries in terms of internal conflict) are Libya, Egypt, Sudan, Syria, Lebanon and Turkey.

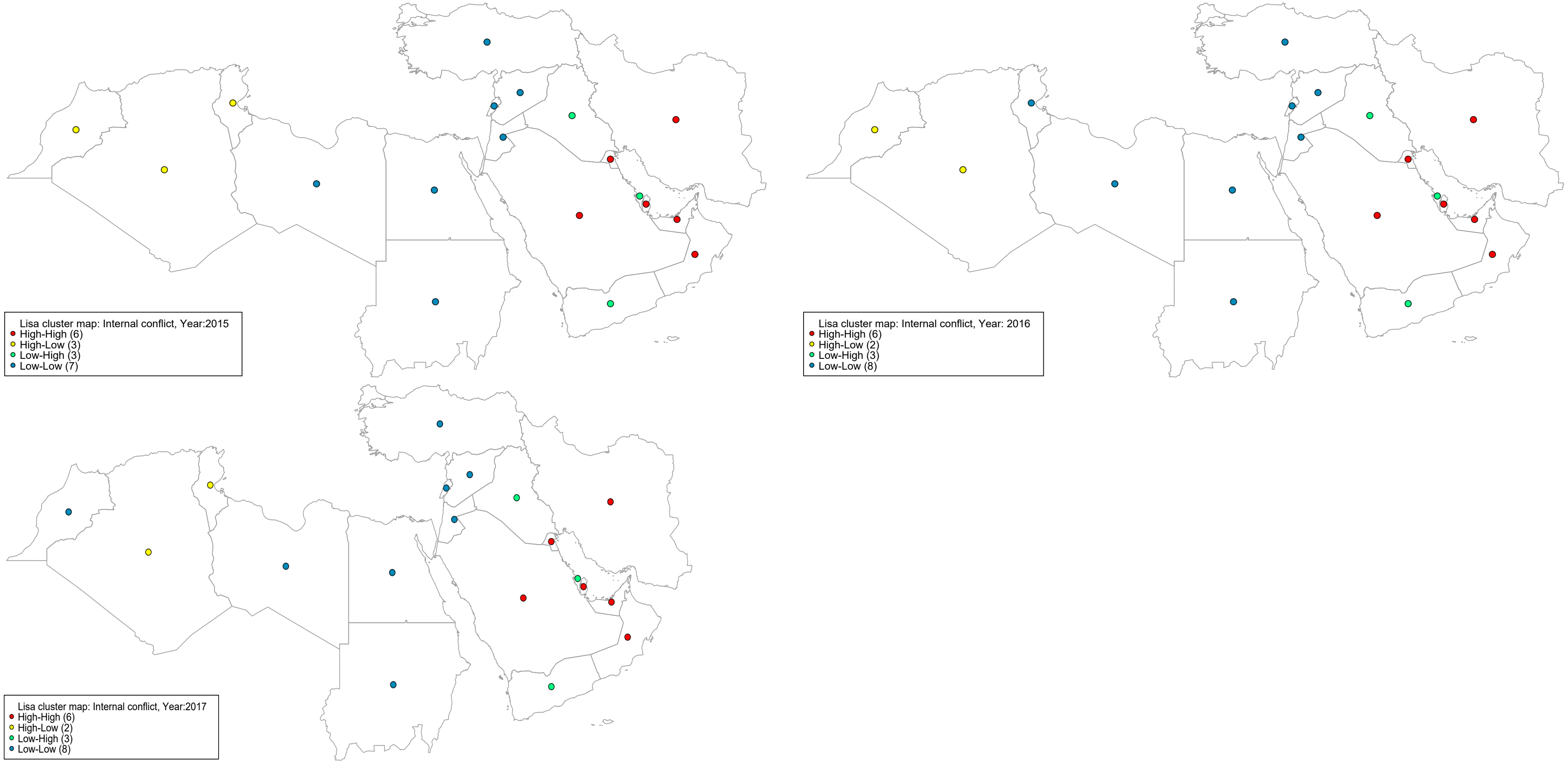
The external conflict maps disclose the existence of hot spots (the relatively safest countries in terms of external conflict) in Tunisia, Algeria and Morocco and some GCC countries. By contrast, Egypt, Sudan and Syria are the riskiest countries (the blue spots). Based on these results we can advance the existence of spatial structure. In other words, countries with similar values tend to cluster. In addition, given the presence of hot spots and cold spots, we assume the presence of neighbors' positive spatial autocorrelation (in terms of both external and internal conflict) resulting from the association of Low-Low values in one hand and the High-High values in the other hand. Probably, there are interactions and spillovers between the neighbors' countries explaining this spatial structure. Hence, it would be interesting to know whether these spillovers are spreading locally (in contiguous countries or countries in immediate proximity) or they diffuse in the whole region. To answer this question, we should run the spatial econometric models.

Figure 7a. Lisa cluster map: internal conflict, year: 2011, 2012,2013, 2014



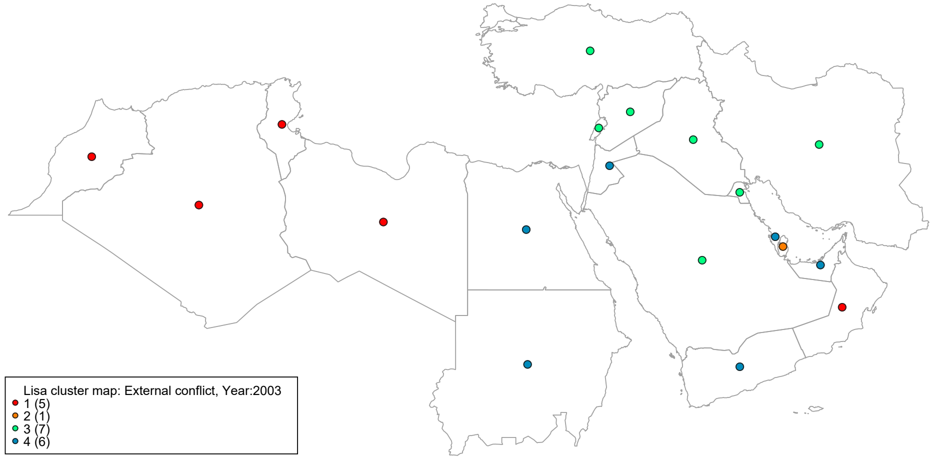
Source: Author's calculation using ICRG data.

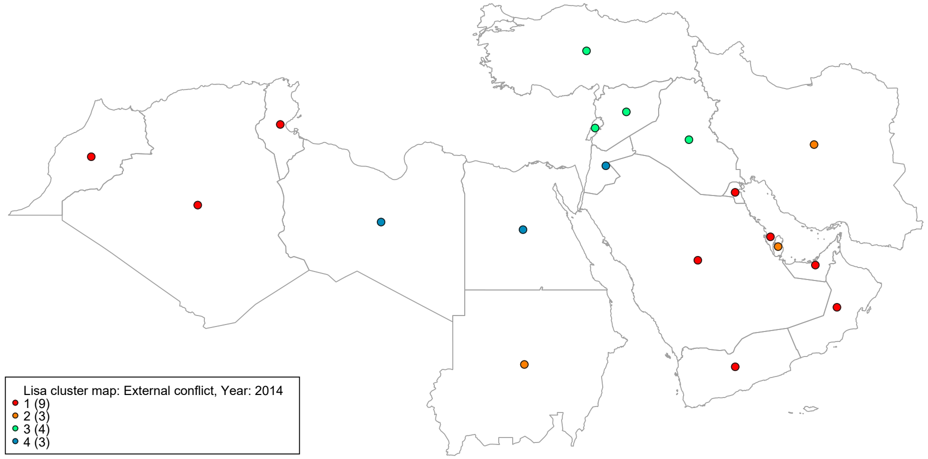
Figure 7b. Lisa cluster map: internal conflict, year: 2015, 2016,2017

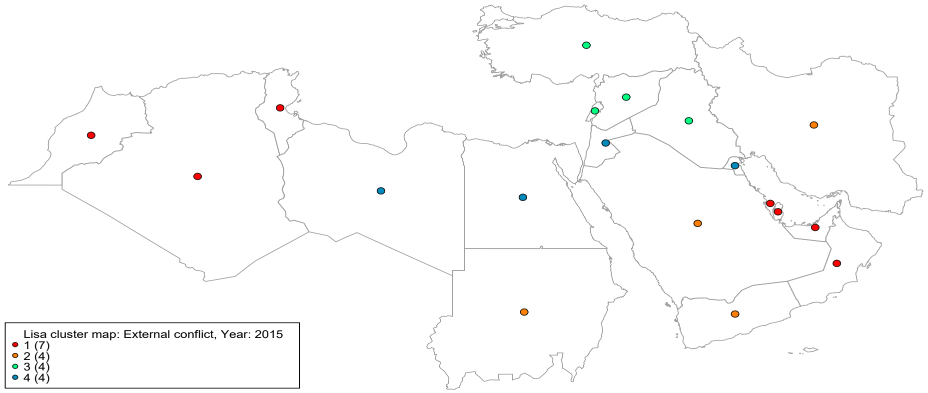


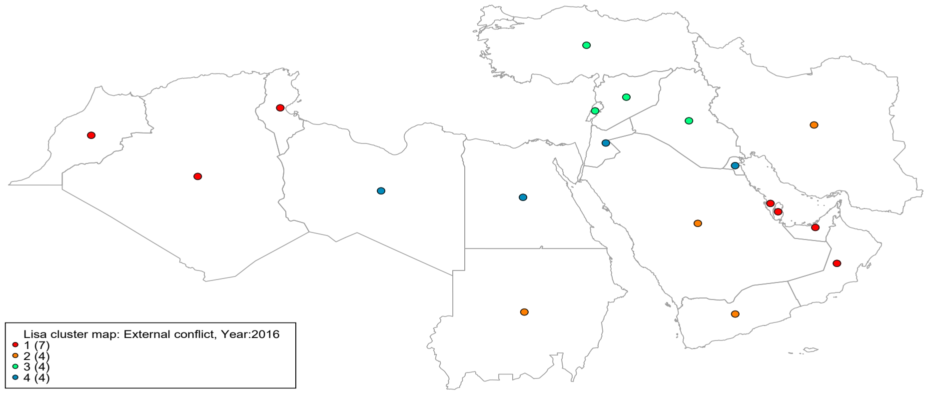
Source: Author's calculation using ICRG data.

Figure 8. Lisa cluster map: external conflict, year: 2003, 2014,2015,2016









Source: Author's calculation using ICRG data.

2.4. *Why spatial autocorrelation matters?*

Before embarking in the econometric work, an analyst should ask whether or not the data show spatial autocorrelation. Some tests (like CD tests, Moran's I, Geary's C statistic, etc.) are relevant to deal with this issue. Once the presence of spatial autocorrelation has been proved (i.e., the impact coming from neighbors' interaction is real), the analyst should take into account of this factor in the econometric work. Otherwise, in case where the geographical interdependence is omitted, we risk to get serious misspecification problems and non-BLUE OLS estimators. Accordingly, the OLS economic regressions results will be biased, (Anselin, 1998). It is worthwhile to recall that in the OLS spirit, the n observational units making the panel (for example countries, regions, etc.) are by hypothesis considered as independent2. Another salient point to be stated is the OLS inability of detecting and evaluating the spillovers coming from neighbors (the unobserved determinants of a given variable). Instead, these spillovers are caught by the error term in the OLS models. Fortunately, spatial econometrics are able to fill this gap via different spatial econometric models namely spatial lag models and spatial error models. Hence, in the presence of geographical interaction, spatial models offer a reliable alternative to OLS or non-spatial regressions by accounting for the spatial dependence influencing the dependent as well as the explanatory variables, (LeSage & Pace, 2009).

3. Empirical work

3.1. *The space configuration and connectivity measures*

The weighted spatial matrix W is set-up to parametrize the countries' connectivity and to measure the interaction potential among each observational units' pairs i, j. The weight is attributed for each pair according to their proximity based on the hypothesis that geographically close locations have higher interaction potential whereas far-off locations have lower potential.

$$W = \begin{pmatrix} w_{1,1} & \cdots & w_{1,n} \\ \vdots & \ddots & \vdots \\ w_{n,1} & \cdots & w_{n,n} \end{pmatrix}$$

The construction of this matrix is a necessity to run the spatial econometric models. It is built ex ante and on ad-hoc basis. The matrix has a $n \times n$ size3, positive and symmetric with $W_{i,j} = 0$ for the matrix diagonal (by convention a location cannot be a neighbor with itself). To make the regression result easier to interpret, the spatial weighted matrix is row is standardized (each weight in row i is divided by the sum of row i's weight).

The spatial weight matrix can be specified via several techniques. This latter can, for instance, be weighted by contiguity: when two sites are contiguous, or share a border (respectively

[2] Formally this can be expressed by the following equation: $E[u_i\, u_j] = 0;\ \forall\ i \neq j$

[3] n equal to the number of spatial units.

values of 1 and 0 are attributed to the matrix elements when the locations are contiguous and 0 otherwise). Accordingly, a binary matrix is created. Also, we can use an inverse distance (based on the hypothesis that the impact decays with the distance) or a cutoff distance (i,j locations interact while within a distance band). The kernel distance criteria (KNN) (the nearest neighbor) is another way to establish a spatial matrix weighted: the interaction scope is confined to a well-defined neighbor order (1, 2, 3, 4 and so on).

We employed four different types of matrices (contiguity weighted matrix, matrix based on inverse distance, matrix with band distance, and matrix with economic distance[4]) since it is advised to experiment with a variety of weighted spatial matrix W in the estimation process (because results may be particularly sensitive to the structure of matrix W). The best of fit has been guaranteed by an inverse-distance spatial-weighting matrix in accordance with the following formula:

$$w_{i,j} = \frac{1}{d_{i,j}} \ \forall\ i \neq j\ ; i,j = 1, \ldots\ldots, N \qquad \text{(Eq.2)}$$

3.2. Spatial dependence Detection

To test for the presence of a spatial pattern, we first run a Pesaran's test of cross-sectional independence before running a Wald test to approve or not the presence of spatial dependence or (spatial Autocorrelation) in OLS residuals. The Pesaran's test results indicate that the null hypothesis of cross-sectional (or observational units) independence is rejected. In the other side, the LR test confirms the rejection of the null hypothesis of the absence of spatial autocorrelation.

Table 1: Unit observational independence test

Test	Statistics
Cross-Sectional Dependence Test (CDD Test):	
Pesaran's test of cross-sectional independence	= 10.389****, Pr = 0.0000
Average absolute value of the off-diagonal elements	= 0.407
Wald Test:	
Wald Test SAR vs. OLS (Rho=0):	= 8.3532**** P-Value > Chi2(1) 0.0039
Acceptable Range for Rho:	-1.6490 < Rho < 1.0000

The test results indicate the potential presence of spatial dependence and contrast with the OLS hypothesis of observational units' independence, accordingly extra steps are required by using the spatial regression models to affirm or not the existence of spatial dependence and to investigate its nature. Hence, an LM diagnostic test is run to select the model with the best good of fitness, and to detect the scope of spillovers (global or local) in the MENA region.

[4] Measured by the countries' bilateral trade.

In the second step we run the Lagrange multiplier (LM) test, and (if necessary) the LR test.

Table 2: Lagrange multiplier test of spatial dependence

Test	Statistics
LM ErrorTest:	
o LM Error (Burridge)	= 4.8547** P-Value > Chi2(1) 0.0276
o LM Error (Robust)	= 4.8520** P-Value > Chi2(1) 0.0276
LM Lag Test :	
H0: Spatial Lagged Dependent Variable has No Spatial Autocorrelation	
H1: Spatial Lagged Dependent Variable has Spatial Autocorrelation	
o LM Lag (Anselin)	
o LM Lag (Robust)	= 0.0031 P-Value > Chi2(1) 0.9557
	= 0.0004 P-Value > Chi2(1) 0.9833
General Spatial Autocorrelation Test:	
H0: No General Spatial Autocorrelation	
H1: General Spatial Autocorrelation	
o LM SAC (LMErr+LMLag_R)	
o LM SAC (LMLag+LMErr_R)	= 4.8551* P-Value > Chi2(2) 0.0883
	= 4.8551* P-Value > Chi2(2) 0.0883

Based on the results of the preceding tests, we can conclude that spatial dependence exists. Accordingly, the OLS might suffer from serious misspecification problems and probably could not adequately provide econometric unbiased results. Henceforth, we should look for the selection of the appropriate spatial models that cope well with the dataset and the research scope. In fact, picking the right spatial model is tricky and challenging given the "panoply" of spatial regression models.

To maximize the goodness-of-fit of the potential model candidates we adopt the strategy established by Anselin (1988), Elhorst and Solmaria (2013), Elhorst (2014) and LeSage and Pace (2009) to select the suitable model from a pool of model candidates.

Following the logic of LM test, if only one of LM Lag (Anselin) or LM Error (Burridge) is significant, we select that model. Otherwise, when LM Lag (Anselin) and LM Error (Burridge) are both significant, we should check the robust test. Since this not the case for our sample (only the LM Error (Burridge) test is significant), we select the model with spatial error dependence and ignore the robust test version. One could stop the investigation at this stage and run the regressions via the model with spatial error dependence. However, to maximize the chance to have the right model with the best good of fitness, it is recommended to use the logic of LeSage and Pace (2009) based on restriction tests. Hence, we start by estimating the SDM model and check if this model could be nested to either the SAR or SEM Models. If the restriction hypothesis is rejected, and the SDM retained we decide via AIK and BIC criteria about which

model the SDM or SAC model should be selected since the two models cannot be nested one against the other.

Table 3: LR Test for model selection

Test	Statistics
SDM is Nested in SAR	
Likelihood-ratio test	LR chi2(4) = 3.29 Prob > chi2 = 0.5102
Assumption:	
The constrained SAR is nested in unconstrained SDM	
SDM is Nested in SEM:	
Llikelihood-Ratio Test	LR chi2(4) = 1.84 Prob > chi2 = 0.7646
Assumption:	
The constrained SEM is nested in unconstrained SDM	

According to the LM and AIC results, the SDM cannot be constrained to nor SAR or SEM, and fit better than the SAC model[5]. In other words, they take account of the dual types of spatial dependence, explicitly spatial lag dependence and spatial error dependence.

Table 4: Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(model)	df	AIC
SDM	361	-3532.898	10	7085.797
SAC	361	-3542.111	5	7094.223

Given the selection model tests outcome (in favor of the SDM) and the benefits and drawbacks of each model, we think it is worthwhile to run the various models in order to benefit from the information connected to the various regression approaches. Hence, the SDM model, the SAR, SEM and SAC regression results will be included in the empirical work. Some of them will be just established for benchmarking and information purposes.

3.3. The spatial econometric models

Spatial regression models are statistical models that account for the presence of spatial effects, i.e., spatial autocorrelation (or more generally spatial dependence) and/or spatial heterogeneity. There are several spatial models[6] that can be subsumed in the Manski all-inclusive model [Eq.3]. This model could be an interesting starting point to assess the spillover effects.

$$y = \rho WY + \alpha\iota_N + X\beta + WX\theta + \mu, \qquad \mu = \lambda W_u + \varepsilon \qquad \text{(Eq. 3)}$$

According to Elhorst (2014), the Manski model is considered as an all-inclusive specification because it encloses all the possible forms of interactions among observational units, namely

[5] Since the SAC and SDM are non-nested, we can rely on information criteria (see Table 4) to test whether the most fitting model is the SDM or the SAC model. In this example, as indicated in the Table 2, Lagrange Multiplier Test of Spatial Dependence (LM SAC) is statistically significant at only 10%. Moreover, the Akaike's information criterion favors the SDM compared to the SAC model (see Table 4).

[6] For more details see Figure 9 in appendix.

(1) endogenous interaction effects of the dependent variable Wy, (2) exogenous interaction effects concerning the explanatory variables WX, and (3) interaction effects about the error terms W_u. ρ and λ measure the amplitude of spatial dependence between the observational units. β and θ are both $k \times 1$ vectors of response parameters. Is not surprising that the model has been named by Elhorst (2014) as the general nesting spatial (GNS) model. The paradox is that the GNS model is rarely used because of serious problem of identification (its parameters are only weakly identifiable). Also, when it is estimated, the GNS model suffers from "overparameterization". In other words, "parameters have the tendency to become insignificant as a result of which this model does not outperform the SDM and SDEM models", (Elhorst, 2013, p.9). This may explain why the SDM[7] is widely used in applied research compared to the GNS model. Given the GNS drawbacks, the model is often constrained to the SAC or SDM model. It is worthwhile to note that choosing the appropriate spatial econometric model for the topic under study is important because there are numerous options available.

Roughly, there are four recognized spatial models used in applied research namely the Spatial Lag Model or Spatial Autoregressive Model (SAR), the Spatial Error Model (SEM), the SAC model (or SARAR, Cliff-Ord model) and the Spatial Durbin model (SDM). The Spatial Lag [Eq.4], Spatial Autoregressive (SAR) model postulates that levels of the dependent variable y depend on the levels of y in neighboring units apprehended by the weighted matrix W and represented by ρW_y. In the Spatial Error Model (SEM) [Eq.5], the spatial influence comes exclusively via the error terms $\mu = \lambda W_\mu + \varepsilon$ and is useless for spillovers detection. The SAC model [Eq.6] is a mixed or a combined spatial autoregressive model involving the endogenous interaction among the dependent variable Wy as well as the autoregressive disturbance λW_μ. If λ = 0, we obtain the Spatial Durbin Model (SDM) [Eq.7] which incorporates the lagged dependent variable y (ρW_y) and the spatially related residuals. Compared to the SEM model, the SDM model just adds average-neighbor values of the independent variables to the specification through the expression $WX\theta$.

SAR: $y = \rho W_y + \alpha + \beta X + \varepsilon$ (Eq.4)

SEM: $y = \alpha + \beta X \mu \quad \mu = \lambda W_\mu + \varepsilon$ (Eq.5)

SAC: $y = \rho W_y + \alpha + \beta X + WX\theta + \varepsilon \quad \mu = \lambda W_\mu + \varepsilon$ (Eq. 6)

SDM: $y = \rho W_y + \alpha + \beta X + WX\theta + \varepsilon$ (Eq.7)

3.4. Dataset and variables description

To estimate the determinants of greenfield FDI we use a dataset of 19 MENA countries over the period spanning from 2001 to 2021. The study period and countries were selected to

[7] Which is a global spillover specification like the GNS model.

ensure both balanced panel data and a large sample size dataset to properly run the spatial regressions. We run different spatio-temporal panel data models to control for the effect of time and space. We regress the variable *Greenf_FDI* expressing the flows of greenfield FDI (in US Million Dollars) toward the MENA economies on: the economic growth [*Gr*] indicated by GDP growth (annual %) ; the natural and human resources endowment respectively approximated by the oil rent of GDP [*Oil_rent*] and labor force [Labor] ; the exchange rate [*XR*] expressed by the official exchange rate (local currency per US$, period average); the economic openness [*Eco_open*] measured by the sum of exports and imports on GDP); a proxy of conflict risk [expressed in terms of the internal conflict [*Intern_Conf.*]; external conflict8 [*Extern_Conf.*]; Military in politics [*Military_politics*] with a score between 0 (very high risk) and 12 (very low risk)]; the state fragility is assessed by the State Fragility Index [*SFI*] (which is calculated by combining the scores of eight indicators and ranges between 0 (no fragility) and 25 (extreme fragility).

The data is compiled from the World Bank9, the United Nations Conference on Trade and Development10(UNCTAD), the International Country Risk Guide database[11], and Armed Conflict and Intervention (ACI) Datasets12. Finally, the data of internal and external conflict is sourced from the International Country Risk Guide database.[13].The internal conflict indicator is designed to measure the risk that a country is exposed to; evaluates the political violence in the nation and its real or projected effects on governance. The nations with the highest scores are those where there is no armed or civil opposition to the government, no direct or indirect arbitrary violence by the government against its own citizens is not practiced. Three subcomponents, each having a maximum score of four points and a minimum score of zero points, combine to form the risk rating that is given. very low risk is equal to a score of 4, and very high risk is equal to a score of 0. According to ICRG (2020, p.11) "the external conflict measure is an assessment both of the risk to the incumbent government from foreign action, ranging from non-violent external pressure (diplomatic pressures, withholding of aid, trade restrictions, territorial disputes, sanctions, etc.) to violent external pressure (cross-border conflicts to all-out war)". External conflicts are sources of uncertainty and extra-transaction costs. They might be harmful for both national and multinational firms by constraining their activities, and inducing trade and investment penalties. Also, to mention just a few, brutal societal changes and economic resources distortions should be mentioned.

[8] https://www.prsgroup.com/explore-our-products/icrg/
[9] https://data.worldbank.org/
[10] https://unctadstat.unctad.org/datacentre/
[11] International Country Risk Guide (ICRG), The PRS Group, Inc. https://www.prsgroup.com/explore-our-products/icrg/
[12] https://www.systemicpeace.org/inscrdata.html
[13] https://www.prsgroup.com/explore-our-products/icrg/

3.5. The Regressions results

We run different maximum likelihood spatial regression models. The reason behind using the maximum likelihood estimation is the OLS bias and inconsistency as a result of endogeneity problems when we run a spatial lag model. However, in the case of spatial error model regression, OLS is unbiased but inefficient due to the error term's spatial autocorrelation. Contrary to the SEM, the SAR, SAC and SDM models allow spillovers to be detected and to manifest. This is one among the reasons to emphasize these three kinds of models.

Generally, the econometric results (by the SAR (see Table 5), SDM (see Table 6), SAC (see Table 7) and SEM (see Table 8) show consistent results. Except the economic growth which is not significant, the other independent variables namely *Oil_rent*, *Labor*, *XR* and *Eco_openess* are significant and show the expected sign. Hence, the greenfield FDI seems to be positively impacted by: the labor force (or human resources availability); the country endowment in terms of natural resources specifically oil. In fact, this result is not surprising and copes with the nature of inbound FDI in the MENA region: by investing in MENA many multinational firms seek access to gas and petroleum in well-endowed countries. This type of greenfield FDI (also known as vertical investment) is driven by natural resources extraction and accounts for a significant portion of international investment flowing into the MENA area (even in non-oil countries).

Table 5. The effect of external and internal conflict and military in politics on greenfield FDI maximum likelihood spatial panel lag model (SAR); y=ρW_y+α+βX+ε sample: MENA19, Period: 2003-2021

Variables	(1) Greenf_FDI	(1) ρW_{Greenf_FDI}	(1) Sigma	(2) Greenf_FDI	(2) ρW_{Greenf_FDI}	(2) Sigma	(3) Greenf_FDI	(3) ρW_{Greenf_FD}	(3) Sigma
Gr	27.96			26.15			32.10		
	(1.290)			(1.165)			(1.424)		
Oil_rent	43.28***			41.81***			42.91***		
	(3.012)			(2.901)			(2.974)		
Labor	4.61E-04***			4.62E-04***			4.67E-04***		
	(8.671)			(8.651)			(8.721)		
XR	-0.294***			-0.333***			-0.347***		
	(-6.238)			(-6.281)			(-6.772)		
Eco_open	41.35***			40.91***			37.38***		
	(6.854)			(6.455)			(5.260)		
Extern_conflict	325.8**								
	(2.048)								
Intern_conflict				341.2***					
				(2.936)					
Military_politics							435.5***		
							(3.492)		
Constant	-7.397***	0.264***	4.805***	-7.027***	0.242***	4.798***	-5.542***	0.263***	4.788***
	(-3.933)	(2.890)	(9.974)	(-6.007)	(2.829)	(9.773)	(-6.022)	(2.972)	(9.840)
Observations	361			361			361		
R^2	0.24			0.21			0.28		
Loglikelihood	-3525			-3524			-3523		
Wald	112.4			97.85			144.2		

*Notes: Robust z-statistics in parentheses. *** p<0.01. ** p<0.05. * p<0.1*

Table 6. Conflicts and military in politics impact on greenfield FDI: a spatial Durbin model estimation maximum likelihood regressions; y=ρW_y+α+βX+WXθ+ε period: 2003-2021, sample: MENA19

VARIABLES	(1) Greenfield_FDI	(1) ρW_{Greenf_FDI}	(1) Sigma	(2) Greenfield_FDI	(2) ρW_{Greenf_FDI}	(2) Sigma	(3) Greenfield_FDI	(3) ρW_{Greenf_FDI}	(3) Sigma
Gr	9.475			17.12			19.47		
	-0.328			-0.589			-0.677		
Oil_rent	52.56***			47.45***			46.65***		
	-3.384			-3.009			-3.029		
Labor	4.94E-04***			4.76E-04***			4.86E-04***		
	-12.87			-12.4			-12.75		
XR	-0.322***			-0.356***			-0.405***		
	(-5.318)			(-5.915)			(-6.399)		
Eco_open	39.61***			42.35***			33.63***		
	-3.694			-4.151			-3.144		
Extern_conflict	624.5***								
	-2.761								
Intern_conflict				319.8*					
				-1.902					
Military_ politic							590.6***		
Spatial: Wx							-3.019		
Wx_Oil_rent	-182.6***			-90.15			-140.1*		
	(-2.638)			(-1.371)			(-1.916)		
Wx_XR	-1.287***			-0.819*			-1.367**		
	(-2.668)			(-1.734)			(-2.518)		
Wx_Extern_conflict	839.1***								
	-3.46								
Wx_Intern_conflict				417.4*					
				-1.809					
Wx_Military_politic							1.558**		
Constant	-12.178***	0.208**	4.728***	-7.640***	0.214**	4.776***	-6.430***	0.219**	4.745***
	(-5.024)	-1.999	-26.64	(-4.881)	-2.05	-26.64	(-5.651)	-2.114	-26.64
Observations	361			361			361		
R^2	0.31			0.30			0.30		
Loglikelihood	-3518			-3522			-3520		
Wald	164.3			152.3			157.3		

*Notes: z-statistics in parentheses, Wx: the spatially lagged variable; *** p<0.01. ** p<0.05. * p<0.1*

Table 7: Effect of external and internal conflict, military in politics on greenfield FDI estimation by maximum likelihood spatial auto correlation model (SAC); y=ρW_y+α+βX+WXθ+ε μ=λW_μ+ε Sample: MENA19, Period:2003-2021

	(1)	(1)	(1)	(1)	(2)	(2)	(2)	(2)	(3)	(3)	(3)	(3)
VARIABLES	**Greenf_FDI**	ρW_{Green_FDI}	**Lambda**	**Sigma**	**Greenf_FDI**	ρW_{Green_FDI}	**Sigma**	**Sigma**	**Greenf_FDI**	ρW_{Green_FDI}	**Lambda**	**Sigma**
Gr	22.85				25.01				31.36			
	(0.807)				(0.880)				(1.120)			
Oil_rent	41.07***				41.28***				42.06***			
	(2.767)				(2.758)				(2.833)			
Labor	4.70E-04***				4.67 E-04***				4.74E-04***			
	(12.37)				(12.26)				(12.46)			
XR	-0.295***				-0.338***				-0.357***			
	(-4.918)				(-5.674)				(-5.866)			
Eco_open	32.99***				38.26***				33.59***			
	(3.120)				(3.904)				(3.226)			
Extern_conflict	496.0**											
	(2.262)											
Intern_conflict					347.8**							
					(2.099)							
Military_politics									463.5**			
									(2.445)			
Constant	-8.267***	0.325***	-0.162*	4.770***	-6.908***	0.275***	-0.0798	4.788***	-5.429***	0.315***	-0.116	4.770***
	(-4.682)	(3.738)	(-1.753)	(26.55)	(-4.967)	(2.891)	(-0.811)	(26.60)	(-5.531)	(3.247)	(-0.999)	(26.53)
Observations	361				361				361			
R^2	0.27				0.28				0.27			
Loglikelihood	-3523				-3524				-3523			
Wald	132.2				140.8				135.2			

*Notes: z-statistics in parentheses. *** p<0.01. ** p<0.05. * p<0.1*

Table 8: The effect of external and internal conflict, and military in politics on greenfield FDI estimation by maximum likelihood spatial error model (SEM) sample: MENA19, period:2003-2021

VARIABLES	(1) Greenf_FDI	(1) Lambda	(1) Sigma	(2) Greenf_FDI	(2) Lambda	(2) Sigma	(3) Greenf_FDI	(3) Lambda	(3) Sigma
Gr	36.02			31.90			37.20		
	(1.245)			(1.106)			(1.298)		
Oil_rent	45.17***			43.09***			43.80***		
	(2.948)			(2.816)			(2.857)		
Labor	4.42E-04***			4.42E-04***			4.43E-04***		
	(11.37)			(11.54)			(11.60)		
XR	-0.289***			-0.318***			-0.327***		
	(-4.723)			(-5.289)			(-5.385)		
Eco_open	47.25***			44.88***			41.82***		
	(4.885)			(4.795)			(4.235)		
Extern_conflict	189.1								
	(0.701)								
Intern_conflict				326.3*					
				(1.854)					
Military_politics							376.1**		
							(2.001)		
Constant	-5.678**	0.0516	4.874***	-6.337***	0.0549	4.855***	-4.730***	0.0954	4.849***
	(-2.444)	(0.406)	(26.69)	(-4.204)	(0.601)	(26.69)	(-4.449)	(0.985)	(26.69)
Observations	361		361		361		361		
R^2	0.30		0.30		0.30		0.30		
Loglikelihood	-3528		-3528		-3527		-3527		
Wald	155.3		155.3		158.2		158.6		

*Notes: z-statistics in parentheses. *** p<0.01. ** p<0.05. * p<0.1*

According to the econometric results, the economic openness plays as a catalyst in attracting transnational corporations by lowering the transaction costs associated with trade barriers. The exchange rate has a significant negative sign. In other words, the rise of the exchange rate (depreciation of local money) impedes the greenfield FDI. If we consider the exchange rate as a proxy of cost factor or form a price competitiveness point of view, we can advance that the obtained result is counterintuitive if we consider the foreign affiliates' strategy to export back (totally or partially) the production to their home countries or shifting it to a third country (export platform FDI). In both cases the depreciation of the local currency against the dollar (an increase of the exchange rate) will positively affect the competitiveness of the products being exported by dropping the factor costs in the host country and/or increasing the products price competitiveness at export. However, if we focus on exchange rate volatility and pinpoint the risk aspect of high and unexpected fluctuations, this could be a dissuasive factor for investors, and would be interpreted as an economic risk factor.

The regressions results point out to that the three conflict risk proxies' variables (internal conflict, external conflict and military in politics) are statistically significant and have the expected positive sign. In fact, based on the regression results the variable describing internal conflict is significant at 5% for the SAR (see Table 5) and SAC model (see Table 7), and 10% for the SDM (see Table 6). The external conflict independent variable is significant at 1% for both SAR and SDM models, and 5% for the SAC model. This is exactly what we obtain for the variable military in politics from the indicated models. Based on the estimation outcome, we can state that a lower internal and external conflict risk (i.e., a higher score of internal and external conflict indicator) encourages and promotes greenfield investment. Also, this is true for the participation or interference of the military in politics. In fact, the positive and significant sign of the variable *Military_politics* indicate that a lower political risk associated with a lower degree of military participation (measured by higher risk ratings) favor the greenfield FDI country's attractiveness.

It is worthwhile to note that the risk conflict variables are relatively highly correlated[14]. Accordingly, to avoid serious problems of multicollinearity they have been included separately in the regression equations. The high correlation between the conflict indicators means that the different kinds of conflict risk are not disconnected but interlinked to each other, and in certain cases one kind of conflict may contribute to the outbreak of another type of conflict. For example, during the Arab Spring the riots and protestations against the regime in Libya and Syria have rapidly turned into internal conflicts before converging to an external conflict with the intervention of foreign countries.

Concerning the state fragility index [*SFI*], the SAR, SEM, SDM and SAC regression results (see Table 9) show that the *SFI* coefficient has the expected negative sign and is significant at 1%. In other words, when the risk of state fragility increases in a given country (expressed by a higher *SFI* score), this could lead to a decrease of inward greenfield FDI. After all, whatever the targeted activities, the investors are generally averse to risk and prefer to invest in countries with less uncertainty and incertitude. Investors are usually averse to risk of losing money, especially when "sunk costs" related to the initial investment are considerable and irrecoverable. The state fragility, can be interpreted by foreign firms as a sign of instability, law enforcement weakness, and a higher incertitude, etc. This could dissuade potential investors from investing in the countries suffering from this issue.

[14] See Figure 10 in appendix.

Table 9. The impact of state fragility on greenfield investment (*SFI*): estimation by SAR, SEM, SDM and SAC model maximum likelihood regressions, *Sample: MENA19, Period: 2003-2021*

VARIABLES	SAR Greenf_FDI	(1) ρW_{Greenf_FDI}	(1) Sigma	SEM Greenf_FDI	(2) Lambda	(2) Sigma	SDM Greenf_FDI	(3) ρW_{Greenf_FDI}	(3) Sigma	SAC Greenf_FDI	(4) ρW_{Greenf_FDI}	(4) Lambda	(4) Sigma
Gr	30.64			31.53			22.54			30.37			
	-1.446			-1.105			-0.783			-1.084			
Oil_rent	54.26***			55.08***			54.31***			53.65***			
	-3.488			-3.537			-3.382			-3.525			
Labor	4.62E-04***			4.40E-04***			4.63E-04***			4.66E-04***			
	-8.562			-12.36			-12.15			-12.28			
XR	-0.327***			-0.314***			-0.340***			-0.331***			
	(-6.464)			(-5.390)			(-5.736)			(-5.604)			
Eco_open	32.11***			30.57***			33.67***			30.51***			
	(-3.907)			(-2.857)			(-3.008)			(-2.837)			
SFI	-163.8***			-187.8***			-165.6***			-163.2***			
	(-3.759)			(-3.369)			(-2.752)			(-2.753)			
Spatial: Wx													
Wx _Oil_rent							-3.67						
							(-0.0735)						
Wx _XR							-0.559						
							(-1.255)						
Wx _SFI							74.68						
							-0.393						
Constant	-2.218	0.238**	4.775***	-927	0.211**	4.796***	-2.211	0.227**	4.763***	-2.257*	0.291**	-0.091	4.764***
	(-1.613)	(-2.522)	(-9.97)	(-0.651)	-(1.98)	(-26.64)	(-1.268)	(-2.196)	(-26.64)	(-1.698)	(-2.292)	(-0.525)	(-26.44)
Observations	361			361			361			361			
R^2	0.27			0.31			0.3			0.28			
Loglikelihood	-3522			-3523			-3521			-3522			
Wald	132.6			163.8			152.3			142.4			

*Notes: z-statistics in parentheses, Wx: the spatially lagged variable. *** p<0.01. ** p<0.05. * p<0.1*

Regarding the spatial variables of interest, notably the spatial dependent variable $[\rho W_{Greenf_{FDI}}]$, the results of the SAR (see Table 5), the SAC (see Table 7) and SDM (see Table 6) indicate a positive spatial dependence (positive neighboring effect) in terms of greenfield FDI. This can be explained by a positive interaction of the spatial dependent variable in a given MENA countries with their neighbors. The positive and significant sign of the spatial dependent variable $[\rho W_{Greenf_{FDI}}]$ indicates the existence of multiplicative effect or loop feedback-effect in terms of greenfield FDI in the whole sample.

Moreover, as shown in the indirect effect in the SDM model (see Table 6), the greenfield FDI in a given MENA country seems to be boosted indirectly by the diffusion of neighboring positive spillovers via an increase of stability (or a decrease of conflict risk) captured by the three indicators Internal conflict, external conflict and Military in politics. Indeed, as shown in the SDM regression results (see Table 6) the spatial variables *Wx_Extern_conflict* and *Wx_Military_politic* are both positive and significant at 1%, however the variable *Wx_Intern_conflict* is positively significant at 10%. Henceforth, an increase in the stability (or a decrease of conflict risk) in a given MENA country may enhance the stability in its neighboring countries which in turn would promote the greenfield FDI in that country and its neighbors. This process is similar what Nwaogu and Ryan (2014), Blongein et al. (2007), Baltagi et al. (2007) and Blanco (2012) describe as agglomeration and externalities (demonstration and contagion effects for example) to explain the positive interdependence of FDI across a number of observed host countries.

It is useful to mention that, compared to the other models, the SDM has the advantage to detect the spatial autocorrelation effect of the independent variables by converting them to spatial lagged variables $[W_X]$ in addition to the neighboring effect captured by the spatial dependent variable $[\rho W_{Greenf_{FDI}}]$. However, this advantage is not without cost. Indeed, in the SDM specification, the independent variable is included twice in the regression to obtain the spatial independent variables $[W_X]$ and might therefore lead to some multicollinearity problems. To avoid serious multicollinearity problems as well as the lost degrees of freedom (DFM). Accordingly, instead of converting all the independent variables we just select some explanatory variables *Intern_Conf*, *Extern_Conf*, *Oil_rent* and *XR* based on a benchmark regression test model including all the explanatory variables. Only those with a significant coefficient have been retained.

4. Conclusion

The purpose of this study is to investigate the effects of conflict on greenfield FDI by using a spatial approach. Empirical results revealed that country risk matters for this kind of FDI (the lower the conflict risk, the higher the greenfield FDI will be). In addition, the greenfield FDI as well as political stability in MENA region benefit from feedback loop effect via substantive spatially lagged variables (ρW_{Green_FDI} and W_x). Of course, this multiplicative effect in terms of greenfield investment and political stability is good news for the policy makers. Moreover, the spatial regression (SDM) models indicate the presence of spillovers (the indirect effects) within the MENA countries, and these spillovers are global in nature. In other words, they don't concern only the neighbors of immediate proximity (neighbors of first order or contiguous neighbors) but spread to neighbors with higher order, and perhaps reach the whole region. Unfortunately, the MENA region is considered as a hot spot of conflicts and instability.

Policymakers should adopt a proactive approach to addressing the causes rather than just treating the symptoms. Fighting corruption, inequality, poverty and promoting inclusive growth is a must to mitigate at least the internal conflicts. A new sustainable social contract should be established to promote the quality of life as well as human rights. This could alleviate social tensions and promote peace and stability in the country and probably in neighboring countries.

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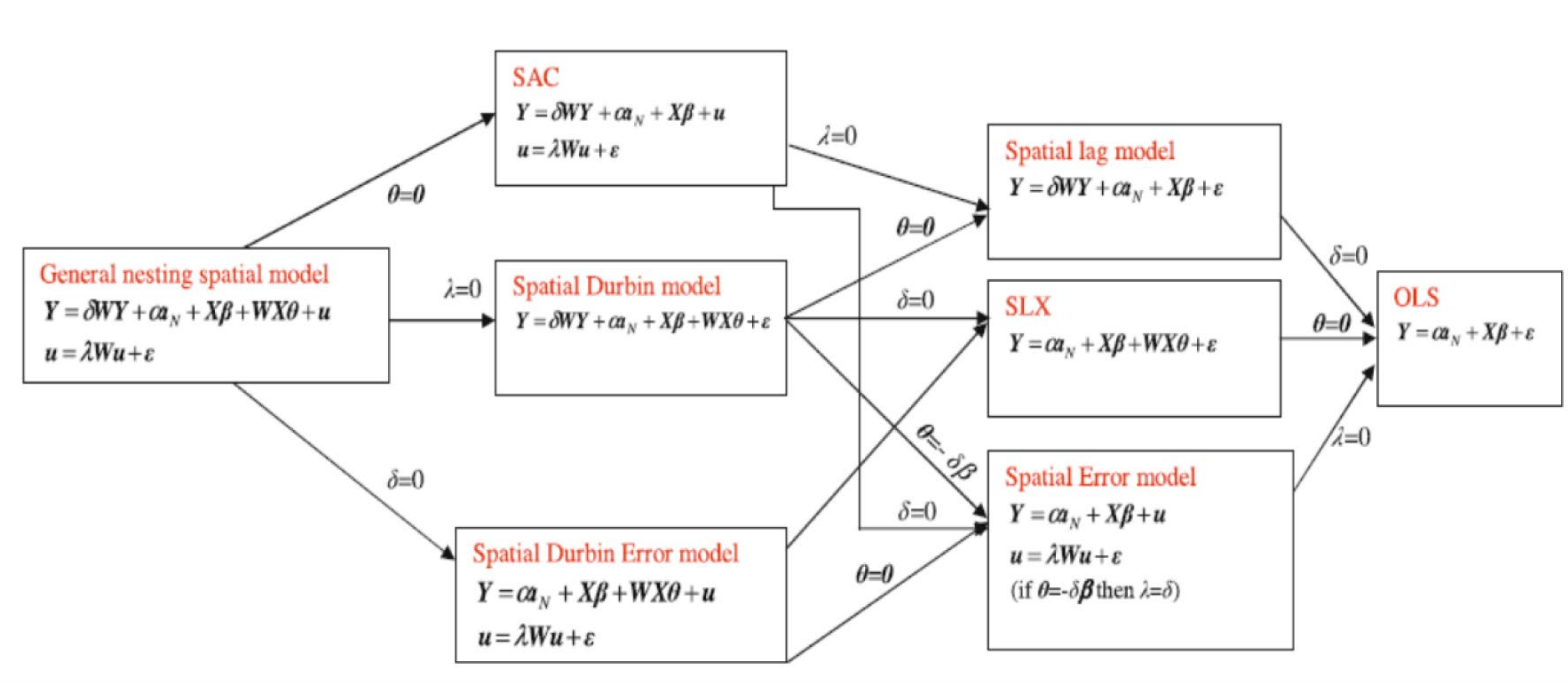
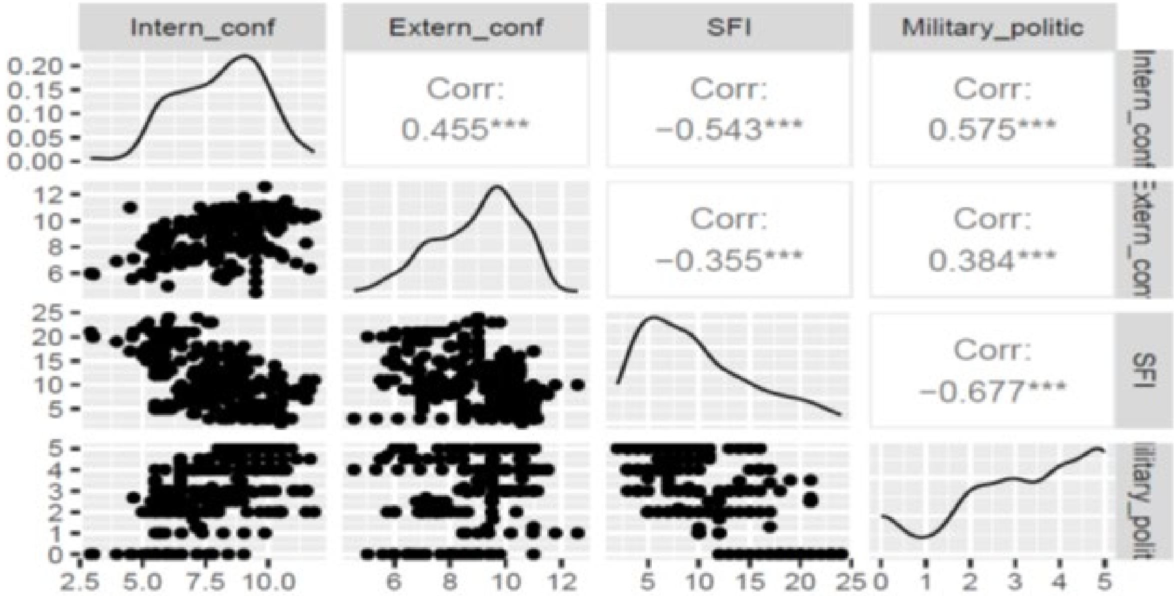
Figure 9. The selection strategy of the fitting spatial econometric model



Source: Elhorst (2014, p.9)

Figure 10. Correlation matrix of risk indicators



Source: Author's calculation from ICRG database