The spatial impact of neighbouring on the exports activities of COMESA countries by using spatial panel models

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Abstract. In this paper, spatial panel models were used and the method for selecting the best model amongst the spatial fixed effects model and the spatial random effects model to estimate the fitting model by using the robust Hausman test for analysis of the exports pattern of the Common Market for Eastern and Southern African (COMESA) countries. And examine the effects of the interactions of the economic statistic of explanatory variables on the exports of the COMESA. Results indicated that the spatial Durbin model with fixed effects specification should be tested and considered in most cases of this study. After that, the direct and indirect effects among COMESA regions were assessed, and the role of indirect spatial effects in estimating exports was empirically demonstrated. Regarding originality and research value, and to the best of the authors’ knowledge, this is the first attempt to examine exports between COMESA and its member countries through spatial panel models using XSMLE, which is a new command for spatial analysis using STATA.

1. Introduction
Spatial panel data are commonly used in modern data science because of the availability of global positioning system (GPS) and other systems. These devices enable researchers to collect information on spatial coordinates and topology. Using the geographic information system (GIS) attributes, the coordinates and distances can be mapped and then categorised as spatial data. One important feature of spatial data is that neighbourhood structure can be defined for observation units in space via individual metrics. As a result, the modelling and examination of spatial data differ from those of traditional data. Since spatial data analysis, geospatial methods are helpful and have become the de facto option, especially when using spatial weight matrix. The first law of geography established by Tobler [1] is the motivation behind spatial data analysis, that is, ‘everything is related to everything else, but near things are more related than distant things’ [2].

The present study intends to explore the direct and indirect impacts of the trade intensity of COMESA by using spatial weight matrix (contiguity matrix). The current study makes a two-fold contribution to the extant literature on economic growth. First, it provides further insights on how fixed and random effects models can lessen the disparities between the exports of COMESA countries. Second, it helps capture the cross-country spillovers. Toward these objectives, the methodological approach adopted extends previous contributions that either employed non-spatial econometric techniques or used spatial econometric techniques, which can only partially capture spatial interactions, namely, spatial error model (SEM), spatial autoregressive model (SAR), spatial Durbin model (SDM) and SAC model. The proposed approach also
integrates the interaction effects among the error terms and the endogenous interaction effects to further investigate the impact of such interactions.

This article describes how the spatial panel models for COMESA trading are implemented in the STATA program, and chooses between spatial fixed or random effects models by using the robust Hausman test [3,4]. We adopted the modified AIC criterion as in [5] to test the most appropriate model between the SAC and SDM, which are non-nested models. This study is different from prior research, in that it employs spatial econometric techniques to distinguish between fixed and random effects for COMESA trading.

One useful approach for examining global spatial autocorrelation is Moran’s I [6]. A spatial weight matrix, $W$, is specified as a row-normalised binary contiguity matrix, and this measure is evaluated by its magnitude and significance. Here, $W_{ij} = 1$ if a common border is shared by two spatial neighbourhoods, and $W_{ij} = 0$ otherwise. Some scholars [3,4] also used similar specifications. The standard approach shows that the $W_{ij}$ of each row in $W$ is equal to 1 [7]. However, the majority of spatial econometric studies lacked theoretical support in the selection of spatial weight matrices [8]. The econometric methodology is presented in Section 2, the data descriptions are presented in Part 3, the experimental results are discussed in Part 4, and the conclusion is presented in Section 5.

2. Research method

We used global Moran’s I to check for spatial interdependencies in the exports of COMESA countries, in order to reveal spatial dependencies in the exports of COMESA countries. The same statistical tool was adopted by many spatial studies [9,10] to measure the similarity of activities in proximate locations. In econometric analysis, Moran’s I can be used to generate data that can theoretically or statistically justify the use of spatial models. Before the econometric analysis, however, the exploratory analysis must be performed. Then, using non-spatial panel models, baseline results can be generated as pooled OLS model, fixed and random effects models [11]. Such baseline results are considered initial evidence of the relationship between the exports of COMESA countries and explanatory variables. Then, to expand these baseline results, the spatial models were estimated. To closely match the theoretical model of exports, as statistically supported by test results, we used SAR, SDM, SAC and SEM in our analysis.

2.1 Spatial panel data models

The SAR, SEM, SDM and SAC models were used to study spatial dependence in the exports of COMESA countries. SAR is expressed as

$$Y_{it} = \rho \sum_{j=1}^{n} w_{ij} Y_{jt} + \beta X_{it} + \mu + \epsilon_{it} \quad (1)$$

where the expression is related directly to the dependent variables $Y_{jt}$ of other cross-sectional units to the dependent variable $Y_{it}$ of cross-sectional unit $i$ in period $t$. Moreover, $X$ and $\beta$ are the regional independent variables and their coefficients, respectively; $\sum_{j=1}^{n} w_{ij} Y_{jt}$ represents the interaction effect of $Y_{jt}$ on $Y_{it}$; $(\rho)$ is a spatial autoregressive coefficient; $w_{ij}$ is the $i,j$-th element of a prespecified nonnegative $N \times N$ spatial weight matrix $W$ and $\varepsilon$ is assumed to be identically and independently distributed for all $i$ with 0 mean and variance $\sigma^2$ term [3,4,12]. In the random-effects case, we assumed that $\mu$ is a vector of parameters to be estimated in the fixed-effects variant and that $\mu \sim N(0, \sigma^2)$ [2]. SAR can be used to determine whether the exports of COMESA country for a specific time period are influenced by those of other COMESA countries.

By imposing a certain structure on the unobserved factors that affect the dependent variable, SEM can prevent the error term from capturing such a dependent variable [3,4,12]. This model is expressed as

$$Y_{it} = \beta X_{it} + \mu + u_{it}, \quad u_{it} = \lambda \sum_{j=1}^{n} w_{ij} u_{jt} + \epsilon_{it} \quad (2)$$
where the spatial autocorrelation coefficient is represented by $\lambda$. Meanwhile, SEM can be used to investigate the effects on the dependent variable of country $i$ of the shocks in the dependent variable of other cross-sectional units (i.e., countries). SDM, which is an extension of SAR and SEM [4,13], can be expressed as

$$Y_{it} = \rho \sum_{j=1}^{n} w_{ij} Y_{jt} + \beta X_{it} + \theta \sum_{j=1}^{n} w_{ij} X_{jt} + \mu + \epsilon_{it}$$

(3)

where $\theta$, similar to $\beta$, refers to a $K \times 1$ vector of fixed yet unknown parameters that must be estimated. The aforementioned model is a generalized version of the SAR model, which also includes explanatory variables serving as spatially weighted independent variables. The dependent variable of a unit is influenced by the independent explanatory variables of the other units’ dependent variables.

Spatial Autocorrelation Model (SAC). This model is also called ‘spatial autoregressive with spatially autocorrelated errors’ (SARAR); it combines the SAR with a spatial autoregressive error. The SAC model is expressed as

$$Y_{it} = \rho \sum_{j=1}^{n} w_{ij} Y_{jt} + \beta X_{it} + \mu + \epsilon_{it} , u_{it} = \lambda \sum_{j=1}^{n} w_{ij} u_{jt} + \epsilon_{it}$$

(4)

The following general nesting spatial (GNS) model was also used, and included all types of interaction effects [3,4,13]:

$$Y_{it} = \rho \sum_{j=1}^{n} w_{ij} Y_{jt} + \beta X_{it} + \theta \sum_{j=1}^{n} w_{ij} X_{jt} + \mu + u_{it}, u_{it} = \lambda \sum_{j=1}^{n} w_{ij} u_{jt} + \epsilon_{it}$$

(5)

In selecting a spatial estimator, a researcher must choose between conventional and spatial econometric techniques. Consequently, a Lagrange multiplier (LM) test [14] must be performed to discover a spatial error autocorrelation and identify a spatially lagged dependent variable. Here, a robust LM test must be performed to determine the spatial dependence type [15] that is reliant on another kind, which can be determined through Wald and likelihood ratio tests [4]. Burridge mentioned that when $H_0: \theta = 0$ and $H_0: \theta + \rho \beta = 0$ are rejected [16], SDM is preferred, whereas the spatial lag model or SEM is preferred when either one of the hypotheses cannot be rejected. Model selection is another common task that is typically undertaken by spatial practitioners.

The SDM can be employed as a general specification and test for the alternatives by using the strategy of [13] and [17]. In other words, even though we can estimate an SDM, we would also like to determine whether it is the best model to analyse the data at hand. This procedure can be implemented easily using XSMLE. The point estimates of one or more spatial regression model specifications ($\rho$, $\theta$, and/or $\lambda$) were predominantly used in previous works to identify spatial spillovers. However, this approach could generate false inferences [13]. To test this hypothesis, a partial derivative interpretation of the impact of the changes on the variables of different model specifications can be formulated [3,4].

The above-mentioned models often used the maximum likelihood (ML) method and the generalised method of moments (GMM). However, with the endogeneity of the spatially lagged dependent variable $WY_t$, the GMM estimator may yield biased results [4,18]. For instance, if a proposed robust GMM procedure results in slightly better (less biased) point estimates than slightly (more biased) robust Bayes producing markedly inferior variance–covariance estimates, which are used for the inference, then the proposed procedure may be regarded as an inferior estimation procedure for obtaining estimates and inferences in applied settings. Thus, in selecting an appropriate model, the standard procedure is used along with ML.

Due to unsatisfactory and unstable forecasting performance when the sample size is finite, the GMM is theoretically preferred over ML for the dynamic spatial panel model, especially under conditions wherein there exist a large number of spatial units and only a short period of time is considered [19]. The direct
effects were also distinguished from the indirect ones by our analysis (ML). Potential heteroscedasticity was controlled through the robust standard errors [20].

3. Data description

A total of 19 countries are included in the COMESA: Burundi, Comoros, Democratic Republic of Congo, Djibouti, Egypt, Eritrea, Ethiopia, Kenya, Libya, Madagascar, Malawi, Mauritius, Rwanda, Seychelles, Sudan, Swaziland, Uganda, Zambia and Zimbabwe.

This research included in our panel data, those we collected from the annual bilateral exports of 14 COMESA countries from 2005–2013 provided by different sources, including the World Bank Datastream and its own database (http://comstat.comesa.int/Home.aspx). The export value indices of the 14 selected countries, which are reported in the World Development Indicators database of the World Bank, represent the actual export figures of these countries. Table 1 presents the actual export values.

For the time being, this is the only available data for the past five years as provided by COMESA centre, However, if there will be any available data for the year 2017 then it will for sure consider it in this research for better inputs and further outcomes. Stata/SE 14 and the software packages XSMLE [2] were used to estimate the selected spatial models through ML.

Table 1. Reports the actual Import and Export values.

| Variable                                      | Description and Transformation Data                                      |
|-----------------------------------------------|--------------------------------------------------------------------------|
| Real import                                   | Dependent variable Values in US$ (Millions) scaled by the Import value index. |
| Real export                                   | Dependent variable Values in US$ (Millions) scaled by the Export value index. |
| General government final consumption expenditure (GGFCE) | The final consumption of general government expenditure includes all the current expenditure for purchases of services and by all levels of the government. At current price in US$. |
| Exchange rate                                 | The rates of the exchange expressed in the national currency unit per US dollar unit as reported at the end period of the exchange rates of the market and the official rates. IMF (International financial statistics) |
| Population (POP)                              | Independent variables (Millions) The overall population is based on the de facto definition of the population which counts the whole residents regardless of their legal status citizenship except the refugees who are not permanently settled in the country of the asylum. |
| Cost to Import                                | US$ per container                                                        |
| Cost to Export                                | US$ per container                                                        |
| Real GDP                                      | The gross domestic products within market prices are the total of the gross value added by the whole resident producers in the economy, plus any product taxes and minus any subsidies that not include the value of the product. GDP in current US$ |

Source and Availability : World Bank national accounts data, OECD National Accounts data, DATASTREAM Center and http://comstat.comesa.int/.

4. Results and Discussion

The spatial autocorrelations measured through global Moran's I are shown in table 2. Positive and vigorous spatial interdependencies in COMESA exports are indicated by the positive and significant global Moran’s I for each year.
Table 2. Global Moran I statistics for regional COMESA’s export.

| Spatial Weight       | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 |
|----------------------|------|------|------|------|------|------|------|------|------|
| Matrix               |      |      |      |      |      |      |      |      |      |
| Export(Contiguity)   | 0.19 | 0.282*| 0.21 | 0.265*| 0.219*| 0.291*| 0.246*| 0.214*| 0.277** |

Notes: (*, **) denotes significance at (10%, 5%) level.

The results show the geographic concentration of countries with similar export levels. As can be seen, global Moran’s I increased from 0.196 to 0.291 from 2005 to 2013, indicating the spatial integration of COMESA exports over time. Next, we transformed SDM into a logarithmic (because the data has huge numbers) form for export (dependent variable) and expressed it using equation 6 as

\[
\ln Export_{it} = c_0 + \rho \sum_{j=1}^{n} w_{ij} Export_{jt} + \beta_1 \ln GDP_{it} + \beta_2 \ln POP_{it} + \beta_3 \ln GGFC_{it} + \\
+ \theta_4 \ln COSTtoExport_{it} + \theta_5 \ln ExchangeRate_{it} + \theta_1 \sum_{j=1}^{n} w_{ij} \ln GDP_{it} + \\
+ \theta_2 \sum_{j=1}^{n} w_{ij} \ln POP_{it} + \theta_3 \sum_{j=1}^{n} w_{ij} \ln GGFC_{it} + \theta_4 \sum_{j=1}^{n} w_{ij} \ln COSTtoExport_{it} + \\
+ \theta_5 \sum_{j=1}^{n} w_{ij} \ln ExchangeRate_{it} + \varepsilon_{it}.
\]

The above expression reveals the robustness of ML in identifying non-normality and heteroscedasticity. We limited our analysis to these variables because this study is focused on the relationship between the explanatory variables and the COMESA and export spillovers. Next, our process of model selection is discussed, and the relevant model diagnostics is presented before our findings are examined.

The relevant model diagnostics were shown in table 3 indicate that the variables lack any joint explanatory power; thus, the null hypothesis of the Wald test has a slim chance of being supported. This trend suggests that the exports in one COMESA country may be related to those in neighbouring countries.

Table 3. Model diagnostics.

| Export | Number of observations | 126 |
|--------|------------------------|-----|
|        | Number of units (regions) | 14 |
|        | Log likelihood function | -134.84 |
|        | Wald test              | 463.102*** |
|        | LR TEST SDM vs. OLS H0: \( \rho = 0 \) | 11.638*** |
|        | LR TEST H0: \( \beta X' s = 0 \) | 33.357*** |
|        | \( \rho \)             | 0.312*** |
|        | Acceptable range for \( \rho \) | -1.2435 < \( \rho \) < 1.0000 |
|        | Spatial Error Autocorrelation Tests |
|        | H0: (no spatial error autocorrelation) |
|        | Global Moran MI        | 0.196*** |
|        | Global Geary GC        | 0.832** |
|        | Moran MI Error Test    | 2.691*** |
|        | LM Error (Burridge)    | 4.113** |
|        | LM Error (Robust)      | 9.014*** |
|        | H0: Spatial Lagged Dependent Variable has No Spatial Autocorrelation |  |
The magnitude of influence falls within the acceptable range at approximately ($\rho$) 0.312 (export). Accordingly, the dependent variable follows a spatially integrated process $SI(0)$ [13]. The results of the LR test are shown in table 3. As can be seen, the null hypotheses (i.e., the spatial lag of regressors and the spatially lagged dependent variable are equal to 0) have a very high chance of rejection in the model. Spatial estimation techniques are favoured over conventional econometric analysis in these cases (export) [4]. Meanwhile, when the LM, conventional LR, and robust LM test results for SAR and SEM are significant, SDM is preferred [4]. Furthermore, the diagnostics in the specification model suggest using SDM over other spatial estimators. The robustness of our selected model is demonstrated by these diagnostics, which lend confidence to the interpretation of our findings.

The estimation results are presented in table 4. GDP for intra-regional exports and cost to export are statistically significant, and ($wX1_{lnPOP}$) ($wX1_{lnGGFCE}$), and ($wX1_{lnCOSTtoExport}$) for inter-regional exports affect exports (the third column in table 4). The significant variables for explaining COMESA exports include GDP and cost to export. In particular, a 1% increase in the GDP increase COMESA exports by 93%, whereas a 1% increase in cost to export can decrease the COMESA exports by 72%.

One classical question often discussed in spatial panel data empirical analyses deals with the choice between the variants in spatial random effects and spatial fixed effects when both can be estimated. This issue can be addressed by using the robust Hausman test [2], the results of which indicate that the spatial random effects estimator is outperformed by the spatial fixed effects estimator. In table 4, the null hypothesis is firmly rejected, with a $\chi^2$ test statistic that is equal to 262.70 for SDM (Export) as well as a $p$-value that is less than 1%.

The fixed-effects models are more appropriate for analysing such data [2,9] because rather than a random sample drawn from that population, the sample represents the complete population of COMESA countries. This claim is supported by the evidence presented in the last two lines of table 5, in which all the static random-effect specifications are strongly rejected by the Hausman test results.

| Table 4. FEE (Non-Spatial), SDM and SAC. |
|------------------------------------------|
| Export                                   | FEM(no n-spatial) | SDM Fixed Effects time | SAC |
| lnGDP                                    | -0.208            | 0.927***               | 1.040*** |
| lnPOP                                    | 5.115***          | 0.0501                 | -0.130 |
| lnGGFCE                                  | 0.155             | 0.12                   | -0.095 |
| lnCOSTtoExport                           | -0.132            | -0.722***              | 0.022 |
| lnExchangeRate                           | -0.032            | 0.046                  | 0.182*** |
| $wX1_{lnGDP}$                            |                  |                        |      |
| $wX1_{lnPOP}$                            |                  |                        |      |
| $wX1_{lnGGFCE}$                          |                  |                        |      |
| $wX1_{lnCOSTtoExport}$                    |                  |                        |      |
| $wX1_{lnExchangeRate}$                   |                  |                        |      |
| Hausman test (FE VS. RE)                 | 13.66**           |                       |      |
| Robust Hausman test (FE VS. RE)          |                  | 262.70***              |      |
| Log Likelihood                           | -124.231          | -142.836               |      |
| $P$                                      | 0.312***          | -0.028                 |      |

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As previously mentioned, false assumptions can be a result of interpreting the point estimates in spatial regressions. Thus, a partial derivative interpretation of the indirect and direct spatial effects is ideal. Often, a change in the independent variable of a specific region is interpreted as an indirect impact on the dependent variables of other regions, but a direct one on the dependent variable of the same region. In this case, the dependent variables of other regions can be indirectly influenced by a change in the independent variable of a specific region [13]. The direct, indirect and total effects of the independent variables in our model are presented in table 5.

Some interesting patterns are observed in table 5. First, the direct effects have slight differences with the coefficient estimates shown in table 4. Such differences can be explained by the endogenous interaction effects WY in SDM, which in turn, creates feedback effects. Specifically, the effects on the exports of specific COMESA countries may extend to the origin of such effects and even to nearby countries. Meanwhile, GDP (for export) has a direct effect of 0.926, as indicated in Table 5. Table 4 indicates a 0.927 coefficient estimate of this variable. Then, we compute the feedback effect as 0.927–0.926 = 0.001, which corresponds to 0.1% of the coefficient estimate (GDP).

For export, the feedback effects of all explanatory variables account for 0.6%, 9% and 0.1% of the exchange rate, the cost to export and coefficient estimates of GDP, respectively. Meanwhile, a 1% increase in the cost to export and POP in all COMESA countries — except for one — increases the exports of that country by 206.6% and 71.5%, respectively.

These results are strengthened by the estimates of the indirect effect. However, a 5% increase in the GGFCE in all COMESA countries — except for one — reduces the exports of that country by 95%. Finally, as shown in table 6, information criteria can be used to test whether the most appropriate model is the SAC or SDM, given that both are non-nested models. All test results indicate a fixed-effects SDM for both exports.

### Table 5. Total, direct and indirect effects (SDM with fixed effects).

| Variable   | Total  | Direct | Indirect |
|------------|--------|--------|----------|
| lnGDP      | 1.013  | 0.926  | 0.087    |
|            | (0.438)| (0.151)| (0.397)  |
| lnPOP      | 0.794  | 0.0789 | 0.715    |
|            | (0.369)| (0.12) | (0.271)  |
| lnGGFCE    | -0.858 | 0.0956 | -0.95    |
|            | (0.424)| (0.160)| (0.404)  |
| lnCOSTtoExport | 1.434   | -0.632 | 2.066    |
|            | (0.360)| (0.225)| (0.364)  |
| lnExchangeRate | 0.007   | 0.040  | -0.038   |
|            | (0.076)| (0.041)| (0.052)  |

(1) Standard errors in parentheses (2) Note: (**, * and *) denote statistical significance at (1%, 5% and 10%) level of significance respectively.

### Table 6. Test for model selection.

| Export | AIC    | BIC    |
|--------|--------|--------|
| SDM    | 272.462| 306.497|
| SAC    | 301.673| 324.362|
5. Conclusion

To evaluate the regional economic growth estimates at different geographic scales, the current study employed spatial panel models, thereby allowing us to gather evidence in support of the assumption regarding the presence of spatial dependence in the exports of COMESA member countries. We find that the exports of a COMESA country highly dependent on those of another COMESA country and other factors. The results of this study prove that the spatial Durbin model with fixed effects specifications should be tested and considered in most cases. Furthermore, we examined the total, direct and indirect effects of such dependency on the exports of COMESA countries. Moreover, the direct and indirect effects (i.e., spillover effects) must be considered as they play significant roles in the trading activities of COMESA.

This study recommends the extension of spatial autoregressive and spatial Durbin models with a dynamic specification by implementing the bias-corrected ML approach. Moreover, COMESA countries can improve their per capita income by being actively involved in collaborative projects and by exploring their internal markets.

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