DIRECT AND INDIRECT SPATIAL EFFECTS OF SPATIAL PANEL DATA MODELS FOR TRADE OF COMESA

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by

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LIST OF ABBREVIATIONS

AIC	Akaike Information Criterion
COMESA	Common Market for Eastern and Southern Africa
FEM	Fixed Effect Model
FGLS	Feasible Generalized Least Squares
GDP	Gross Domestic Product
GIS	Geographic Information System
GLS	Generalized Least Squares
GMM	Generalized Method of Moments
GNS	General Nesting Spatial Model
IID	Identically and Independently Distributed
IMF	International Monetary Fund
IV	Instrumental variables estimation
LCU	Local Currency Units
LM	Lagrange Multiplier Test
LR	Likelihood-ratio Test
LSDV	Least Squares Dummy Variable
ML	Maximum Likelihood
OLS	Ordinary Least Squares
POLS	Pooled Ordinary Least Squares

PRM	Pool Regression Model
REM	Random Effect Model
SAC	Spatial Autoregressive Combined Model
SAR	Spatial Autoregressive Model
SARAR	Spatial Autoregressive with Spatially Autocorrelated Errors
SDM	Spatial Durbin Model
SDEM	Spatial Durbin Error model
SEA	Spatial Error Autocorrelation
SEM	Spatial Error Model
SFE	Spatial Fixed Effects
SLDV	Spatial Lagged Dependent Variable
SLX	Spatial Lag of X
SRE	Spatial Random Effects
SSE	Sum of Squared Errors

LIST OF SYMBOLS

Y	Dependent Variablest
X	Independent Variablest
β	Coefficient of Independent Variablest
t	Time Series Dimension
$\alpha_{0(i)}$	Incidental or Nuisance Parameters
χ^2	Chi-squared Distribution
n	Number of Observations
S_0	Standardisation factor
H_0	Null Hypothesis
H_1	Alternative Hypothesis
J_i	Neighbourhood Set
ρ	Spatial Autoregressive Coefficient
W	Spatial Weight Matrix
σ^2	variance of population
α	Constant Term Parameter
ε	Error Term
μ_i	Vector of the Parameters to be Estimated in the Fixed-Effect
τ_N	$N \times 1$ Vector of Cases Associated With theConstant Term Parameter α
λ	Spatial Autocorrelation Coefficient

θ	Vector of the Fixed but Unknown Parameter that Must be Estimated
ξ_t	Time- Specific Effects

KESAN LANGSUNG DAN TAK LANGSUNG RERUANG OLEH MODEL PANEL RERUANG UNTUK PERDAGANGAN COMESA

ABSTRAK

Ketepatan maklumat georeruang membolehkan kajian kesan reruang terhadap pemboleh ubah ekonomi pada aktiviti perdagangan negara COMESA. Oleh itu, tesis ini menerangkan model panel reruang untuk menganalisis aktiviti perdagangan negara COMESA. Pemilihan antara model rawak atau kesan tetap reruang ditentukan oleh Ujian Hausman. Dalam tesis ini, terdaput bukti kukuh bahawa terdapat kebersandaran reruang terhadap eksport dan import COMESA. Kebersandaran reruang adalah situasi di mana dapatan negara tertentu bersandar kepada dapatan atau faktor lain dari negara lain. Keputusan menunjukkan bahawa model Durbin reruang dengan spesifikasi kesan tetap harus diuji dan dipertimbangkan dalam kebanyakkan kes dalam kajian ini. Tambahan pula, kesan langsung dan tidak langsung dalam kalangan negara COMESA dianggarkan, dan peranan kesan reruang langsung dan tidak langsung dalam menilai import dan eksport diterangkan secara empirik. Mengenai keaslian dan kepentingan penyelidikan, dari pengetahuan penulis yang terbaik, tesis ini merupakan pertama yang memberi gambaran menyeluruh perdagangan wilayah COMESA. Kajian ini juga menyumbang kepada teori dengan menyediakan carta aliran metodologi untuk membantu penyelidik baru menjimatkan masa mereka dengan menggunakan langkah-langkah yang jelas untuk analisis model panel reruang dan memilih model reruang terbaik. Semua pemboleh ubah penjelasan untuk import intra-negara adalah bererti secara statistik termasuk KDNK, populasi, GGFCE, kos import dan kadar pertukaran (0.377, -0.206, 0.448, 0.648 dan 0.079 masing-masing). Selain itu, KDNK untuk eksport antara negara dan kos untuk eksport masing-masing bererti secara statistik (0.927,

-0.722). Dapatan ini mengesahkan bahawa terdapat pemboleh ubah yang mempunyai kesan tidak langsung dan langsung kepada perdagangan negara COMESA, yang mana dapatan menunjukkan kesan langsung dari KDNK, POP, GGFCE, kos untuk mengimport dan kadar tukaran bererti secara statistik ke atas import semua negara COMESA dan kesan tidak langsung dari KDNK, GGFCE dan kos untuk mengimport semua import dari negara COMESA adalah signifikan secara statistik. Di samping itu, kesan langsung KDNK, kos untuk eksport dan kadar pertukaran dalam semua eksport negara COMESA adalah signifikan secara statistik, dan kesan tidak langsung POP, GGFCE dan kos untuk dieksport di semua eksport negara COMESA adalah signifikan secara statistik. Keupayaan kajian untuk menerang kesan langsung dan tidak langsung adalah salah satu sumbangan utama kewujudan kebersandaran reruang dalam eksport dan import COMESA. Selain itu, tesis ini menyumbang kepada amalan dengan mengesahkan bahawa SDM dengan masa kesan tetap adalah yang terbaik di antara tiga jenis (individu, masa dan keduanya) model tetap untuk kedua-dua eksport dan import, yang belum diterokai oleh kajian sebelumnya di negara-negara COMESA. Tambahan pula, tesis ini mencipta matriks bersebelahan ratu dengan menggunakan arahan perisian STATA dalam menentukan lokasi melalui garis bujur dan latitud oleh GPS.

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ABSTRACT

The accuracy of geospatial information enables to study the spatial effects of economic variables on the trading activities countries of Common Market for Eastern and Southern Africa (COMESA). Hence, this thesis describes the spatial panel models for the analysing the trading activities of COMESA countries. The selection between spatial random or fixed effects models is determined by Hausman Test. In this thesis, it found strong evidence that there is a spatial dependence on the export and import of COMESA. Spatial dependence is a case where results in a given country seem to depend on results or other the factors from another country. Results showed that the Spatial Durbin Model with fixed time effect specification should be considered and tested in most of the states in this thesis. Furthermore, the indirect and direct effects among COMESA countries were estimated, and the role of direct and indirect effects in measuring imports and exports were empirically explained. Concerning research significance and originality, and to the best of researcher's knowledge, this is the first thesis that delivers a comprehensive picture of COMESA regional trade. This study also contributes to the theory by providing a methodological flowchart to help new researchers save their time by using clear steps to analysis of spatial panel models and choosing the best spatial model. All explanatory variables for intra-country imports are statistically significant that include GDP, population, GGFCE, import costs and exchange rate (0.377, -0.206, 0.448, 0.648 and 0.079 respectively). Moreover, the GDP for intra-countries exports and the cost to export are statistically significant (0.927, -0.722) respectively. The results confirm that there are variables that have in-

direct and direct effects on the countries of COMESA trade, as the results showed the direct effects of GDP, POP, GGFCE, cost to import and exchange rate in all import of COMESA countries are statistically significant and the indirect effects of GDP, GGFCE and cost to import in all import of COMESA countries are statistically significant. Also, the direct effects of GDP, cost to export and exchange rate in all export of COMESA countries are statistically significant, and the indirect effects of POP, GGFCE and cost to export in all countries of import COMESA are statistically significant. The ability of the study to illuminate indirect and direct effects is one of the major contributions to the existence of spatial dependency in the export and import of COMESA. Moreover, this thesis contributes to the practice by confirming that SDM with fixed effect time is the best among the three types (individual, time and both)of fixed models for both export and import, which has not been explored by previous studies on COMESA countries. In addition, the thesis also created a queen contiguity matrix by using the commands of STATA software in determining the locations through longitude and latitude by GPS.

CHAPTER 1

INTRODUCTION

1.1 Introduction

This chapter begins with the significant discussion about the background of the study. Problem statements are given before the discussions proceeded on to the objectives, scope, limitations and concluded with the significance of the thesis. The structure of the research is presented at the end of this chapter.

1.2 Background of the Study

Most of the studies in spatial econometric motivated by the study questions appearing in geographical economic and science geography. Later, their definition and scope advanced to econometrics and other the social sciences, such as political science or sociology. Econometrics has many subfields, one of them is spatial econometrics that it is dealing with spatial interaction effects amongst geographic locations. Places could be municipalities, cities, regions, countries, states, zip codes and so forth be depending on the kind the studies.

Besides, the spatial econometrics model can be applied to describe the demeanour of factors that have economy specifications other than geographic locations, such as governments, companies or individuals if all are linked to each other by geographic networks, however, this kind of the studies, although progressing, is less well known. Despite literature of time-series concentrates on the dependency between observations across the time and uses a "$t-1$" to indicate the variables lag the time, the spatial economic studies are inspired by the dependency between the observations over the space. Where a Spatial Weight Matrix (W) is used to interpret spatially order of geographic locations in a data. It should be emphasised that the spatially econometric is not a straightforward extension for time-series econometric to the two directions. The two geographic locations have one obvious distinction that they can influence each other mutually, whereas the two observations in time-series cannot. While spatial autocorrelation is important in the spatial econometric models, which it is similar the temporary autocorrelation but more complex.

The idea is that the autocorrelation for time series can just run one way that is mean everything occurs at one time can be influenced by what happened only in the past. Whereas, spatial autocorrelation of spatial economic can go in any direction that is mean anything occurs at any one time can be affected by both the future and the past. Based on this logic, it is inappropriate to shift temporary autocorrelation models to the spatial models directly because the basis of spatial panel data analysis is that what occurs in one location is associated with what occurs in other neighbouring locations or countries.

The spatial autocorrelation of spatial economic is the relationship between values of the variable related to their close neighbouring locations, inducing a violation of the explanatory observations assuming of a traditional statistic. The reason existing spatial autocorrelation because real-world phenoms are exemplified by systematic concentration and orderliness rather than the randomness. Tobler more precise indicates to as the First Law of Science Geography "Everything is related to everything else, but near things are more related than distant things" (Tobler(1970). Moreover, the spatial autocorrelation calculation by a Moran's I Test.

The inference from regression models including the spatial data can be questionable. In reality, because nearby items are similar, and it may not be reasonable to judge individual situations as an independent (they may be pseudo-replicates). Accordingly, such models need to be diagnosed before reporting them. Precisely, it is important to evaluate for the spatial autocorrelation in the residuals (as these are supposed to be independent, not correlated) by Moran's I Test as mentioned above. If the residuals have spatial autocorrelation, this means that this model is misspecified. In this case, the model can be improved by it can try formulating a regression model that controls for spatial autocorrelation.

Spatial regression processes enable to estimate spatial dependence among observations by Moran's I Test as mentioned above and Lagrange Multiplier Test (LM), which often occurs when observations are obtained from regions or points placed in space. The observations could be explained income, population levels or employment, tax rates, import, export and so on, for several areas defined within locations, countries, census regions or postal. There might further have particular firm establishment point locations referenced by latitude-longitude coordinates that can be obtained by employing geocoding software to particular postal address. That is commonly recognised that the sample data obtained for points or regions in the space are not independent, but dependent on neighbouring, this indicates that is the dependency between observations of nearby locations.

In time series analysis, time dependency is usually defined by theoretical models that include a particular modification that gives time lags of a response variable where this differs from spatial dependence which is in all directions. This thesis employs the concept of "spatial spread with investigating" to explain and estimate a spatial lag. One justification is that an observed variation in the dependent variable may arise from unobserved or unknown influences. Hidden unobservable powers were related to a host of other factors as culture, infrastructure, recreational amenities which it has not available the sample data can be estimated for by relying on neighbouring values. Spatial panel data are employed by the dependent variable that works as a spatial lag variable in the spatial panel model by using spatial weight matrix W.

Spatial econometrics is a field in which analytic methods are produced to include spatial dependency between observations that are related to locations (geographic proximity). Developing the standard linear regression model through spatial patterns identify groups of "nearest neighbours" and allow for dependence among these countries/ locations observations (Anselin, 1988; LeSage and Pace,2009; Elhorst, 2017; Greene,2017). Remark that also with observational units such as firms working in the world markets where a concept of the spatial contiguity is not fitting, researchers might still see the dependence in the behaviour of rival companies, those that are incredibly similar to each other.

Spatial regression methods explained here can be implemented in these cases through relying on a relationship that set of saying m-nearest neighbours from a case of spatial regression can be interpreted as the group of m rival companies. Here is the generalisation of neighbours based on the distance or contiguity that could be utilised to building dependence on behaviour, leading to the model that is formally similar to a geographical the nearest-neighbours.

Geographical science theory denotes explanation that the economic factors may reverse their decision depending on (1) market circumstances in the area of location as compared to the other areas and (2) the contiguity or distances among areas. While determining the spatial dependency between the observations of the sample, a model involves the spatial autoregressive approach in error terms, or comprise the spatial autoregressive of the response variable. Here, the first one is identified as a Spatial Error Model (SEM) and the second as a Spatial Autoregressive Model (SAR) (Anselin and Hudak, 1992)(details discussion about these models in Chapter Four).

1.3 Problem Statement

This thesis casts new light on an essence problem in research related to the geographical, economic growth for import and export of COMESA and regional development policy evaluation. As discussed throughout the thesis, the selection of a spatial measure of analysis is a problematical issue in applied research. Toward this meaning, the thesis attempts to examine to what extent vaguenesses about the spatial scale undermine, or familiarise, the understanding of regional growth policies for import and export of COMESA. Related to this investigation, it also sheds light on a possible theoretical reason for various results obtained across the models estimated at different spatial scales.

The thesis discusses some recent econometric and statistical issues in studying regional economic growth for import and export of COMESA. The focus is on spatial econometrics literature that seeks to measure the effects of spatial interactions among neighbouring regions by spatial panel models; the spatial parameter heterogeneity as well as the discussion of a measurement problem that may cause variability in econometric estimations.

The main dilemma of insufficiency of understanding concerning the spatial spillover affecting export and import in COMESA gives a strong motivation for taking out this study. Many previous studies apply the point estimations of the spatial panel analysis specifications to infer as to whether or not the presence of direct and indirect effects. The critical contribution of LeSage and Pace's book (2009, p. 74) is noted a point estimation that this may guide to incorrect inferences and that the estimating a partial derivative analysis of the influence of variations in variables of models specifications signifies a more accurate foundation for testing this hypothesis (see also Elhorst, 2017). Moreover, the partial derivative analysis produces the direct and indirect effects.

1.4 Research Questions

1. The critical issue that must be asked is: does the data for countries of COMESA exhibit spatial autocorrelation or not?

2. How does spatial interaction influence on export and import of COMESA and how are indirect and direct effects from the import and export in countries of COMESA?

   The answers to the following questions will make up evidence needed to develop the understanding of the direct and indirect effects (spatial spillovers) that affect import and export in COMESA.

3. What is the spatial pattern of export and import in COMESA from one location to the others?

4. Is there spatial dependence on export and import in countries of COMESA and do geographical contiguity and economic linkages matter in import and export between countries of COMESA?

Answers to the first and second questions shape the theoretical frame needed to answer the following the third to fourth questions.

1.5 Objectives of the Study

The research objectives are summarised in the following points:

1. To examine the spatial autocorrelation for data of COMESA. If spatial autocorrelation is present, the study will need to formulate more complicated models.

2. To find spatial interdependence that it can originate from direct effects and indirect effects stemming from unobserved heterogeneity and to estimate and explain the indirect and direct effects of import and export in the COMESA countries.

3. To determine the spatial pattern of export and import in COMESA from one location to the others.

4. To estimate the spatial dependence in export and import of COMESA and explain geographical proximity and economic linkages matter in import and export between countries of COMESA.

1.6 Justificatins of Study

Why is COMESA **an interesting case study?**

The COMESA comprises 19 member countries: Burundi, Comoros, Democratic Republic of Congo, Djibouti, Egypt, Eritrea, Ethiopia, Kenya, Libya, Madagascar, Malawi, Mauritius, Rwanda, Seychelles, Sudan, Swaziland, Uganda, Zambia, and Zimbabwe (Wanjala Musila, 2004; Otman and Karlberg, 2007; Events, 2016).

The COMESA, the largest free trade organisation in Africa, aims to improve their human and natural resources to solve their problems in poverty, crime, and war. By signing the COMESA Treaty in Kampala in 1994, these countries all agreed to the inauguration of a customs exemption in Harare, Zimbabwe in 2009 (Tumwebaze and Ijjo, 2015). COMESA, which is home to almost 400 million people, presents an interesting status study for couple reasons. First, that is a collaborative project among 19 countries that cover 42.6% of African land, 44.6% of the entire African population, and a combined Gross Domestic Product (GDP) of 32.2% (US$ 345 billion) (Katunze and Kuteesa, 2016; COMESA, 2016). Despite their weak development and highly diverse economic and social backgrounds (Tumwebaze and Ijjo, 2015), all of these countries have managed to establish positive regional and spatial relationships with one another. Second, COMESA is an ambitious policy harmonisation program that aims to establish a monetary union in Africa by 2025 (Carmignani, 2006; Vieira and Vieira, 2013; Elmorsy, 2015).

The principal focus of COMESA, which is recognised as one of the building fields of the African Economic organisation under the Abuja Treaty, is outward oriented. Its vision is to encourage provincial integration through trade investment promotion, development and sustainable natural resource utilisation for the common benefit of all the citizens of the countries.

COMESA has made considerable progress towards beneficial economic integration since its establishment. Beyond trade liberalisation and facilitation achievements in general, notable growth has been achieved in the specific fields of the customs management, trade and project finance, transport facilitation, technical cooperation, institutional development and capacity building. Progress has also been achieved in cooperation and policy coordination in the productive sectors. The net outcome has been tangible progress in trade and increased investment among Countries of COMESA (COMESA, 2011).

The research on spatial econometrics is expanding, both in cross-sectional and panel models. There is some ongoing research on spatial panel models' econometrics. This thesis is the first to investigate and explore the nature of the spatial dependencies rather than just prove their presence. The goal of this thesis is the estimation of export and import of COMESA models considering spatial dependence to obtain efficient estimates and unbiased.

The ability of this research to clarify such the spatial spillovers is one of the main contributions it has made and examines the existence of spatial dependence and to catch the spatial dependence in the data, this study specifies. The spatial econometric literature offers different spatial panel models for data for the spatial autocorrelation.

1.7 Scope of Study

The thesis focused on the spatial analysis of regional import and export, and this study includes the spatial consideration by changing the coefficients between clusters, though, is a thesis that not only proves the existing of spatial dependency between countries of COMESA but further aims to classify the spatial direct and indirect effects which produce the dependence. Suitably examining the partial derivative influence of variations in import and export is another contribution of this thesis. Under a spatial Durbin model SDM, the change in import and export in country i can influence own (direct effect) and the neighbouring countries' j ($i \neq$j) import and export (indirect effect). Explicitly, this thesis separates the effects of volatility on import and export into indirect and direct (spillover) effect.

Determine the impacts of changes of export and import, which is crucial for the economy of COMESA, on rural economies. The target of the thesis is to investigate variables that are considered to explain total export and import to identify spatial interaction on export and import on the countries of COMESA.

1.8 Significance of study

This thesis will help the COMESA organisation to know the spatial effects on export and import which will help to develop them and to come out with solutions that will improve the income level, reduce the poverty level in the COMESA member's countries and encourage other countries to be included with COMESA.

The contribution of the thesis to literature is the analysis of spatial models trade of COMESA, which investigate the interactions of economic export and import across space, time and spatial dependence.

The import and export of COMESA are influenced by the import and export of their neighbours, and the results are interdependent. The power of the interaction depends on a contiguity matrix, which can be based on the geography or constructed from the economic theory. Estimating for spatial interactions provides one to quantify both the direct effects of export and import and their indirect effect through impacting neighbours.

The thesis provided a flowchart for spatial panel models to help new researchers by using clear steps to analysis spatial panel models. As far as we know, this is the first study to examines spatial panel models of trade of COMESA. Thus, this thesis adds to the literature by presents a study about spatial panel data models of COMESA, along with direct and indirect effects of export and import COMESA.

1.9 Organization and Summary of the Remaining Chapters

This thesis is arranged in the following form. The first chapter is an include the background of spatial econometrics and the problem statement is presented before research questions the discussions, then proceeded on to the objectives, justification, scope and limitations of research. Finally, it concluded with the significance of the study.

Following, the second chapter is the literature review. In the third and fourth chapters, the theoretical motivation and methodology for the panel and spatial panel models are provided along with the model assumptions and their implications, and it had outlined the econometric analysis which it was performed after the more straightforward. It produced estimated the number of the models to afford extra information to answer the study questions, and the characteristics of these models would be defined in this chapter. As with the information of the exploratory analysis, in this part, it had the aim to present enough details for researchers new to the field of the spatial econometrics.

In these chapters, it had planned the methodology of econometric used in this thesis. This methodology of the study included estimating the ordinary panel data models to afford the baseline estimates and then the spatial panel data models to present results with remarkable significance to the study questions.

In terms of statistical and theoretical considerations that using the SDM specifications as the starting point for spatial panel data modelling and estimating whether this selection is fitting. It is measured the spatial panel models by STATA software. Its choice of the spatial weight matrices is made. In the fifth chapter is results and discussing. Finally, the sixth chapter is conclusion and recommendations.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The spatial econometrics researchers have shown increasing interest in spatial economy studies that based on panels data by using geographic locations in the last decade. These studies of spatial panel data can be leading the advanced availability of additional spatial data in which geographical locations are followed over time. It can also be justified that spatial panel data provide researchers advanced modelling possibility compared with cross-sectional data. The cross-sectional data had been the principal concerning of the spatial economy literature for the lengthy time. (Elhorst, 2003; Lee and Yu, 2010b; Elhorst, 2014b; Baltagi et al.,2015).

Crucial relationships exist between cross-sectional models that have the spatiotemporal specification. These relationships have been disregarded by most studies on the spatial panel data models, as the literature has mostly concentrated on the error covariance structures from ordinary panel models to justify the spatial dependency (LeSage and Pace, 2009). The main significance of operating with the spatial panel data models is that it can manage the time effects and spatial effects.

The different spatial locations related their background variables, which are commonly space-specific and time-invariant independent variables that affect the response (dependent) variable, but these effects are challenging to obtain or difficult to measure. Therefore, neglecting to account for them, as in the cross-sectional data, raise the risk of getting biased the estimations. Also, the time-specific effect is that control for spatial-invariant variables whose avoidance could bias the estimates in the classical time-series studies (Baltagi and Levin, 1986; Baltagi and Levin, 1992).

The principal goal of the spatial economy models is to test the presence of spatial interactions between regions, like as direct and indirect spatial effects and this is the focus of this study. These effects are the main concern in economics, geography, regional science and related fields. Several theories predict that changes in the independent variables in certain location i influence a dependent variable not just in location i itself but other locations $j(\neq i)$ too.

Other studies have discussed spatial economy analysis. For example, the third edition book on the econometric analysis of panel models introduces an extensive discussion on spatial panel models by Baltagi 2005. This analysis is maintained in the subsequent editions and studies (Baltagi and Li, 2001; Lee, 2002; Andrews, 2005; Pesaran, 2006; Baltagi, 2008; Robinson, 2008; Baltagi, 2013). Particularly, Baltagi and Li (2004) contribute increased theoretical insights that serve as a foundation for statistical tests and estimation methods. Although introductory works continue to avoid the topic mostly, the spatial economy has become a known subfield in many popular "handbooks" of spatial econometrics.

The work of Anselin and Bera (1998), the Companion to Theoretical Econometrics (Baltagi, 2003), the Handbook of Applied Economic Statistics (Ullah and Giles, 1998), and the Palgrave Handbook of Econometrics Volume 1 (Anselin, 2006), that they focus on the theory of spatial econometrics. Also, The Econometrics of Panel

Data (Matyas and Sevestre, 2008) all contain a chapter on spatial economy analysis (Anselin, 2001; Matyas and Sevestre, 2008; Mills et al., 2009). As The Handbook of Applied Spatial Analysisand (LeSage and Pace, 2010) and recently handbook about spatial econometric by LeSage (2015).

2.2 Estimation Methods and Spatial Models

Maximum Likelihood (ML) and the Generalized Method of Moments (GMM) are the two primary estimation methods used for spatial regression models (Elhorst, 2001; Elhorst, 2003; Elhorst and Zeilstra, 2007; Kapoor et al., 2007; Fingleton, 2008b; Lee and Yu, 2010a). Spatial regression models include, among others, an asymptotic distribution ML estimators (Lee, 2004) and the derivation GMM estimators (Lee, 2003; Das et al., 2003; Kelejian and Prucha, 2004; Lee, 2007).

The generalisation of the GMM estimators is equally significant to spatial models that involve heteroscedasticity and spatial dependency (Kelejian and Prucha, 2010; Arraiz et al., 2010), and autocorrelation consistent approach based on kernel estimation by Kelejian and Prucha (2007). Jenish and Prucha (2009) propose a set of laws the central theorems on the large numbers that make the foundation for several of these results.

Kapoor et al. (2007) indicate the GMM method estimation of the SEM with random effects for specific time period. Pfaffermayr (2009) examines the ML estimation of Spatial Autoregressive Combined Model (SAC) with random effects for both unbalanced and balanced spatial panel data sets. Montes-Rojas (2010) tests a serial correlation in the SAR with random effects.

Parent and LeSage (2010, 2011) introduce the Bayesian Markov chain Monte Carlo estimation of dynamic spatial models. Baltagi and Bresson (2011) presented the instrumental variable estimators of the random effects for SAR (Kelejian and Prucha, 1998; Lee, 2003). Baltagi and Pirotte (2011) examine the inferences based on ordinary panel estimators when the correct model is Random Effect Model (REM) with either a spatial moving average error or a spatial autoregressive process.

Many specification tests have been developed for a variety of alternatives consisting of random effects and spatial effects, among others (Baltagi, 2003; Baltagi and Li, 2004; Pesaran and Kapetanios, 2005; Baltagi and Li, 2006; Baltagi et al., 2007c; Pesaran et al., 2008; Fingleton, 2009; Baltagi and Liu, 2016). Models for latent spatial variables, particularly spatial Tobit models and the spatial probit models, have been further explored (LeSage and Pace, 2010; Qu and Lee, 2012; Anselin and Rey, 2012; Qu and Lee, 2013; Amaral and Anselin, 2014; Ai et al., 2015; Xu and Lee, 2015). Kelejian and Prucha (2001) who generalised other studies normally applied the Hausman Test for spatial panel data models to compare the random effect model with the fixed effect model. These models are the basis of spatial models in the literature.

The spatial dependence models are known in urban economics and regional science focus on heterogeneity and spatial interaction [see also (Anselin, 1988; Anselin and Bera, 1998)]. The dependency can be related to distance and geographic location, both in space and in a social network or economy considerations. The SAR and SEM models are commonly used in the spatial economy analysis. These two variants of spatial panels models have been considered; one is discussed by Anselin (1988) and the other by Kapoor et al. (2007) and Fingleton (2008b).

The best linear unbiased predictors for Anselin-type model have been derived (Baltagi and Li, 2004). Baltagi et al. (2012) derive the best linear unbiased predictors for the variants of Kapoor et al. (2007) and Fingleton (2008a). Debarsy et al. (2012) extend the Mundlak approach to the SDM to examine the sufficiency of the random effects specification of this spatial econometrics model for applied research. Burridge (1980) and Anselin (1988) develop LM Tests for a Spatial Error Autocorrelation (SEA) and a Spatial Lagged Dependent Variable (SLDV) to test for spatial effects in the cross-sectional data analysis. Anselin et al. (1996) also develop robust LM Tests that check for the SLDV in the local presence of the SEA and the SEA in the local presence of SLDV. These tests have got widely common in the previous study. Newly, Anselin et al. (2008) have specified the LM Tests for spatial models.

Some spatial econometrics models are not considered or used in econometric theoretical and empirical studies. Specifically, these models are group of nine linear spatial econometric models, including the Ordinary Least Squares (OLS), General Nesting Spatial Model (GNS), the Spatial Autoregressive with Spatially Autocorrelated Errors (SARAR) or Cliff–Ord type spatial model (Kelejian and Prucha, 1998), and the spatial autoregressive combined SAC model that includes the interaction effects of the error term and the endogenous interaction effects. LeSage and Pace (2009) presented spatial models that include exogenous and endogenous effects. Concerning Durbin (1960) for the time-series, Anselin (1988) named the last model as SDM.

Corrado and Fingleton (2012) criticise the SDM, SEM, and SAR models because of an identification issue, and they advocate the spatial lag of X model to provide enhanced understanding. Kelejian and Prucha (1998, 1999) and Lee (2004) presented some the assumptions to evidence the consistency of ML and GMM estimators of the parameters in the SAR (see Elhorst, 2014b). Listing types of spatial panel models with features, advantages, disadvantages, limitations, references and years of development were summarised in Table 2.1.

Table 2.1: Types of Spatial Panel Models

Type of Model	**Advantages**	**Features**	**Disadvantages and Limitations**	**References and Year Development**
GNS	GNS includes all types of interactions.	$(\rho \neq 0)$, $(\lambda \neq 0)$, $(\theta \neq 0)$.	Overparameterised and GNS fails to outperform SDM and SDEM. GNS is typically not used in the applied analysis. (see P48 and P49 and P64).	Anselin, (1988); Manski, (1993); Elhorst,(2014b).
SAR	SAR estimates endogenous interaction effects WY (See P47).	$(\rho \neq 0)$. $(\lambda = 0)$, $(\theta = 0)$.	SAR includes one type of interaction.	Anselin, (1988); LeSage and Pace, (2009); Baltagi and Bresson, (2011); Elhorst, (2014b).
SEM	SEM detects interaction effects among the error terms Wu.	$(\lambda \neq 0)$, $(\rho = 0)$, $(\theta = 0)$.	SEM includes one type of interaction.	Anselin and Hudak, (1992); Kapoor *et al.*, (2007); Fingleton (2008b); LeSage and Pace, (2009).
SDM	SDM is an extension of SAR and SEM.	$(\rho \neq 0)$, $(\theta \neq 0)$, $(\lambda = 0)$.	SDM includes two type of interaction.	Anselin, (1988); LeSage and Pace, (2009).
SAC	SAC combines endogenous interaction effects WY and interaction effects among the error terms Wu.	$(\rho \neq 0)$, $(\lambda \neq 0)$, $(\theta = 0)$.	SAC includes two type of interaction.	Kelejian and Prucha, (1998); LeSage and Pace, (2009).

SDEM	SDEM combines exogenous interaction effects WX and interaction effects among the error terms Wu.	$(\lambda \neq 0)$, $(\theta \neq 0)$, $(\rho = 0)$.	SDEM is commonly not part of the toolbox of researchers interested in the econometric theory of spatial models. For more details see Elhorst, (2014b).	Elhorst and Vega, (2013); Elhorst, (2014b).
SLX	SLX exhibits the exogenous interaction effects WX. (See P47 and P48).	$(\theta \neq 0)$, $(\rho = 0)$, $(\lambda = 0)$.	SLX is generally not part of the toolbox of researchers interested in the econometric theory of spatial models. For more details see Elhorst, (2014b).	Gibbons and Overman, (2012); Halleck Vega and Elhorst, (2015).

2.3 The Softwares of Spatial Panel Models

Advanced accessibility to the spatial panel data and the software advanced to deal with the spatial economy analysis has increased the using the spatial panel data models over recent decades. By the beginning 21st century, the spatial economy had developed entirely. The studies have continued and produced specialised toolboxes, some of which are connected with software such as STATA, R and Matlab and other software that are open source, So there is no longer excuse not to conduct spatial panel data analysis.

Some of the important reviews of software can be got in the work of Anselin (2000, 2005), Rey *et al.* (2006), and Bivand (2008). Millo (2014) discusses the software explanation of spatial models with, a SLDV, fixed effects and random effects. Baltagi *et al.* (2013) presented spatial autocorrelation test in both the spatial random effects and the residuals.

Shehata (2013b, 2013a), Shehata and Mickaiel (2014) and Belotti *et al.* (2016) describe the software tools in STATA. Specific examples require further discussion. Applied econometricians, particularly LeSage, Pace, and Elhorst *et al.*, have had tremendous success in the field. They developed spatial econometrics software for Matlab can conduct spatial panel modelling (see LeSage and Pace, 2009). At the same time, the researchers developed the R software, which they focus on operations for spatial models, is expanding (Anselin, 2010). The spatial panel models are measured by STATA software in this thesis and the choice of the common spatial weight matrices which they present in Table 2.2 that used in economic studies.

Table 2.2: Types of Spatial Weight Matrices with Features

Contiguity Matrix	1. The weights simply indicate whether spatial units (countries) share a boundary or not. $W_{ij} = 1$ if regions or countries i and j are neighbours (spatially related) where as $W_{ij} = 0$ Otherwise. Here each spatial weight, w_{ij}, (elements of the matrix) typically reflects the "spatial influence" of unit j on unit i, where i and $j = 1,2,\ldots,n$; (Anselin and Smirnov, (1996); Anselin, (1999); Anselin, (2014)). 2. Following standard convention, here exclude "self-influence" by assuming that $W_{ii} = 0$ for all $i = 1,2,..,n$. (so that W has a zero diagonal). The contiguity matrix is a commonly used matrix because of it easy measures it and has three type (see P55-P58).
Distance Matrix	1. Between some of the easiest to calculate are the "distance" or "threshold" spatial weights matrices. These methods are based on neighbouring areas meeting a specific spatial distance criterion being counted equally as "close", while all those not meeting the criterion are "not close". Similar to contiguous spatial weights matrices, all "close" areas are equally weighted, irrespective of their specific distances (Anselin, (1999); LeSage and Pace, (2009)). 2. The distances are measured by Kilometer or Mile (Anselin, (2014)).

2.4 Empirical Applications

The present overview of studies that have applied spatial panel data model is limited to those based on Baltagi and Li (2004) spatial panel of cigarette demand. Baltagi and Levin (1986, 1992) initially used the dataset (cigarette demand), which was then utilised separately from 1963 to 1980 and 1988. Table 2.3 presents the different studies and shows their progress. Currently, most studies have controlled for the spatial time fixed effect.

Elhorst (2014b) tested time fixed and spatial effects and found that this model specification surpasses its counterparts, including the REM. Various researches have also used dynamic spatial panel models with dependent variable lagged in time to control short- and long-term indirect and direct effects; mathematical formulas for these effects are provided by Debarsy *et al.* (2012) and Elhorst (2014b). Some of studies have proposed the inclusion of exogenous interaction effects; however, the Spatial Durbin Error model (SDEM) or SDM best describes the data remains unclear.

Vega and Elhorst (2015) claimed that justifying the inclusion of endogenous interaction effects is challenging because it indicates that an income or price change in a special state potentially influences the consumption of all locations (countries), such as those that W (as California and Illinois state) regarded as unconnected. Finally, the majority of researchers have adopted contiguity matrix with a row-normalised except for Debarsy *et al.* (2012) that they considered a row-normalised matrix based on the country boundary distances that between countries have in common (Elhorst, 2017).

Among the first researchers who went beyond the exogenous pre-specified W with fixed weights are Kelejian & Piras (2014) and Vega & Elhorst (2015). Ever since the first empirical method for static panel data was introduced by Baltagi & Li (2004), lots of the models had been invented and tested in developing a better spatial panel model. Descriptions of the rest of models are as in Table 2.3 below. Table 2.3 summarises the previous studies that used the contiguity matrix, symmetric spatial panel models and a balanced panel data, most of which reached the best model is the SDM, which is the best model in this thesis.

Table 2.3: Spatial panel data studies and spatial model that had been used

Study by	**Year**	**Panel**	**Dataset**	**Spatial model**	**W**
Baltagi and Li	(2004)	SFE or SRE	The study about demand for cigarettes based on a panel data of 46 U.S states. Time periods: from 1963 to 1992	SEM	CM
Elhorst	(2014c)	SFE+TFE	The study about demand for cigarettes based on a panel data of 46 U.S states. Time periods: from 1963 to 1992	SDM	CM
Kelejian and Piras	(2014)	SFE+TFE	The study about demand for cigarettes based on a panel data of 46 U.S states. Time periods: from 1963 to 1992	SAR	CM
Lorenzini *et al.*	(2014)	SFE	20 countries of origin to Italy for tourist flows and expenditures. Time Period: 2012 (monthly)	SDM	DM
Silver and Graf	(2014)	SFE+TFE	Transaction price houses and commercial property price indexes for 34 area in the US. Time period: 2000: Quarter 1 to 2012:Q4	SAR	DM

Arbués, Baños *et al.*	(2015)	SFE	The road, railway, airport and seaport infrastructure projects are tested by estimating a production function for 47 Spanish peninsular provinces. Time period: from 1986 to 2006	SDM	CM
Cho *et al.*	(2015)	SFE	Electricity demands manufacturing, agricultural, residential, and retail in 16 regions of South Korea as a case study. Time period: from 2004 to 2012	SAC	DM
Montresor and Quatraro	(2015)	SFE+Both	The Combining regional patent and economic data for a panel of 26 European countries. Time Period: from 1980 to 2010	SDM	DM
Yamamoto	(2015)	SFE	The spatial study amplification of the network origins of the aggregate fluctuation effect on cross-border bank flows for 64 countries. Time period: from 2001 to 2013	SDM	DM
Abate	(2016)	SFE+Both	The link between macro volatility and economic growth in a panel of 78 countries. Time period: from 1970 to 2010	SDM	BTM
Álvarez *et al.*	(2016)	SFE	Public investment and road infrastructure the 17 Spanish provinces. Time Period: from 1980 to 2007	SAR	CM
Belotti et al.	(2016)	SFE	The dataset on electricity usage at the state level in the US. 48 states in the continental US plus the District of Columbia. Time period: from 1990 to 2010	SDM	CM

Glass *et al*.	(2016)	SFE+TFE	An aggregate production frontier using 41 European countries. Time period: from 1990 to 2011	SAR	DM
Kang *et al*.	(2016)	SFE+TFE	The impacts of energy-related CO2 emissions using a balanced panel dataset of 30 provinces in China. Time period: from 1997 to 2012	SDM	CM
Chen *et al*.	(2017b)	SFE+IFE	The spatial distribution of 41 Chinese airports. Time Period: from 2002 to 2012	SDM	CM
Ganau	(2017)	SFE+Both time and individual	50 African countries observed to investigate whether and how institutional factors, i.e. democracy, legislature effectiveness and regime instability affect the short-run GDP per capita growth. Time period: from 1981 to 2001	SDM	CM+DM
Hayashi *et al*.	(2017)	SFE + TFE	Information on local fiscal performance through the Fiscal Index Tables for Similar Municipalities (FITS-M). (1,637 municipalities). Time period: from 2008 to 2010	SAC	CM+DM
Huang	(2017)	SFE+TFE	Influence of the government's environmental protection expenditure on Sulfur Dioxide (SO2) emissions in China for 30 provinces. Time period: from 2008 to 2013	SDM	CM