Fiscal Decentralization, Provincial Economic Growth and Spillover Effects

A Spatial Panel Data Analysis

A Dissertation of M.Phil. Econometrics

By

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Qasim Raza

وَلَقَدْ كَتَبْنَا فِي الزَّبُورِ مِن بَعْدِ الذِّكْرِ أَنَّ الْأَرْضَ يَرِثُهَا
عِبَادِيَ الصَّالِحُونَ ﴿١٠٥﴾

اور بیشک ہم نے زبور میں نصیحت کے بعد لکھ دیا کہ اس زمین کے وارث میرے نیک بندے ہوں
گے (ف۱۸۷)

And We have already written in the book [of Psalms] after the [previous] mention that the land is inherited by My righteous servants.

(Surat Al-'Anbyā, 105)

وقتِ فرصت ہے کہاں کام ابھی باقی ہے
نورِ توحید کا اتمام ابھی باقی ہے

This is no time for idle rest, Much yet remains undone;

The lamp of tawhid needs your touch to make it shame the sun!

Allama Muhammad Iqbal

DEDICATATION

I DEDICATE MY WORK TO MY GRADUATE ECONOMIC TEACHER "SIR TAHIR MEHMOOD" PROFESSOR AT F.G POST GRADUATE COLLEGE, ISLAMABAD. HE GIVE ME SENSE HOW TO THINK ECONOMICS.

Abstract

This study examines the spatial dependence, direct and indirect effects of fiscal decentralization on the provinces economic growth of Pakistan. Due to spatial dependence, spatial econometric technique is applied on the augmented growth of Mankiw, *et al*. (1992) by incorporating the fiscal decentralization variable in the theoretical framework. The empirical analysis is based on the spatial panel data set which used from 1990 to 2011 of provinces. Model is selected on basis of specific to general and general to specific approach, and decided two-way fixed effects Spatial Durbin model (SDM) is appropriate for our data. We have estimated the SDM by maximum likelihood (bias corrected and random effect) estimation technique, otherwise, if we applied OLS and ignore the spillover effect which make our estimated parameters biased and inconsistent. Results show that revenue decentralization has positive while expenditure decentralization has negative effect to provincial economic growth. Spillover effects are found to be significant in case of revenue decentralization and insignificant in case of expenditure. Negative and insignificant spillover effect of expenditure decentralization is due to weak institutions, lack of intra governmental competition and absence of political vision which may increase the level of corruption and less accountability.

On the basis of econometric analysis, it may be suggested that federal government should transfer the resources to provinces as determined in 18th amendment, and it is the responsibility of provincial government to train their officials in the area of professional ethics, technical and administrative skills by different programs.

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Chapter 1

Introduction

1.1 Background of Federalism:

Federalism is adopted to bring administrative association between federating units and the center. Generally there are economic gains and security concerns, in presence of strong neighbor which motivate the weaker units to make a federation. Federation was first adopted by America and this system became popular after Second World War. At the beginning thirteen states of US felt weaker to British Empire and they joined the federation because they had common concern against same foe (Khalid, 2013). In this system power is partially devolve to their units but major issues are addressed at the federal level.

Federal system is decent way of combining the heterogeneous units without harming their independence. It allows state level of governments to handle their problems in their jurisdiction in better way. In this regard concept of decentralization emerge which are of three types, political, administrative and fiscal. Due to data limitations this study only concern with the fiscal decentralization.

1.2 Fiscal Decentralization:

Fiscal decentralization is the transfer of fiscal responsibilities from central to sub-central governments in devolving its functions of taxes and expenditures. It is considered as a sign of efficiency from few decades. Owing to this approach the local governments can independently figure out their problems rather consulting to federal government (Oates, 1972; 1999). This is the basic logic behind the Tiebout hypothesis (1956).

1.3 Fiscal decentralization in Pakistan:

Pakistan has a federal government structure, in which the resources are distributed among the provinces have a significant impact on income and living standard of the people. The NFC (National Finance Commission) award is considered as a step toward federalism (Mustafa, 2011), which makes mechanism to distribute resources from center to the provinces, and Provinces Finance Commission (PFC) for distribution of resources from provinces to district level. The 7^{th} NFC award is the gesture of hope and sacrifice which strengthen federation and realizing the people that other provinces are equally caring about their development (Mustafa, 2011). In this award provinces are granted more financial resources not based on population only but also on the regional backwardness.

In addition 18^{th} amendment has been done to bridge the gap between provinces and federation disparities. In this amendment provinces are given more autonomy, and financial resources are devolved by some extent, which will strengthen the process of decentralization in Pakistan.

1.4 Motivation of Study

Fiscal decentralization results in stronger intergovernmental competition due to spatial dependence one region's government policy may affect the other regions (Crowley and Sobel, 2011). Moreover, each province provide the local public good in his jurisdiction. The public goods benefit to those citizen in which province they are located, but may also have favorable spillovers to the other provinces. Therefore, the performance of centralized and decentralized system depends upon spillovers and differences in tastes of public expenditures (Besley and

Coate, 2003). The spillover effects among the provinces motive to check the direct and spillover effect of fiscal decentralization on economic growth at provincial level in Pakistan.

1.5 Objectives

Objective of this study is to answer the following questions:

1. Is spatial dependence (spatial interaction effect) exist among the provinces of Pakistan?
2. What is the direct and indirect (spillover) effects of fiscal decentralization on provincial economic growth (real per capita income).
3. Is these effects (direct and spillover) exist, significantly or not?

1.6 Methodology

Due to spatial dependence, spatial panel data econometric will be applied on the modified theoretical framework of Mankiw, *et al*. (1992) by incorporating the decentralization variable. Estimation is performed by employing maximum likelihood technique instead of OLS method to obtain unbiased and consistent parameters in the presence of spillover effect.

1.7 Organization of study

This study is organized as: Chapter 2, reviews theoretical and empirical literature on decentralization and economic growth in case of spatial and non-spatial econometrics. Chapter 3, discusses the empirical model, econometrics methodology and data. Chapter 4 empirically examines the role of fiscal decentralization and provinces economic growth and discusses the findings. Chapter 5 concludes the results, gives policy implementation, limitation and way forward of the study.

Chapter 2

Review of literature

2.1 Introduction:

There is a need to explore the literature of current development in theoretical and empirical studies of fiscal decentralization and economic growth. In this chapter we have explained the research gap in available literature and also depicts the nature of relationship between fiscal decentralization, provincial economic growth and their spillover effects due to spatial dependence.

Section 2.2 deals with the literature to develop the relationship between fiscal decentralization and economic growth. Empirical literature on fiscal decentralization nexus has been discussed in section 2.3 and 2.4. Section 2.5 explores the linkages between spatial dependence and spillover effects in spatial econometrics literature and at last we conclude the discussion.

2.2 Nexus between fiscal decentralization and economic growth

Traditional discussions of fiscal decentralization were not concerned with the effects of fiscal decentralization (FD) on economic growth. In case of multilevel government structures, many have discussed the cost and benefits that provide by their establishment. In fact, the main focus, till now, in analyzing how decentralization can promote the economic efficiency of the system. The argument in favor of the decentralization that sub-central governments can satisfy the necessities of the individuals of their jurisdiction in better way (Esteban, *et al*., 2008).

The theory of the fiscal federalism have provided diverse arguments about the assignment, objective and the function of competitions among the different government level, mostly, in term of efficiency and redistribution of public revenues and spending (Oates, 1972). Restriction on fiscal implements at the removal of the different government levels add realism to the analysis proposed and at the same time stand out the existence of a tradeoff between efficiency and redistribution. Asymmetric information is the cause to arise this tradeoff (Bird, 1993) or discrepancies among the objectives wanted by central and sub central government levels (Oates, 1998).

The advantage and inconvenience of fiscal decentralization, are more outstanding, in connection the social welfare. On one hand, it have to be pointed out that when we quantify the profit of social wellbeing that could be produce by fiscal decentralization we should focus mainly the grade of heterogeneity amid the different territories, same as different of costs in provision of public services (Oates, 1972). In general, sub-central governments possess the knowledge about preferences and cost conditions which are not within reach to central government, since natural tendency to distribute resources of this last one is the uniform provision although there are differences among regions. Furthermore, sub-central governments present a better bias and capacity for internalize economic spill overs (externalities) that take place in their territories (Esteban, *et al*., 2008).

On another view, fiscal decentralization can improve regional development and technical progress (Oates, 1999). When an environment of asymmetric information and, furthermore, a variety of innovative measures are carried out to try to resolve the same regional economic and social problems, innovative jurisdictions generate information that can very valuable for the rest. In turn, competition amid fiscal communities able to make public officials from certain regions give services at the lowest possible cost, which cause to increase the technical efficiency in their jurisdiction (Martinez-Vazquez and McNab, 2003). The disadvantage of that competition can lead to some sub-central governments undersupply public services and basic infrastructures, that will negatively effect to regional economic growth (Break, 1967).

On the other hand, a problem of fiscal decentralization creates fiscal competition amid different tiers of government. The doctrinal literature about this topic observed an inefficiency cause more than like an improvement due to the competitive behavior between administrations of different regions. Nevertheless, there are political economists who think the competition plays an important role in the disagreement of public spending (Brennan and Buchanan, 1980; Oates, 2001). On other way, alternative to this the competition offers the coordination or cooperation among jurisdiction at different level of governments. This coordination provides the social welfare that minimize the political uncertainty and it favor to the negotiation and the resolution of interregional conflicts (King, 1995). Hence, fiscal decentralization advantages are usually superior to inconveniences with regard to their relation with the social wellbeing.

There are three main objectives of government regarding public finance, and efficiency (total productivity) was first in them (Musgrave, 1959), and decentralization increase efficiency at sub-national level. The literature which is concerned with fiscal decentralization and economic growth, implicitly assumes that FD affects growth through its impact on these factors (Bodman, 2006).

The theory of fiscal federalism is not the dichotomy between centralization and decentralization. Each form of government level has an important role to carry out. Therefore, the responsibilities and authority are assign for government function to the appropriate level. Thus, fiscal institutions have to be designed to be able to incorporate incentives so that the governing class can select that policies which promote the economic growth of their jurisdiction. Due to this, the traditional vision of the theory of fiscal federalism changes and new lines support this argument that decentralization promotes economic growth.

The idea underlies to the fiscal federalism is that, the fiscal decentralization of public sector promotes economic efficiency, from a dynamic one it is able to promote economic growth (Oates, 1993). The administrators of local level know the necessities of different infrastructure of their territories better than the central government. Only in countries with relatively high per capita income levels, decentralization being attractive, in the sense that its benefits can be much more exploited that their shortcomings. Economic literature offers one more possible explanation on the phenomenon cause-effect of economic growth and fiscal decentralization. It is widely acknowledge that high-income countries are observing higher economic growth than transition economies, because they are more decentralized (Bahl and Linn, 1992).

2.3 Empirical review of decentralization and economic growth

On the relationship between fiscal decentralization and economic growth from cross country level to group of countries, there is extensive literature. World is divided into two groups, high income industrialized countries and developing countries, and different empirical studies in both group found different results.

Zhang and Zou (1998) used methodology of Barro (1990), Lvine and Renelt (1992) and Davoodi and Zou (1998) to find the relationship between decentralization and economic growth for China, they estimated panel data fixed effect model of 28 provinces (from 1980-1992) by using the estimation technique generalized least square. They find negative and significant impact of the fiscal decentralization on the economic growth.

Jin, *et al*. (2005) reexamine the study of Zhang and Zou (1998) including the variable of volatility, they extended the empirical methodology of Zhang and Zou (1998) by including (data from 1982 to 1992 of 29 provinces of China) the variable of dummy that capture the effect of a national macroeconomics fluctuations. They conclude that the fiscal decentralization promotes economic growth of Chinese provinces.

Xie, *et al*. (1999) used the theoretical model for decentralization that is elaborated in Davoodi and Zou (1998) for 50 American states (from time period 1948-1994), empirically they applied time series methodology by OLS estimation. They concluded that existing expenditure share for local and state governments in USA are consistent with the objective of maximizing the growth of the economy, the effect of decentralization is highly insignificant.

Lin and Liu (2000) used the methodology of Mankiw, *et al*. (1992) and they specify a model of growth of Solow (1956). They used data of 28 provinces of China for the time period 1970-1993, their empirically analysis based on provinces panel data, with two way (provinces and time dummies) fixed effects. They found, the fiscal decentralization contributes economic growth in China, significantly, which is consistent with the hypothesis that fiscal decentralization can enhance economic efficiency.

Zhang and Zou (2001) developed a new model with accordance Barro (1990) and Zhang and Zou (1998) that connects the different public spending categories in the diverse government levels with the economic growth of the region. They selected 28 provinces of China (from 1987-1993) and 16 major states of India (from1970-1994). In empirical analysis, they applied provincial fixed effect model (in case of China) and regression analysis based on panel data, with estimation a five year forward-moving average of real per capita income growth (in case of India). They concluded, in case of China, as in Zhang and Zou (1998), a negative and significant association between province economic growth and fiscal decentralization. However, in case of India, they found a positive and significant association between fiscal decentralization and economic growth.

Behnisch, *et al*. (2003) conducted a study in Germany (from time period 1950-1990), but they did not make any reference to their theoretical model. They applied linear and time series regression analysis (further details are not available). The analysis shows an inverse significance of state expenditure, and therefore, indicates polices among state level governments as part of cooperative federalism is not efficient with regard of productivity growth.

Vazquez and McNab (2003) used panel data set (from 1972-1997) for 52 transitional countries. They examined direct and indirect relationship among fiscal decentralization and economic growth and macroeconomic stability. They concluded that decentralization leads to reduce the rate of inflation, and positively effect on economic growth through its positive impact on macroeconomic stability.

Desai *et al*. (2003) used the regression analysis of (80 Russian) regions and average data with time specific effects as a base of simultaneous regression models. They applied three stage least squares (3SLS) and OLS with panel-corrected standard error estimation. They don't mention the reference of any theoretical pattern. Thus, the proxy for sub-national (tax retention) fiscal autonomy, has a positive impact on the output regaining of regions since the break-up of the Soviet Union.

Feld, *et al.* (2004) used the methodology of neoclassical growth model of Mankiw, *et al*. (1992) on panel data for the 26 Swiss cantons from 1980 to 1998. In their empirical study the effect of diverse instruments of fiscal federalism on economic performance measured by GDP per capita. The results concluded that matching grants have a negative impact on economic performance, while tax competition is not least harmful to economic performance, competition among the different sub-national governments enhance efficiency.

Akai, *et al.* (2004) provided the theory (from *Barro (1990)* analytical framework) that describes how to decentralization effect economic growth under different structure of regional complementary. They estimated panel data model with time and state fixed effects of fifty states of USA over the period of 1992-1997 which support the theoretical specification of the production function, by using the technique of maximum likelihood estimation. They observed the "hump-shaped" association between fiscal decentralization and economic growth.

Jin and Zou (2005) applied the methodology of Barro (1990) and Davoodi and Zou (1998) in a panel dataset for 30 provinces in China to examine the association between fiscal decentralization and economic growth over two stages of fiscal decentralization in China: first, 1979–1993 under the fiscal contract system, and second, 1994–1999 under the tax assignment system. In their empirical analysis, they estimated the coefficients with fixed-effects with correction for panel heteroskedasticity and panel serial correlation. They concluded, for time period 1979 to 1993, results suggest, that revenue decentralization encourage revenue mobilization from local sources, it is suggests, expenditure centralization enhance growth, because the central government spends more efficiently than the provinces and for second time period from 1994 to 1999, results suggest that at a certain level of expenditure decentralization, more revenue centralization promotes economic growth in China.

Carrion-i-Silvestre, *et al.* (2006) analyzed the influence of the Spanish fiscal decentralization on economic growth at aggregate and regional level. They followed the methodology of Xie, *et al*. (1999) based on Davoodi and Zou (1998), take the data set of aggregate and regional level of 17 Autonomous Communities from 1980 to 1998 and 1991 to 1996 respectively. On their panel data estimation they conclude that the Spanish decentralization process has a positive effect on both aggregate and regional economic growth.

Akai and Sakata (2007) used same theoretical model applied by Xie, *et al*. (1999), based on the pattern of Davoodi and Zou (1998). They applied OLS and Fixed Effect Model with time dummies, on the panel data of 50 states of USA (from 1992 to 1997), their estimated coefficients on fiscal decentralization is significant and have a positive effect on economic growth.

RODRÍGUEZ-POSE, *et al.* (2009), used the regression model based on methodology of Levine and Renelt (1992) to investigate the significance of fiscal decentralization in sixteen Central and Eastern European countries. They applied panel data approach with dynamic effects over the 1990–2004 period of time, findings says expenditure decentralization has a negative effect on economic growth due to the weak institution structure in many of countries and in case of decentralization of revenues, they investigated that if revenues are decentralized at sub-national level their own revenue source behave better to local public demands and promote economic efficiency.

2.4 Empirical review in case of Pakistan

Malik, *et al*. (2006) investigated the positive association between fiscal decentralization and economic growth, they use time series data from 1972 to 2005 and Ordinary Least Square estimation method is applied.

Iqbal (2013) analyzed the effect of fiscal decentralization on economic growth and macroeconomic stability by using the endogenous growth model. In his analysis time series data is used from 1972-2010 and Generalize Method of Moment technique is applied. It is concluded by him that revenue and expenditure decentralization have positive and negative effect on economic growth respectively. The reason of negative effect of expenditure decentralization is weak institution and administrative framework at provinces level.

2.5 Decentralization, economic growth, spillover effects and spatial econometrics

Spatial econometrics is the advancement in econometrics literature which capture the spatial effect due to spatial autocorrelation (Yang and Zheng, 2010).

Yamoah (2007) used the growth model of Carlino and Mills (1987) to check the effect of decentralization on economic growth in three thousand counties of forty six states of USA. In her study she take cross sectional data, and result indicate that fiscal decentralization have negative effect on economic growth, spatial spillovers in county government decision making does not investigate and this limitation is acknowledge by her, and give way forward of new research in the area of spatial econometrics.

Tosun and Yilmaz (2010) applied the panel data (1976-2001) and cross-sectional spatial regression analysis in 67 and 81 provinces in Turkey respectively. In cross sectional regression analysis there exists spatial correlation among the contiguous provinces (spatial effect incorporate in regression analysis due to this reason) and the model of spatial dependence account for any direct effect of spatial neighbor and spillover effects, hence, it is concluded that decentralization contracting positive effect on economic growth through greater degree of competition among the provinces government.

Hammond and Tosun (2011) investigated the impact of fiscal decentralization on economic growth in counties of USA. Their sample size divide into metropolitan counties and non-metropolitan counties (period from 1970 to 2000). Since they use county-level data then spatial spill-overs across counties exist, and these spill-over effects which imply that growth shocks to one county may be transferred feedback effect to other counties nearby, and will basis the residual variance in an OLS regression to be non-spherical. To correct this problem they used spatial error model in order to distinguish between metropolitan and nonmetropolitan impacts. They estimates that 10% increase in revenue centralization in metropolitan counties causes the decrease in long rune per capita income growth of 0.28%, and no correlation between decentralization and non-metropolitan economic growth exist. This recommends that metropolitan fiscal decentralization benefits long-run income growth. It also advises that generating revenue in a decentralized way, makes the county a more attractive. Therefore, they examine significant positive spillover growth shocks to other counties, which suggests that counties whose neighbor grow faster than expected, to grow faster than expected.

Zheng, *et al*. (2013) taken 21 province data (from time period 1994-2006) to investigate the supply of healthcare expenditures which are cause to slow economic growth from last two decades. They use spatial panel data econometrics and find that the supply of healthcare resources is negatively related to the degree of decentralization. It is credited to the presence of strategic alternatives (spillovers) in healthcare spending across city governments.

2.6 Conclusion:

Effect of decentralization on economic growth is diverse in different regions. This difference exist on some extent due to misspecification of the model, because regional governments are interlinked on base of strategies and boarders, the act of one government have feedback effect (spillover effect) to another. If spatial dependence and spillover effect are not account for then they could lead to biased and inconsistent parameter estimates (LeSage, 1998). In case of Pakistan there is not conducted the study of fiscal decentralization and its effect on economic growth at provinces level, where provinces effect their neighbors significantly.

Chapter 3

MODEL DESCRIPTION AND METHODOLOGY

3.1 Introduction

This chapter presents the economic framework of fiscal decentralization and economic growth by introducing the fiscal decentralization variable in growth model of Mankiw, Romer and Weil (1992) and the rest of the chapter focuses on the development of spatial econometrics methodology.

This chapter is organized as follow: Section 3.2 explain the economic framework and section 3.3 and its sub section extend the economic model to spatial panel data model. Section 3.4 explains the method to develop a spatial weight matrix. Section 3.5 discusses possible spatial interaction effects in spatial econometric models and also elaborates the methodology to explore the direct and spillover effects of the model. Different types of spatial and non-spatial models and their estimation procedures are discussed in section 3.4 and finally, section 3.7 describes the data and construction of variables

3.2 Economic Framework

There is no way to explain the growth model that completely specifies the factors that one has to hold constant, while directing statistical analysis on the relationship between growth and the other variables (Levine and Renelt, 1992). Production function based estimation is mostly used to find the effect of fiscal decentralization on economic growth.

Cobb-Douglas production function of provinces i at time t is given by Mankiw, Romer and Weil (1992) as

$$y_{it} = A_{it} k_{it}^{\alpha} h_{it}^{\beta} \quad (3.1)$$

where y is output labour ratio, *k* is physical capital ratio, *h* is the human capital ratio and A is total factor productivity or overall efficiency. Taking log on both sides of equation (3.1).

$$\ln y_{it} = lnA_{it} + \alpha lnk_{\,it} + \beta lnh_{\,it} \quad (3.2)$$

The formal theoretical models can be used to justify the inclusion of fiscal decentralization or some other control variables in regression analysis. Literature suggests that fiscal decentralization is likely to affect economic growth through its impact on efficiency. Bodman, (2008), uses this framework to build the relationship between efficiency growth and fiscal decentralization. The growth rate of TFP or efficiency is assumed to be determined by an exogenous factors,γ_A and either change in fiscal decentralization FD.

$$lnA_{it} = \gamma_{Ai} + \gamma_{A1} FD_{it} \quad (3.3)$$

Equation (3.3) shows that changes in FD leads to growth in efficiency. Now we substitute equation (3.3) into (3.2)

$$\ln y_{it} = \gamma_{Ai} + \gamma_{A1} FD_{it} + \alpha lnk_{\,it} + \beta lnh_{\,it} \quad (3.4)$$

Equation (3.4) is mathematical model of panel data set, which will further extent as spatial panel data econometrics model by incorporating the spatial interaction effects.

3.3 Spatial Econometrics

Spatial econometrics is a sub dimensional field of econometrics which deals with spatial interaction effects among geographical regions. Spatial spillover effects have main interest in regional science. A valuable point of spatial econometrics is that, the magnitude and spatial spillovers can be empirically investigated. Spatial econometrics models are used to explain the behavior of economic agents of different geographical units (Elhorst, 2014).

3.3.1 Spatial Panel Data Econometrics

Recent literature of spatial econometrics has great interest on the specification and estimation of econometrics relationships based on spatial panel data. Spatial panel data refer to data which containing time series observations of a number of geographical units. Panel data set is generally more informative, and they deal more variation and less co-linearity among the variables. Panel data use greater availability of degree of freedom for results, and therefore increase efficiency in estimation. More complicated behavioral hypothesizes are allowed for specification in panel data set by including effects that not able to addressed using pure cross sectional data (Baltagi, 2008).

3.3.2 Standard Model for Spatial Panel

A pooled regression linear model with spatial specific effects but without spatial interaction effects of our data:

$$y_{ti} = x_{ti}\beta + \mu_i + \varepsilon_{ti} \tag{3.5}$$

where i is an index for the cross-sectional units (spatial units), with $i = 1, \ldots, N$, and t index for time dimension, with $t = 1, \ldots, T$. This data is sorted first by time and then by cross section (spatial unit) but in classic panel data literature data is sorted first by spatial unit and then by time. y_{ti} represents an $NT \times 1$ vector consisting of dependent variable and $NT \times K$ matrix for x_{ti}.

By incorporating spatial interaction effect in our model in equation 3.5, our general nesting model (GNM) will be:

$$y_{ti} = \delta \sum_{j=1}^{N} W_{ij} y_{jt} + \alpha + x_{ti}\beta + \sum_{j=1}^{N} W_{ij} x_{jt}\,\theta + \mu_i(optional) + \tau_t(optional) + \varepsilon_{ti} \tag{3.6}$$

where

$$\varepsilon_{ti} = \lambda \textstyle\sum_{j=1}^{N} W_{ij}\varepsilon_{ti} + \upsilon_{ti} \tag{3.7}$$

Equation 3.6 and 3.7 can also be written as:

$$Y_t = \delta W Y_t + X_t\beta + W X_t\theta + \mu_i + \tau_t + \varepsilon_t \tag{3.8}$$

$$\varepsilon_{ti} = \lambda W \varepsilon_t + \upsilon_t \tag{3.9}$$

where

$$W = W_{NT} = (I_T \otimes W_N) \tag{3.10}$$

a vector of spatially lagged dependent variable follows as:

$$WY = W_{NT}Y = (I_T \otimes W_N)Y$$

a matrix of spatially lagged explanatory variables as:

$$WX = W_{NT}X = (I_T \otimes W_N)X$$

and a vector of spatially lagged error terms as:

$$W\varepsilon = W_{NT}\varepsilon = (I_T \otimes W_N)\varepsilon$$

the variable $W_{ij}y_{jt}$ represents the interaction effect of the dependent variable of neighbor units, where W_{ij} *and* W is nonnegative $N \times N$ and $NT \times NT$ spatial weight matrix respectively (into two different equations), describing the arrangement of the spatial units in the sample. x_{ti} a

$1 \times K$ vector of exogenous variables, and β a matching $K \times 1$ vector of fixed unknown parameters. Error term (ε_{ti}) is an independently and identically distributed by term for t and i with zero mean and constant variance σ^2, μ_i denotes a spatial specific effect and τ_t a time period fixed effect. Time period fixed effect control for all time specific effects whose omission could bias the estimates in atypical time-series study while spatial fixed effects control all space specific time invariant variables whose omission could bias the estimates in a cross sectional study (Baltagi, 2008). Therefore, in fixed effects model a dummy variable (demean approach) is introduced for each spatial unit and time period, while in random effects model, ε_t is treated as random variables that are independently and identically distributed (Elhorst, 2014).

Figure 3.1: Classification of Linear Spatial Dependence Models

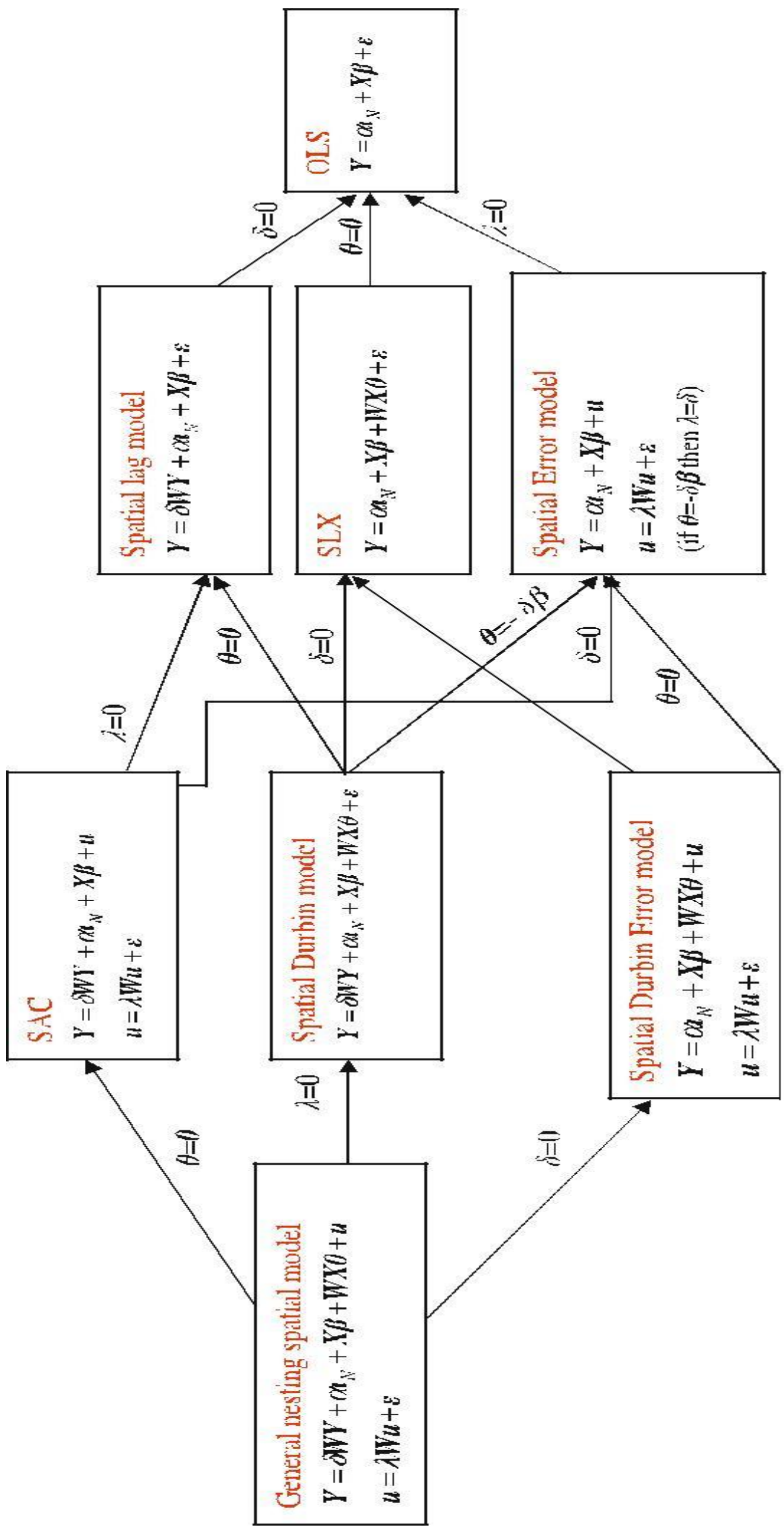

Fig. 3.1 The relationship between different spatial dependence models for cross sectional data which can extend to panel data easily (source Elhorst 2014)

We refer Equation 3.8 as the general nesting spatial (GNS) model since it include all types of interaction effects, δ and λ are called spatial autoregressive coefficient and spatial autocorrelation coefficient respectively, while θ just as β, represent a $K \times 1$ vector of unknown parameters. The literature of spatial econometrics has shown that ordinary least square *(OLS)* estimation is not appropriate for models which incorporating spatial effects. In the presence of spatial autocorrelation OLS estimation of spatial error model provides unbiased but inefficient estimators. But in the case of model specification contains spatially lag dependent variable (SAR), the OLS estimator not only loses the property of being unbiased but inconsistent (Elhorst, 2003). Therefore, spatial econometrics literature suggests to overcome this problem by using the estimation technique of maximum likelihood (Anselin, 1988).

3.4 W matrix and normalizing W matrix

W representing an $n \times n$ spatial weight matrix (in case of cross sectional data) of binary numbers, in which one is assign for neighbor, and zero is assign to prevent a region to the neighbor of itself (LeSage and Pace, 2009), in our case study (of Pakistan) we have four regions (Punjab, Sind, KPK and Baluchistan). Where each column represent one region, 1st for Punjab, 2nd for Sind, 3rd for KPK and 4th for Baluchistan.

$$W = \begin{bmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{bmatrix}$$

$$W_{RN} = \begin{bmatrix} 0 & 0.33 & 0.33 & 0.33 \\ 0.5 & 0 & 0 & 0.5 \\ 0.5 & 0 & 0 & 0.5 \\ 0.33 & 0.33 & 0.33 & 0 \end{bmatrix}$$

As another way, W might be normalized in such a way that the elements of each column sum to one. There is a point that the column elements of a spatial W matrix show the impact of a particular unit on all other units, while the row elements of spatial W matrix display the on a specific unit by all other units. Therefore, column normalization has the effect, the impact of each region on all other regions is equalized, while row normalization (W_{RN}) has the effect, the impact of a particular region on all other regions (Elhorst, 2014).

3.5 Spatial econometrics models and possible spatial interaction effects

In Figure 3.1 we have different spatial econometrics models which have been considered in the literature. The simplest model in this figure is the familiar linear regression model that takes the form

$$Y = \alpha_N + X\beta + \varepsilon \tag{3.11}$$

Therefore, this regression model is commonly estimated by ordinary least square *(OLS)* it is often referred as OLS model. In the literature of spatial econometrics there has developed some models which treat different types of interaction effects among regions and these interaction effects are of three different types (Elhorst, 2013):

1. Endogenous interaction effects among the dependent variable.
2. Exogenous interaction effects among independent variables, and
3. Interaction effects among the stochastic error term

The model in the Figure 3.1 that include all possible spatial interaction effects takes the form

$$Y = \delta WY + \alpha\iota_N + X\beta + WX\theta + u,\ u = \lambda Wu + \varepsilon \tag{3.12}$$

We refer to model 3.12 as the general nested spatial *(GNS)* model which includes all possible interaction effects (in cross sectional data). The lag dependent variable WY denotes the endogenous interaction effects among the dependent variable, WX and Wu are the interaction effect among the explanatory variable and disturbance terms respectively. The scalar parameters δ and λ measures the strength of dependence between units, whereas θ, like β is a $K \times 1$ vector of response parameter. Therefore, the GNS model includes all interaction effects, and we can get different types of model (which have less interactional effect) by imposing restrictions on parameters.

3.5.1 Direct and Indirect (or Spillover) Effects

Simultaneous feedback (direct and indirect effect) is a main feature of spatial regression model which arise from dependence relations. These direct or feedback effects, occur due to change in neighboring region *j*, from a change originating in region *i*, to understand it (in better way) we first consider the data generating process that associated with the spatial regression model (LeSage and Pace, 2009).

By rewriting the general nesting spatial (GNS) model (3.12) in reduce form as

$$\boldsymbol{Y} = (\boldsymbol{I} - \boldsymbol{\delta W})^{-\mathbf{1}}(\boldsymbol{X\beta} + \boldsymbol{WX\theta}) + \boldsymbol{Q} \tag{3.13}$$

Equation 3.13 represents GNS model of cross sectional data which further can be extended to Spatial Panel data set which become

$$\boldsymbol{Y} = [\boldsymbol{I_T} \otimes (\boldsymbol{I_N} - \boldsymbol{\delta W_N})^{-\mathbf{1}}](\boldsymbol{X\beta} + \boldsymbol{WX\theta}) + \boldsymbol{Q} \tag{3.14}$$

$$\boldsymbol{Q} = Intercepts + [\boldsymbol{I_T} \otimes (\boldsymbol{I_N} - \boldsymbol{\delta W_N})^{-\mathbf{1}}]\boldsymbol{u}$$

Where $\boldsymbol{Q}$ is a rest term which containing the intercept and the error terms. The subscripts indicating the dimension of the matrices, the inverse matrix can be expanded, and considered one cross-section at a time, due to the block-diagonal structure of the inverse. A result, for each $N \times 1$ cross-sectional at time $t = 1, 2, \ldots, T$:

$$\boldsymbol{Y_t = Intercepts + X_t\beta + \delta W_N X_t \beta + \delta^2 W_N^2 X_t \beta + \ldots . + u_t \delta W_N u_t + \delta^2 W_N^2 u_t \ldots ..}$$

The above expand model indicating that the expected value of each observation $\boldsymbol{Y_{ti}}$ mean value of $\boldsymbol{X_t\beta}$ plus a linear combination of the values taken by *j* neighboring observations scaled by the dependence parameter $\boldsymbol{\delta}$**.** The data generating process (DGP) expresses the simultaneous nature of the spatial autoregressive process. Since, if we consider power of the row stochastic spatial weight matrix, where $\boldsymbol{W_N}$ represent first order contiguous neighbor. The $\boldsymbol{W_N^2}$ will reflect second order contiguous neighbor, those which are neighbor to first order neighbor (Anselin, 1988, LeSage and Pace, 2009).

Another way to express this simultaneous relation is to take partial derivative (equation 3.14) of the matrix of expected value of $\boldsymbol{Y}$ with respect to *kth* explanatory variable of X is:

$$\begin{bmatrix} \frac{\partial E(y_t)}{\partial x_t} & \cdot & \frac{\partial E(y_t)}{\partial x_{tNk}} \end{bmatrix} = \begin{bmatrix} \frac{\partial E(y_{t1})}{\partial x_{1t}} & \cdot & \frac{\partial E(y_{t1})}{\partial x_{tNk}} \\ \cdot & \cdot & \cdot \\ \frac{\partial E(y_{tN})}{\partial x_{1tk}} & \cdot & \frac{\partial E(y_t)}{\partial x_{tNk}} \end{bmatrix}$$
$$= \left[I_T \otimes (I_N - \delta W_N)^{-1} \right] = \begin{bmatrix} \beta_k & w_{T12}\theta_k & \cdot & w_{1TN}\theta_k \\ w_{T21}\theta_k & \beta_k & \cdot & w_{TN2}\theta_k \\ \cdot & \cdot & \cdot & \cdot \\ w_{T21}\theta_k & w_{TN2}\theta_k & \cdot & \beta_k \end{bmatrix} \qquad (3.15)$$

If we interpret above partial derivative (equation 3.15) of expected value of dependent variable with respect to kth explanatory variables, we have three important properties (Elhorst, 2014):

1. If a specific explanatory variable in a particular region changes, will not change the dependent variable of that region itself but also the dependent variable in other region. First, is called direct effect and second is an indirect (or spillover) effect. It should be

kept in mind that every diagonal element of the matrix represents a direct effect and every off-diagonal element represents spillover effects. As a result, indirect effects do not occur if both $\delta = 0$ and $\theta_k = 0$, because all off-diagonal elements will become zero [see (3.15)]

2. Direct and spillover effects are different for different regions in the sample. The reason of direct effects are different is that the diagonal elements of the matrix $(\boldsymbol{I_N} - \boldsymbol{\delta W_N})^{-\mathbf{1}}$ are different for different region, whereas $\delta \neq 0$, [see diagonal elements of 3.15]. Spillover effects are different because both elements of off-diagonal matrix $(\boldsymbol{I_N} - \boldsymbol{\delta W_N})^{-\mathbf{1}}$ and $\boldsymbol{W}$ different.
3. Spillover effects occur due to $\theta_k \neq 0$ are known as local effects and indirect effects occur if $\delta \neq 0$ and that are known as global effects. Local effect arises from a unit's of neighborhood and global effect arises from region that do not belong to a unit's neighborhood set. If both $\delta \neq 0$ and $\theta_k \neq 0$ then both global and local effects occur which cannot separated from each other.

When we estimate the spatial spillover effect the next step is to check whether it is significant or not. Since, if the coefficient of δ, β_k and θ_k in GNS model happen to be significant, this does not mean that the spillover effect of *kth* explanatory variable is also significant. In another way if one or two of these coefficient are insignificant, the spillover effect may still be significant. Testing for hypothesis of spillover effects we refer to Elhorst (2014).

The spillover effects of different model specification are reported in Table 3.1. By construction, the ordinary least square model does not allow for indirect effects because it makes the implicit assumption that outcome for different regions are independent of each other (Elhorst, 2013).

Table 3.1: direct and spillover effects corresponding to different model specifications

	Direct effect	Spillover effect
OLS/SEM	β_k	0
SAR/SAC	Diagonal elements of $(\boldsymbol{I_N} - \boldsymbol{\delta W_N})^{-\mathbf{1}}\beta_k$	Off-diagonal elements of $(\boldsymbol{I_N} - \boldsymbol{\delta W_N})^{-\mathbf{1}}\beta_k$
SLX/SDEM	β_k	θ_k
SDM/GNS	$(\boldsymbol{I_N} - \boldsymbol{\delta W_N})^{-\mathbf{1}}[\beta_k + W_N\theta_k]$	$(\boldsymbol{I_N} - \boldsymbol{\delta W_N})^{-\mathbf{1}}[\beta_k + W_N\theta_k]$

Source Halleck Vega and Elhorst (2013)

In addition spatial dependence in the disturbance process takes into account in the SEM, but it also no provide the information about spillovers, as in show in above table 3.1. It is a limitation of the SEM if over main interest is to estimate the effect of spillover. It provides the information only of direct effect on dependent variable due to the explanatory variable. Therefore, if objective is to inference on spillovers, we chose to alternative models.

3.6 Models and their Estimation

As we mention above, if we imply OLS estimation technique (when spatial interaction effect exist) to estimation parameters, parameters become inconstant and biased, to avoid this problem we move to the other estimation technique that is Maximum Likelihood (LeSage, 1998).

In this section we will discuss the different spatial and non-spatial panel data models and their estimation technique and compare the results of each model to the specification of other model (as a fixed and random effect). First we start our estimation technique from non-spatial model (one way and two way fixed effects) and then we extend it by incorporating the spatial interaction effects in dependent and independent variables, which is called Spatial Durbin Model.

3.6.1 Fixed Effects Model

If the spatial specific effects are correlated to the disturbance term then fixed effect model is specified (Wooldridge, 2010), in equation (3.8) $\delta = \theta = \lambda = 0$ we get two way non-spatial fixed effect model, parameters of the model can be estimated in two steps. First, the spatial fixed effects μ_i and time effects τ_t, eliminated from the regression equation by demeaning the variables *y* and *x* (Elhorst, 2003).

$$Y_t^* = y_{it}^* = y_{it} - \bar{y}_i - \bar{y}_t + \bar{\bar{y}} \tag{3.16}$$

on

$$X_t^* = x_{it}^* = x_{it} - \bar{x}_i - \bar{x}_t + \bar{\bar{x}}$$

where the spatial, period-specific and overall means are

$$\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it}\ ,\ \ \bar{y}_i = \frac{1}{N}\sum_{i=1}^{N} y_{it} \text{ and } \bar{\bar{y}} = \frac{1}{T}\sum_{i=1}^{N}\sum_{t=1}^{T} y_{it}$$

and likewise for $\bar{x}_i,\ \bar{x}_t\ and\ \bar{\bar{x}}$. The overall constant and the dummy variable coefficients can then be recovered from the normal equations (Greene, 2002) as

$$\hat{\eta} = C = \bar{\bar{y}} - \bar{\bar{x}}^T\,\beta$$

$$\hat{\mu}_i = \mu_i = (\bar{y}_i - \bar{\bar{y}}) - (\bar{x}_i - \bar{\bar{x}})^T\,\beta \tag{3.17}$$

$$\hat{\tau}_t = \tau_t = (\bar{y}_t - \bar{\bar{y}}) - (\bar{x}_t - \bar{\bar{x}})^T\,\beta$$

Second, the transformed regression equation $Y_t^* = X_t^*\beta + \varepsilon_t^*$ is estimated by *OLS*: $\boldsymbol{\beta} = (\boldsymbol{X}^{*\boldsymbol{T}}\boldsymbol{X}^*)^{-\mathbf{1}}(\boldsymbol{X}^{*\boldsymbol{T}}\boldsymbol{Y}^*)$ and $\boldsymbol{\sigma}^{\mathbf{2}} = (\boldsymbol{Y}^* - \boldsymbol{X}^*\boldsymbol{\beta})^{\boldsymbol{T}}(\boldsymbol{Y}^* - \boldsymbol{X}^*\boldsymbol{\beta})/\boldsymbol{NT} - (\boldsymbol{N} - \mathbf{1}) - (\boldsymbol{T} - \mathbf{1}) - \boldsymbol{K} - \mathbf{1}$

this estimator is known as the least square dummy variables (LSDV) estimator. The advantage of the demeaning procedure is that the computation of $\boldsymbol{\beta}$ involves the inversion of a $K \times K$ matrix rather than $(K+N+T) \times (K+N+T)$ as in equation (3.8) and spatial interaction effect is set to zero. This would slow down the computation and worsen accuracy of the parameter estimates.

Instead of estimating the demeaned equation by OLS, it may also be estimate by Maximum Likelihood. Therefore, the log-likelihood function of the demeaned equation is

$$LogL = -\frac{NT}{2}\log(2\pi\sigma^2) - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum\nolimits_{t=1}^{T}(\boldsymbol{Y}^* - \boldsymbol{X}^*\boldsymbol{\beta})^2 \qquad (3.18)$$

The ML estimators of $\boldsymbol{\beta}$ and $\boldsymbol{\sigma^2}$ are $\boldsymbol{\beta} = (\boldsymbol{X}^{*\boldsymbol{T}}\boldsymbol{X}^*)^{-\boldsymbol{1}}(\boldsymbol{X}^{*\boldsymbol{T}}\boldsymbol{Y}^*)$ and $\boldsymbol{\sigma^2} = (\boldsymbol{Y}^* - \boldsymbol{X}^*\boldsymbol{\beta})^{\boldsymbol{T}}(\boldsymbol{Y}^* - \boldsymbol{X}^*\boldsymbol{\beta})/\boldsymbol{NT}$**,** respectively. In other words, the Maximum Likelihood estimator of $\boldsymbol{\sigma^2}$ is slightly different to LSDV estimator because it does not correct for degree of freedom. Variance matrix of parameters asymptotically is

$$Asy.Var(\boldsymbol{\beta}, \boldsymbol{\sigma^2}) = \begin{bmatrix} \frac{1}{\sigma^2}\boldsymbol{X}^{*\boldsymbol{T}}\boldsymbol{X}^* & 0 \\ 0 & \frac{NT}{2\sigma^2} \end{bmatrix}^{-1} \qquad (3.19)$$

3.6.2 Random Effects Model

If in non-spatial regression model the unobserved individual heterogeneity, are assumed to be independent from the explanatory variables, random effect model is specified.

To get the ML parameter estimates of the random effect model (REM), a two-stages estimation procedure may be used (Elhorst, 2014). The log-likelihood of the REM is

$$LogL = -\frac{NT}{2}\log(2\pi\sigma^2) + \frac{N}{2}\log\phi^2 - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum\nolimits_{t=1}^{T}(\boldsymbol{Y}^\circ - \boldsymbol{X}^\circ\boldsymbol{\beta})^2 \qquad (3.20)$$

where ϕ for the weight given to the cross sectional component of the data, with $0 \leq \phi^2 = \sigma^2 / (T\sigma^2{}_v + \sigma^2) \leq 1$, and symbol $\circ$ denotes a transformation of the variable which dependent on ϕ

$$Y_t^\circ = y_{it}^\circ = y_{it} - (1-\phi)\frac{1}{T}\sum_{t=1}^{T} y_{it} \text{ and } X_t^\circ = x_{it}^\circ = x_{it} - (1-\phi)\frac{1}{T}\sum_{t=1}^{T} x_{it} \qquad (3.20a)$$

If $\phi = 0$ this transformation become the demeaning procedure and hence the REM to the fixed effects model. By first order maximization conditions given ϕ, β and σ^2 can be solved: $\beta = (\boldsymbol{X}^{\circ \boldsymbol{T}}\boldsymbol{X}^\circ)^{-\mathbf{1}}(\boldsymbol{X}^{\circ \boldsymbol{T}}\boldsymbol{Y}^\circ)$ and $\sigma^2 = (\boldsymbol{Y}^\circ - \boldsymbol{X}^\circ\boldsymbol{\beta})^{\boldsymbol{T}}(\boldsymbol{Y}^\circ - \boldsymbol{X}^\circ\boldsymbol{\beta})/\boldsymbol{NT}.$ Variance matrix of parameters asymptotically is

$$Asy.Var(\boldsymbol{\beta}, \phi, \boldsymbol{\sigma^2}) = \begin{bmatrix} \frac{1}{\sigma^2}\boldsymbol{X}^{\circ \boldsymbol{T}}\boldsymbol{X}^\circ & 0 & 0 \\ 0 & N(1+\dfrac{1}{\phi^2}) & -\dfrac{N}{\sigma^2} \\ 0 & -\dfrac{N}{\sigma^2} & \dfrac{NT}{2\sigma^4} \end{bmatrix}^{-1} \qquad (3.21)$$

3.6.3 Spatial Durbin Model with Two-Way Fixed Effects

Basically, the main focus of spatial econometrics has been on the spatial lag model and the spatial error model (SEM) with one type of interaction effect. This approach too limited and our focus have to shift to the spatial Durbin model (SDM). The general nesting spatial (GNS) model is not much helper, it generally leads to a model, which is over-parameterized, so that the significance level of the variables tend to go down (Elhorst, 2014).

Spatial Durbin Model (SDM) is special case of spatial autoregressive (SAR) model (LeSage and Pace, 2009). This model is developed because the dependencies in the spatial associations not only occur in the dependent variable but also in the independent variable (Bekti and Rahayu, 2013).

SDM model is specified as equation (3.8), in this model we have two-way fixed effects which we can eliminate by using demean approach (3.16), then our demean SDM become:

$$Y_t^* = \delta W Y_t^* + X_t^* \beta + W X_t^* \theta + \varepsilon_t^* \tag{3.22}$$

SDM can be formed into equation (3.23)

$$Y_t^* = [\boldsymbol{I_T} \otimes (\boldsymbol{I_N} - \boldsymbol{\delta W_N})^{-\mathbf{1}}] Z_t^* \beta + \varepsilon_t^* \tag{3.23}$$

where:

$$Z_t^* = [X_t^* \quad W X_t^*] \,, \; \beta = [\beta \quad \theta]^{\,T} \tag{3.24}$$

Parameter estimation (of SDM) was done by Maximum Likelihood Estimation (Elhorst, 2013). The equation of SDM:

$$Y_t^* = \delta W Y_t^* + Z_t^* \beta + \varepsilon_t^* \tag{3.25}$$

Develop error in this equation (3.26)

$$\varepsilon_t^* = Y_t^* - \delta W Y_t^* - Z_t^* \beta \tag{3.26}$$

Or:

$$\varepsilon_t^* = (\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}}) Y_t^* - Z_t^* \beta$$

Then, the likelihood function is in Equation (3.27-3.28):

$$L(\sigma^2; \varepsilon_t^*) = \left(\frac{1}{2\pi\sigma^2}\right)^{\frac{NT}{2}} \exp\left(-\frac{1}{2\sigma^2}\left({\varepsilon_t^*}^T \varepsilon_t^*\right)\right)$$

$$L(\delta,\beta,\sigma^2|Y_t^*) = \left(\frac{1}{2\pi\sigma^2}\right)^{\frac{NT}{2}} (\mathrm{J})\exp\left(-\frac{1}{2\sigma^2}({\varepsilon_t^*}^T\varepsilon_t^*)\right) \tag{3.28}$$

The Jacobian function from equation (3.26) can differentiate it by dependent variable Y_t^* in equation (3.29)

$$\mathrm{J} = \left|\frac{\partial\varepsilon_t^*}{\partial Y_t^*}\right| = |\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}}| \tag{3.29}$$

Substitute Equation (3.26) into (3.28), so that likelihood function is:

$$L\left(\delta,\beta,\frac{\sigma^2}{Y_t^*}\right) = \left(\frac{1}{2\pi\sigma^2}\right)^{\frac{NT}{2}} |\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}}| \tag{3.30}$$

$$\exp\left(-\frac{1}{2\sigma^2}\{((\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}})Y_t^* - \ Z_t^*\beta)^T((\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}})Y_t^* - \ Z_t^*\beta)\}\right)$$

Then, the natural logarithm of equation (3.30) is equation $(3.31 - 3.32)$:

$$\ln(L) = \frac{NT}{2} ln\left(\frac{1}{2\pi\sigma^2}\right) + ln|\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}}| \tag{3.31}$$

$$-\frac{1}{2\sigma^2}\left(((\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}})Y_t^* - \ Z_t^*\beta)^T((\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}})Y_t^* - \ Z_t^*\beta)\right)$$

$$\ln(L) = -\frac{NT}{2}\ln(2\pi) - \frac{NT}{2}\ln(\sigma^2) + ln|\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}}| \tag{3.32}$$

$$-\frac{1}{2\sigma^2}\left(((\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}})Y_t^* - \ Z_t^*\beta)^T((\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}})Y_t^* - \ Z_t^*\beta)\right)$$

β Estimate: Parameter estimate may be performed by maximize natural logarithm in (3.32) that differentiate by β:

$$\frac{\partial\ln(L)}{\partial\beta} = 0$$

$$\frac{\partial \ln(L)}{\partial \beta} = \frac{\partial\left(-\frac{1}{2\sigma^2}\left(((\boldsymbol{I_{NT}}-\boldsymbol{\delta W_{NT}})Y_t^* - Z_t^*\beta)^T((\boldsymbol{I_{NT}}-\boldsymbol{\delta W_{NT}})Y_t^* - Z_t^*\beta)\right)\right)}{\partial \beta} \tag{3.33}$$

$$0 = \frac{\partial\left(-\frac{1}{2\sigma^2}\left(((\boldsymbol{I_{NT}}-\boldsymbol{\delta W_{NT}})Y_t^* - Z_t^*\beta)^T((\boldsymbol{I_{NT}}-\boldsymbol{\delta W_{NT}})Y_t^* - Z_t^*\beta)\right)\right)}{\partial \beta}$$

$$0 = \frac{1}{\sigma^2}(Z_t^{*T}(\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}})Y_t^* - Z_t^{*T}Z_t^*\beta), \beta = (Z_t^{*T}Z_t^*)^{-1}Z_t^{*T}(I_{NT} - \delta W_{NT})Y_t^*$$

So that, the estimation is:

$$\hat{\beta} = (Z_t^{*T}Z_t^*)^{-1}Z_t^{*T}(I_{NT} - \delta W_{NT})Y_t^* \tag{3.34}$$

Or:

$$\hat{\beta} = (Z_t^{*T}Z_t^*)^{-1}Z_t^{*T}Y_t^* - \delta(Z_t^{*T}Z_t^*)^{-1}Z_t^{*T}WY_t^* \tag{3.35}$$

The estimator is unbiased. It is evidenced by:

$$E(\hat{\beta}) = E((Z_t^{*T}Z_t^*)^{-1}Z_t^{*T}(I_{NT} - \delta W_{NT})(I_{NT} - \delta W_{NT})^{-\mathbf{1}}Z_t^*\beta) = \beta$$

σ^2 Estimate: Such as estimate Parameter of β, estimate σ^2 can be performed by differentiation of equation (3.32) by σ^2:

$$\frac{\partial \ln(L)}{\partial \beta} = 0,\ \frac{\partial \ln(L)}{\partial \beta} = -\frac{NT}{2\sigma^2} + \frac{1}{(2\sigma^2)^2}\left(((\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}})Y_t^* - Z_t^*\beta)^T((\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}})Y_t^* - Z_t^*\beta)\right)$$

$$0 = -NT + \frac{1}{\sigma^2}\left(((\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}})Y_t^* - Z_t^*\beta)^T((\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}})Y_t^* - Z_t^*\beta)\right)$$

$$\hat{\sigma}^2 = \frac{\left(((\boldsymbol{I_{NT}}-\boldsymbol{\delta W_{NT}})Y_t^* - Z_t^*\beta)^T((\boldsymbol{I_{NT}}-\boldsymbol{\delta W_{NT}})Y_t^* - Z_t^*\beta)\right)}{NT}$$

The estimation is biased. It is evidenced by $E(\hat{\sigma}^2) \neq E(\sigma^2)$

$$E(\hat{\sigma}^2) = \frac{1}{NT}E\left(((\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}})Y_t^* - Z_t^*\beta)^T((\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}})Y_t^* - Z_t^*\beta)\right)$$

$$E(\hat{\sigma}^2) = \frac{1}{NT}E\left({\varepsilon_t^*}^T\varepsilon_t^*\right)$$

$$E(\hat{\sigma}^2) \ = \frac{1}{NT} E(RSS)$$

The unbiased estimator of σ^2 is:

$$\left(\frac{RSS}{(NT - 2tr(S) + tr(S^T S))}\right)$$

where, RSS is residual sum of square and:

$$S = (\boldsymbol{\delta W_{NT}} + Z_t^* (Z_t^{*T} Z_t^*)^{-1} (\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}}))$$

$\boldsymbol{\delta}$ Estimate: Estimation of β and σ^2 have close form solutions. Maximum likelihood estimates for these parameters, there is need to optimize the concentrated log-likelihood function with respect to $\boldsymbol{\delta}$ such as in equation (3.35). Suppose that the estimation of $\boldsymbol{\delta}$ is $\hat{\delta}$, then equation (3.35) become:

$$\hat{\beta} = (Z_t^{*T} Z_t^*)^{-1} Z_t^{*T} Y_t^* - \hat{\delta} (Z_t^{*T} Z_t^*)^{-1} Z_t^{*T} W Y_t^* \qquad (3.36)$$

From equation (3.35) we can develop two parameter estimation, these are $\hat{\rho}_0$ and $\hat{\rho}_d$ respectively. Estimate ρ_0 and ρ_d can develop from model $Y_t^* = Z_t^* \rho_0 + \ \varepsilon_{t0}^*$ and $WY_t^* = Z_t^* \rho_d + \ \varepsilon_{td}^*$ by Ordinary Least Square.

$$\hat{\rho}_0 = (Z_t^{*T} Z_t^*)^{-1} Z_t^{*T} Y_t^* \ and \ \hat{\rho}_d = (Z_t^{*T} Z_t^*)^{-1} Z_t^{*T} W Y_t^* \qquad (3.37)$$

So:

$$\hat{\beta} = (Z_t^{*T} Z_t^*)^{-1} Z_t^{*T} Y_t^* - \delta (Z_t^{*T} Z_t^*)^{-1} Z_t^{*T} W Y_t^* = \hat{\rho}_0 - \delta \hat{\rho}_d$$

Then, the error $\varepsilon_{t0}^* = Y_t^* - Z_t^* \rho_0$ and $\varepsilon_{td}^* = WY_t^* - Z_t^* \rho_0$ are substitute in parameter σ^2 the result shows in equation (3.38):

$$\sigma^2 = \frac{(\varepsilon_{t0}^* - \delta \varepsilon_{td}^*)^T (\varepsilon_{t0}^* - \delta \varepsilon_{td}^*)}{NT} \qquad (3.38)$$

Substitute equation (3.38) in equation (3.32) that will perform the natural logarithm to estimate δ the result shows in equation (3.39).

$$\ln(L(\delta)) = -\frac{NT}{2}\ln(2\pi) - \frac{NT}{2}\ln\left(\frac{(\varepsilon_{t0}^{*}-\delta\varepsilon_{td}^{*})^{T}(\varepsilon_{t0}^{*}-\delta\varepsilon_{td}^{*})}{NT}\right) + ln|I_{NT} - \delta W_{NT}| \ -\frac{1}{2} \quad (3.39)$$

$$\ln(L(\delta)) = -\frac{NT}{2}\ln(2\pi) - \frac{NT}{2}\ln\left((\varepsilon_{t0}^{*} - \delta\varepsilon_{td}^{*})^{T}(\varepsilon_{t0}^{*} - \delta\varepsilon_{td}^{*})\right) - \frac{NT}{2}\ln(NT) +$$

$$ln|I_{NT} - \delta W_{NT}| \ -\frac{1}{2}$$

So:

$$f(\delta) = C - \frac{NT}{2}\ln\left((\varepsilon_{t0}^{*} - \delta\varepsilon_{td}^{*})^{T}(\varepsilon_{t0}^{*} - \delta\varepsilon_{td}^{*})\right) + ln|I_{NT} - \delta W_{NT}| \quad (3.39a)$$

Where:

$$C = -\frac{NT}{2}\ln(2\pi) - \frac{NT}{2}\ln(NT) - \frac{1}{2}$$

To get the concentrated log-likelihood yields exactly the same as optimize maximum likelihood. There are many methods to calculate Jacobian $J = |I_{NT} - \delta W_{NT}|$ in equation (3.39a). LeSage and Pace (2009) derived these method, such as scaling weight matrix by its maximum eigenvalues and Monte Carlo approximation.

3.6.4 Bias Correction in Fixed Effect Models

The estimation of fixed effects model, based on the demeaning procedure, show the direct method to estimate the parameters but in this procedure some parameters become biased (Lee and Yu, 2010).

If the model have two-way fixed effects then the parameter estimate of all parameters become biased (in case of N and T are large). Lee and Yu, (2010) give two approaches to obtain consistent parameters. First is transformation approach and second is bias correction procedure.

In transformation approach instead of demeaning there is an alternative procedure to wipe out the spatial, time or spatial and time period fixed effects, which reduces the numbers of observation for estimation, one observation for every spatial unit and time period fixed effects is reduced. From NT to $N(T-1)$ in case of spatial fixed effects and $(N-1)(T-1)$ observation in case of two-way fixed effects.

In second approach Lee and Yu give the method to obtain consistent parameters by bias correction procedure, which obtained by direct approach based on maximizing the likelihood function, which is obtain under the transformation approach.

If our specify model is one (from SAR, SEM, SDM and SDEM) and contain spatial fixed effects but no time period fixed effects then the parameter estimate $\hat{\sigma}^2$ of σ^2 gain by the direct approach is biased (Elhorst, 2014). Therefore, this biasness problem can easily be corrected (BC) (Lee and Yu, 2010) as:

$$\hat{\sigma}^2_{BC} = \frac{T}{T-1}\hat{\sigma}^2 \qquad (3.40)$$

On the other hand , if our specify model contain time period fixed effect but no spatial effects then the parameter estimate $\hat{\sigma}^2$ of σ^2 gain by the direct approach is biased, but can corrected by:

$$\hat{\sigma}^2_{BC} = \frac{N}{N-1}\hat{\sigma}^2 \qquad (3.41)$$

In addition, if Spatial Models (i.e. SAR, SEM, SDM and SDEM) contain both spatial and time period specific effects then the bias correction of other parameters is also needed. But in this case each model have different bias correction. The bias correction in the GNS (3.12) model become in the form

$$
\begin{bmatrix} \hat{\beta} \\ \hat{\theta} \\ \hat{\delta} \\ \hat{\lambda} \\ \hat{\sigma}^2 \end{bmatrix}_{BC} = \begin{bmatrix} 1_K \\ 1_K \\ 1 \\ 1 \\ \frac{T}{T-1} \end{bmatrix} \circ \left[\begin{bmatrix} \hat{\beta} \\ \hat{\theta} \\ \hat{\delta} \\ \hat{\lambda} \\ \hat{\sigma}^2 \end{bmatrix} - \frac{1}{N}\left[-\Sigma\left(\hat{\beta},\hat{\theta},\hat{\delta},\hat{\lambda},\hat{\sigma}^2\right)\ \right]^{-1} \begin{bmatrix} 0_K \\ 0_K \\ \frac{1}{1-\hat{\delta}} \\ \frac{1}{1-\hat{\lambda}} \\ \frac{1}{2\hat{\sigma}^2} \end{bmatrix} \right] \tag{3.42}
$$

where $\Sigma\left(\hat{\beta},\hat{\theta},\hat{\delta},\hat{\lambda},\hat{\sigma}^2\right)$ shows the expected value of the 2nd order derivatives of log-likelihood function multiplied by $-1/_{(NT)}$ and the symbol $\circ$ denotes the element by element product of two vectors and also known as the Hadamard product. The BC for other models can obtained by striking out the irrelevant rows in the matrix in (3.42); 2 and 3 for SEM model, 2 and 4 for SAR model, 4 for SDM model and 3 for SDEM model. Therefore, because the BC parameter estimates replace the parameter estimates by direct approach then the standard error and t values of the parameter estimates also change (Elhorst, 2014).

3.6.5 Random Effect Spatial Durbin Model

If the spatial effect are considered to be random then the log-likelihood of model (3.8) by using transformation of (3.20a) become:

$$
\ln(L) = -\frac{NT}{2}\ln(2\pi\sigma^2) + ln|\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}}| + \frac{N}{2}\ln(\phi^2) \tag{3.43}
$$

$$
-\frac{1}{2\sigma^2}\left(((\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}})Y_t^\circ - \ Z_t^\circ\beta)^T((\boldsymbol{I_{NT}} - \boldsymbol{\delta W_{NT}})Y_t^\circ - \ Z_t^\circ\beta)\right)
$$

This log likelihood function is same the log likelihood function of fixed effect Spatial Durbin model in (3.32). This indicates that the same procedure method can be used to estimate $\beta, \delta\ and\ \sigma^2$ as mentioned above equations (3.39, 3.39a), but in this case the subscript $*$ must be replaced by $\circ$ (Elhorst, 2014). Therefore, $\beta, \delta\ and\ \sigma^2,\ \phi$ can be estimated by maximizing the concentrated log likelihood function with respect to ϕ

$$
f(\delta) = -\frac{NT}{2}\ln\left((\varepsilon_{t0}^\circ - \delta\varepsilon_{td}^\circ)^T(\varepsilon_{t0}^\circ - \delta\varepsilon_{td}^\circ)\right) + \frac{N}{2}\ln(\phi^2) \tag{3.44}
$$

The parameters β, δ, σ^2 and the parameter ϕ are estimated, until convergence occurs by iterative procedure.

3.6.6 Fixed or Random Effect lag model

To select the Fixed Effect or Random Effect model, Huasman specification test might be used, in which we hypothesize that there is no correlation between the random effects μ_i and the explanatory variables (Baltagi, 2005). The hypothesis is $H_o: h = 0$, where

$$h = d^T[var(d)]^{-1}d \tag{3.45}$$

$$d = \hat{\beta}_{FE} - \hat{\beta}_{RE}$$

$$var(d) = \hat{\sigma}_{RE}(Z_t^{oT} Z_t^o)^{-1} - \hat{\sigma}_{FE}(Z_t^{*T} Z_t^*)^{-1}$$

This test statistics follow to a Chi squared distribution with *K* degree of freedom (number of explanatory variables in the model except constant term). In case of spatial lag model, an additional explanatory variable is included in our specification, the Huasman test statistics for this model which should be calculated by $d = \left[\hat{\beta}^T \;\; \hat{\delta}\right]_{FE}^T - \left[\hat{\beta}^T \;\; \hat{\delta}\right]_{RE}^T$, with a Chi squared distribution with *K + 1* degree of freedom (Elhorst, 2014). If the hypothesis is rejected the random effects model must be rejected in favor of the fixed effect model. In addition, one can test the hypothesis $H_o: \phi = 0$ to check whether the random effect model should be rejected in favor of the fixed effect.

3.6.7 Model Comparison and Selection

The specification of spatial interaction effect (either spatially lag or spatial error correlation) in the model, Lagrange Multiplier (LM) tests are applied (Auselin, 1988). In addition, there is one more robust LM test which is developed by Ansline et al. (1996) which test for spatially lagged dependence in the local presence of spatial error serial correlation and for spatial error auto correlation in the local presence of a spatially lagged dependent variable (Elhorst, 2014). But LM test for a spatial panel, specified first time by Ansline et al. (2008)

$$LM_{\delta} = \frac{\left[\varepsilon^T (I_T \otimes W) Y / \hat{\sigma}^2\right]^2}{J} \quad \text{and} \quad LM_{\lambda} = \frac{\left[\varepsilon^T (I_T \otimes W) \varepsilon / \hat{\sigma}^2\right]^2}{T \times T_W} \tag{3.46}$$

where ε indicates the residual vector of a pooled regression which have not spatial or time-specific effects or of a panel data model with one way or two-way fixed effects. Now we defined J and T_W

$$J = \frac{1}{\hat{\sigma}^2}\left[\left((I_T \otimes W) X\hat{\beta}\right)^T \left(I_{NT} - X(X^T X)^{-1} X^T\right)(I_T \otimes W) X\hat{\beta}\right) + TTw\hat{\sigma}^2\right] \tag{3.47}$$

$$T_W = tr(WW + W^T W) \tag{3.48}$$

Robust counterparts of these LM tests, which shows by Elhorst (2014) for spatial panel are:

$$robust\ LM_{\delta} = \frac{\left[\frac{\varepsilon^T (I_T \otimes W) Y}{\hat{\sigma}^2} - \varepsilon^T (I_T \otimes W) \varepsilon / \hat{\sigma}^2\right]^2}{J - TT_W} \tag{3.49}$$

$$robust\ LM_{\lambda} = \frac{\left[\frac{\varepsilon^T (I_T \otimes W) \varepsilon}{\hat{\sigma}^2} - TT_W / J \times \varepsilon^T (I_T \otimes W) Y / \hat{\sigma}^2\right]^2}{TT_W [1 - TT_W / J]} \tag{3.50}$$

Both robust LM and classical LM tests are constructed on the basis of the residuals of the non-spatial model with or without spatial or/and time period fixed effects, and these tests follows Chi square distribution with one degree of freedom. The mathematical derivation of both tests, for a spatial panel data model with spatial fixed effects are derived in Debarsy and Ertur (2010). The difference between robust and conditional LM tests are based on the residual of non-spatial models and on the ML residual of the spatial lag or spatial error model respectively.

The goodness of fit and the squared correlation coefficient between fitted and actual values can be found Elhorst (2014).

3.7 Data Description and Variable Construction

Data which used in this study is at provinces level (from 1990 to 2011) of Pakistan.

Table 3.2: Data Description

Variable	Definition
Dependent variable (y)	*Real per capita income of provinces (base=1999-00)*
Revenue decentralization (*rd*)	$\frac{Provinces\ Revenue}{Total\ Revenue\ (including\ federal)}$
Expenditure decentralization (*ed*)	$\frac{Provinces\ Expenditure}{Total\ Expenditures\ (including\ federal)}$
Human capital (*h*)	*Per capita health and education expenditure of provinces*
Capital (*k*)	*Per capita capital expenditure of provinces*

Data of provincial GDP is estimated and disaggregated by *Shaheen Malik* (Research Analyst at unit SASEP) for World Bank. He used three traditional approaches (to estimate GDP), production, expenditure, and income. More specifically, where detail provincial data were available, i.e. agriculture, mining and quarrying, whole sale and retail trade and manufacturing, sectorial value added were estimated using the production approach. The expenditure approach was used to compute value added of construction, electricity and gas distribution, ownership of dwellings, defence subsectors and public admiration. Moreover, the income approach was applied to value added to transport, communication and storage, banking and insurance, and services sub-sectors. The analysis of estimation has been applied to facilitate the economic assessment for two provinces reports: Development Issue and Prospect of Baluchistan and Public Expenditure Review for Khyber Pakhtunkhwa.

We are also using the education and health expenditures as proxy of human capital and the capital expenditure of provincial governments as a proxy for capital, data on variables are taken from annual Pakistan Statistical Year Book. For transforming the data into per unit form, provinces population has been used, which is collected from the Labor Force Survey, published by Pakistan Bureau of Statistics (PBS). In addition, data of provincial revenue and expenditure is also taken from annual Pakistan Statistical Year Book, and the calculation of decentralization (revenue and expenditure) variables, obtain by the ratio of provinces revenue and expenditure to total revenues and expenditures of the provincial government (including federal) respectively (Oates, 1972).

Table 3.3: Descriptive Statistics

Provinces	Variable	Mean	Median	Min	Max	S.D
	y	*24901.064*	*23250.1*	*18575.9*	*35117.4*	*5043.8*
	rd	0.1439	*0.1453*	0.1244	0.1609	*0.0105*
Punjab	*ed*	0.1367	*0.1386*	0.1332	0.1386	*0.0073*
	h	*305.6*	*285.9*	*167.4*	*541.8*	*151.2*
	k	*1046.5*	*492.8*	*85.7*	*3527.7*	*1421.9*
	y	*45554.7*	*33122.5*	*27583.9*	*39009.5*	*56302*
	rd	0.0776	*0.0768*	0.0611	0.0824	*0.01*
Sind	*ed*	0.0775	*0.0744*	0.0648	0.0878	*0.0103*
	h	*508.8*	*466.1*	*194.5*	*753.9*	*460.3*
	k	*1102.7*	*620.8*	*337.9*	*3315.4*	*973.5*
	y	*20790.8*	*21251.3*	*17577.6*	*26999.5*	*3841.4*
	rd	0.0440	*0.0444*	0.0494	0.0588	*0.0104*
KPK	*ed*	0.0434	*0.0465*	0.0504	0.0263	*0.0087*
	h	*481.2*	*476.9*	*246.1*	*476.9*	*235.2*
	k	*1072.7*	*342.0*	*342.0*	*4164.0*	*1332.5*
	y	*39867.5*	*47644.2*	*24331.2*	*56896.5*	*15848.6*
	rd	0.0278	*0.0275*	0.0252	0.0368	*0.0032*
Baluchistan	*ed*	0.0215	*0.0217*	0.0209	0.0217	*0.0023*
	h	*1101.1*	*645.9*	*368.8*	*2982.2*	*861.2*
	k	*2776.9*	*1964.3*	*1041.4*	*6920.4*	*1916.5*

Descriptive statistics shows the actual situation of each region, per capita income is high in Sindh and Baluchistan, but their SD show more inequity in income than others, and the share of the ratio of provinces revenue and expenditure to total revenue and expenditure is more in Punjab than others, because Punjab is more populated province than others.

3.7.1 Estimation Software

To estimate the SAR and SEM models, with spatial fixed effects, without fixed effects, with time period-fixed effects, or with both two-way fixed effects, we use the ***Matlab*** software for estimation of these different types of models, the programs of these model have been written by Paul Elhorst at www.regroningen.nl by file name of sar_panel_FE and sem_panel_FE. Moreover, by replacing the ***X*** of these routines by **[*X* *WX*]** it is then possible to estimate the SDM and SDEM models. The demonstration file "demoLMsarsem_panel" that is posted at the web site, we use this program to estimate the non-spatial models with or without various sets of fixed effect and the robust LM tests to test for spatial correlation. On another hand, the demonstration file "demopanelscmpare" that we use to estimation of different spatial models (with interaction effects) and find the spillover effects, and also check the specification of the model (fixed or random) by implying Hausman test.

Chapter 4
Empirical Analysis

4.1 Introduction

In this chapter we empirically analyze the different spatial econometrics models, by using the spatial panel data that explain the provincial economics performance and decentralization in Pakistan (from 1990 to 2011). The dependent variable is real per capita income and explanatory variables are decentralization (revenue or expenditure), capital and human capital. All variables are in log form, so our specified SDM is equation (3.8), which we can convert to non-spatial models easily by eliminating the spatial interaction effects, with spatial effect or/and time period fixed effects.

4.2.1 Results of Revenue Decentralization

Table 4.1.1 Estimation results of revenue decentralization using panel data models without spatial interaction effects

Determinants	(1)	(2)	(3)	(4)
	Pooled OLS	Spatial fixed Effects	Time-period Fixed effects	Spatial and time-period fixed effects
Log(rd)	0.085 (1.407)	-0.032 (-0.260)	0.162 (2.638)	0.144 (1.065)
Log(h)	0.062 (1.176)	0.039 (0.817)	0.025 (0.325)	0.045 (0.655)
Log(k)	0.222 (7.165)	0.186 (6.39)	0.332 (5.57)	0.180 (2.558)
Intercept	8.637 (27.58)			
σ^2	0.111	0.081	0.092	0.071
R^2	0.428	0.578	0.517	0.631
LogL	-24.905	-12.118	-17.758	-6.499
LM spatial lag	5.669	4.96	7.684	14.565
LM spatial error	3.517	5.596	12.650	17.140
Robust LM Spatial lag	2.346	0.009	7.386	8.557
Robust LM spatial error	0.194	0.638	12.352	11.13

Note: t-value in parentheses

Table **4.1.1** accounts the estimation results of revenue decentralization on economic growth when adopting a non-spatial panel data model. To check which specific effect should include in model (spatial or/and time), we use likelihood ratio test. Therefore, the null hypothesis, the spatial fixed effects are jointly non-significant, the result (*LR*=25.57, with 4 degrees of freedom [df], ${\chi^2}_{0.05} = 9.49$) indicate that null hypothesis is rejected and we should extend our model by including spatial specific effects. Similarly, the hypothesis that the spatial and time period fixed effects are jointly insignificant must be rejected (LR=37.00, 25 df, ${\chi^2}_{0.10} = 34.386$). Results of these test justify the extension of the model with spatial and time period fixed effects that is also known as the two way fixed effects model (Baltagi, 2005).

Therefore, inclusion of spatial and time-period fixed effects, our next step is to determine whether the spatial lag model or the spatial error model is more suitable. For the inclusion of spatial interaction effects we are using classic LM tests, and both the hypothesis of no spatially serial correlated error term and the hypothesis of no spatially lagged dependent variable must be significant at 5% and 1% level of significance. When using the robust LM tests, the hypothesis of no spatially lagged dependent variable may not be rejected at 5% as well as 1% significance. However, hypothesis of no spatially serial correlated error term must still be rejected at 5% and 1% level of significance.

Up to now, our test results point to the spatial error specification of the two-way fixed effect model because LM spatial error test is more significant than LM spatial lag test. But there is ambiguity to selection of the model because both tests reject their null hypotheses in favor of their alternatives. Nevertheless, if a non-spatial model on the basis of robust LM tests is rejected in favor of spatial error model or the spatial lag model, we should be careful to select one of these two models (Elhorst, 2014). The LeSage and pace (2009) recommend to consider the spatial Durbin model when this situation exist. The results that we get by estimating the parameters of (SDM) model, can be test the hypothesis $H_\circ\colon \theta = 0$ and $H_\circ\colon \theta + \delta\beta = 0$. The first hypothesis indicates whether the spatial Durbin model can be simplified to the spatial lag model and the second examines whether it simplified to the spatial error model (Elhorst, 2014). The test statistics of both models follow Chi squared distribution with K degree of freedom.

The spatial Durbin model best describes the data if both hypotheses $H_\circ\colon \theta = 0$ and $H_\circ\colon \theta + \delta\beta = 0$ are rejected. On the other hand if the first hypothesis not able to rejected, the spatial

Table 4.1.2 Estimation results of revenue decentralization: Spatial Durbin model specification with spatial and time-period specific effects

Determinants	(1)		(2)		**(3)**	
	Spatial and Time-period Fixed effects		Spatial and Time-period Fixed effects bias-corrected		Random spatial effects, fixed time-period effects	
W*log(y)	-0.913	(-10.69)	-0.769	(-7.659)	-0.673	(-6.47)
Log(rd)	0.744	(9.110)	0.741	(7.570)	0.724	(8.30)
Log(h)	0.072	(1.691)	0.074	(1.433)	0.076	(1.503)
Log(k)	0.162	(3.608)	0.168	(3.112)	0.163	(3.137)
W*Log(rd)	2.264	(8.896)	2.49	(8.235)	2.493	(8.634)
W*Log(h)	0.147	(1.520)	0.159	(1.367)	0.173	(1.508)
W*Log(k)	0.598	(4.282)	0.655	(3.936)	0.557	(3.636)
Phi					0.209	(2.039)
σ^2	0.013		0.018		0.018	
R^2	0.929		0.919		0.870	
Corrected R^2	0.537		0.562		0.436	
LogL	39.518		39.518		NA	
Wald Test Spatial lag	84.276	(p=0.0000)	72.322	(p=0.0000)	81.10	(p=0.0000)
LR Test Spatial lag	64.027	(p=0.0000)	64.027	(p=0.0000)	NA	
Wald Test Spatial error	33.993	(p=0.0000)	35.356	(p=0.0000)	43.522	(p=0.0000)
LR Test Spatial lag error	46.774	(p=0.0000)	46.774	(p=0.0000)	NA	

Note: t-value in parenthesis**. Hausman test-statistic,** degrees of freedom and probability = 2.987, 7, 0.8862**.**

lag model the best specify the data, the robust LM tests also specify the spatial lag model. Similarly, if second hypothesis can't be rejected, the spatial error model the best describes the data, provided that robust LM tests also specify the spatial error model. Therefore, one of these conditions is not satisfied, i.e. if the robust LM tests point to another model than the LR/Wald test, the Spatial Durbin model should be adopted (Elhorst, 2014). Because, this (SDM) model generalizes both the spatial lag and the spatial error model.

In model specification criteria, the spatial econometric literature is divided regarding to apply specific-to-general or general-to-specific approach (Elhorst, 2014). In above testing procedure we mixes both approaches. Firstly, we estimate non-spatial model to test it's against spatial lag and spatial error model (specific to general approach). In case of non-spatial model is rejected then spatial Durbin model is estimated, and this can test to simplified to the spatial lag or spatial error model (general to specific approach). If both approaches identify same model either spatial lag or spatial error model, it is safe to select this one which model describes best to data. In other hand that is the best to adopt more general model (SDM), when non-spatial model is specified in favor of spatial lag or spatial error model and spatial Durbin model not identify it.

The results which we are obtained by estimating the Spatial Durbin Model (SDM) are reported in Table 4.1.2. The first column indicates the results when model is estimated by using direct approach and the second column shows the bias corrected coefficient by Eq. (3.42), after eliminating the 4th row. These results show that the difference between parameters estimate of independent variable (X) and σ^2 are small through bias corrected estimation. But on another hand, the coefficient of the independent variables ($\boldsymbol{WX}$) and the spatially lagged dependent variables ($\boldsymbol{WY}$) are seeming quite sensitive to bias correction procedure. That's why, the bias-correction technique is part of the Matlab program dealing with the fixed effects spatial lag (SAR) and the fixed effects spatial error model (SEM) (the program "sar_panel_FE" and "sem_panel_FE") (Elhorst, 2014).

We have estimated three models (SDM) by different technique (in three columns), first we check which model specification is the best our data set, either fixed effect model is appropriated or random effect. Hausman's specification test can use to test the random effects against fixed effects model. The results (h=2.987, 7 df, p > 0.05 and 0.10) indicate that random effects model does not rejected against fixed effect.

The Wald test (43.52, p=0.000) indicate that the hypothesis whether spatial Durbin model (SDM) can be simplified to the spatial error model (SEM), $H_{\circ}: \theta + \delta\beta = 0$, must be rejected, similarly the hypothesis that SDM can be simplified to SAR model, $H_{\circ}: \theta = 0$, must be rejected (Wald test: 81.10, p=0.0000). This indicate that both the SEM and the SAR must be rejected in favor of the spatial Durbin model.

In this study we concentrate on decentralization variable as a direct and indirect effects. The coefficient of revenue decentralization in the non-spatial model is insignificant but has an expected sign. In the two-way fixed effects form of this model (the last column of Table 4.1.1), higher revenue decentralization increase regional income positively but effect again is insignificant. In other way, we have discussed (specification procedure of model) that spatial and time period specific effects are not correlate to explanatory variables, and these effects are consider as random (reason to specifying random effect model). However, due to spatial interaction (both in dependent and independent variables) the specification of spatial Durbin random effects model is found to be more appropriate, and the elasticity's in non-spatial and two-way fixed effect SDM consider as biased (due to acceptance of the null hypothesis of Hausman test). In the third column of the estimation results of SDM, the elasticity of revenue decentralization is 0.724 which is significantly overestimated as we compare it to non-spatial fixed effects models. Whereas, the coefficient estimates in the non-spatial model represent the marginal effect of a change in revenue decentralization on provincial per capita income (economic growth) but the coefficients of spatial Durbin model (SDM) do not.

Table 4.1.3 Direct and indirect (spillover) effects estimates based on the parameter estimates of the spatial Durbin model reported in Table 4.1.2.

Determinants	(1)	(2)	(3)
	Spatial and Time-period Fixed effects	Spatial and Time-period Fixed effects bias-corrected	Random spatial effects, fixed time-period effects
Direct effect Log(rd)	0.087	0.145	0.203
	(0.810)	(1.269)	(2.027)
Indirect effect Log(rd)	1.495	1.70	1.732
	(7.264)	(6.928)	(7.087)
Total effect Log(rd)	1.583	1.845	1.935
	(7.970)	(7.052)	(6.914)
Direct effect Log(h)	0.038	0.039	0.045
	(0.889)	(0.856)	(1.034)
Indirect effect Log(h)	0.078	0.095	0.105
	(1.090)	(1.169)	(1.285)
Total effect Log(h)	0.116	0.135	0.150
	(1.649)	(1.494)	(1.603)
Direct effect Log(k)	-0.025	0.005	0.046
	(-0.497)	(0.102)	(0.953)
Indirect effect Log(k)	0.425	0.461	0.385
	(3.928)	(3.775)	(3.295)
Total effect Log(k)	0.40	0.466	0.431
	(4.228)	(3.776)	(3.541)

Notes: t-values in parentheses. Direct and indirect (spillover) effects: $(I-\delta W)^{-1} = I + \delta W + \delta^2 W^2 + \delta^3 W^3 . . .$ are calculated.

For this reason, we should use the direct and indirect effects of estimates and these effects are reported in above Table 4.1.3. The logic that the direct effects of the independent variables are different from their parameter estimates is due to feedback, which arises in response of impacts passing through neighboring provinces and back to the provinces themselves. These feedback effects are relatively due to parameter of spatial lagged dependent variable [**W***log(**y**)] that turns out to be negative and significant, and partially in result of the parameter of the spatially lagged of the independent variable itself. The coefficient of latter turns out to be positive and significant for the revenue decentralization [**W***log(***rd***)], and to be positive effect in both variables [**W***log(***h***) and **W***log(***k***)] but these effects are insignificant and significant respectively. The direct and indirect (spillover) effects estimates are obtained by computing (I-δW)$^{-1}$.

In a random effects spatial Durbin model (column (3) of table 4.1.2) the direct effect of the revenue decentralization variable appears to be 0.724. This means that the revenue decentralization elasticity is 0.144 in the non-spatial model that is underestimate by 80%. Since the direct effect of the revenue decentralization is 0.237 and its coefficient estimate is 0.724 its feedback amount is -0.487 or -67.8% of the direct effect. Therefore, this feedback effects turn out relatively small. In another hand, the indirect (spillover) effects in non-spatial model are equate to zero, the indirect effect of due to change in the explanatory variables in the spatial durbin model appears to be 853.2% of the direct effect in case of revenue decentralization, and this indirect effect is statistically significant on base of t-statistics which calculated from a set of 1000 simulation parameter values. In other word, if the revenue decentralization in a particular provinces changes, not only per capita income of that province itself but also in that of its neighboring provinces will change.

The result interpretation of other explanatory variables are same but we do not focus on their interpretations, because our main variable is fiscal decentralization, but other variables are economically significant, and statistically also except the human capital, respectively. In next section we move to the estimation results of expenditure decentralization.

4.3.1 Results of Expenditure Decentralization

Table 4.2.1 Estimation results of expenditure decentralization using panel data models without spatial interaction effects

Determinants	(1)	(2)	(3)	(4)
	Pooled OLS	Spatial fixed effects	Time-period Fixed effects	Spatial and time-period fixed effects
Log(*ed*)	0.088 (1.389)	-0.246 (0.1641)	0.141 (2.179)	-0.434 (-1.711)
Log(*h*)	0.067 (1.220)	-1.080 (0.873)	0.009 (0.127)	0.092 (1.278)
Log(*k*)	0.230 (7.04)	0.174 (5.706)	0.348 (5.438)	0.130 (1.733)
Intercept	8.576 (27.26)			
σ^2	0.111	0.079	0.095	0.069
R^2	0.428	0.584	0.505	0.639
LogL	-24.930	-11.553	-18.829	-5.591
LM spatial lag	5.533	5.815	6.423	13.501
LM spatial error	3.409	5.409	9.731	14.636
Robust LM Spatial lag	2.315	0.538	16.366	3.281
Robust LM spatial error	0.191	0.132	19.674	4.416

Note: t-value in parentheses

Table **4.2.1** accounts the estimation results (of expenditure decentralization) when adopting a non-spatial panel data model. To check which specific effects should include in model (spatial or/and time), we again use likelihood ratio test as we have used in case of revenue decentralization. Thus, the null hypothesis, the spatial and time period fixed effects are jointly non-significant is rejected because *LR*=38.68 (with 25 df, ${\chi^2}_{0.05} = 37.65$) and we extend our model by including spatial and time specific effects.

Our next step is to check the spatial interaction effects for specification of the model. The procedure of the selection of the model is also the same as we have discussed (in case of revenue decentralization). For inclusion of spatial interaction effects, both hypotheses, no spatially serial correlated error term and the hypothesis of no spatially lagged dependent variable are significant at 5% and 1% level of significance because statistics of LM spatial lag and LM spatial error (see in fourth column of Table 4.2.1**)** are greater than the critical value (which is *Chi (1) .01 value* = 6.64). Therefore, we have applied both techniques specific to general and general to specific (as in revenue decentralization is applied), and conclude that our specify model is Spatial Durbin Model (SDM).

Table 4.2.2 Estimation results of expenditure decentralization: Spatial Durbin model specification with spatial and time-period specific effects

Determinants	(1)		**(2)**		(3)	
	Spatial and Time-period Fixed effects		Spatial and Time-period Fixed effects bias-corrected		Random spatial effects, fixed time-period effects	
W*log(*y*)	-0.864	(-8.894)	-0.683	(-5.992)	-0.706	(-6.377)
Log(*ed*)	-0.482	(-1.906)	-0.473	(-1.550)	0.531	(5.283)
Log(*h*)	0.202	(2.841)	0.202	(2.356)	0.073	(0.952)
Log(*k*)	0.131	(1.505)	0.134	(1.280)	0.397	(5.782)
W*Log(*ed*)	-0.540	(-0.824)	-0.484	(-0.611)	1.509	(4.387)
W*Log(*h*)	0.331	(2.051)	0.339	(1.738)	0.113	(0.640)
W*Log(*k*)	0.183	(0.855)	0.179	(0.696)	0.603	(3.709)
Phi					0.996	(2.753)
σ^2	0.042		0.047		0.047	
R^2	0.824		0.796		0.675	
Corrected R^2	0.132		0.140		0.428	
LogL	8.980		8.979		NA	
Wald Test Spatial lag	10.301	(p=0.0162)	7.098	(p=0.0688)	38.995	(p=0.0000)
LR Test Spatial lag	6.846	(p=0.0769)	6.846	(p=0.0769)	NA	
Wald Test Spatial error	2.871	(p=0.4120)	2.974	(p=0.3956)	18.720	(p=0.0000)
LR Test Spatial lag error	1.1596	(p=0.7627)	1.159	(p= 0.7627)	NA	

In Table 4.2.2 we again estimate three models (SDM) in case of expenditure decentralization by different specification and technique (see column of Table 4.2.2). We check first, which model specification is the best describes our data set, either fixed effect model is appropriated or random effect. For this we apply the Hausman's specification test to check either random effects model is appropriate or fixed effects. The result (*h*=16.18, 7 df, $p < 0.05$) indicate that random effects model is rejected in favor of fixed effects, as a result we ignore the third column. Expenditure decentralization in specification of random effect model, positively affect the real per capita income of the provinces, but these results are biased due to misspecification of the model, in other hand, the correct specification of the model, expenditure decentralization effect negatively to provinces economic growth.

The coefficient of expenditure decentralization in the non-spatial (two-way fixed effects) model (see the last column of Table 4.2.1) show the negative association to provinces income, it indicates that if higher expenditure are decentralized it will decrease the regional income, but this effect is insignificant. However, due to spatial interaction (both in dependent and independent variables) the spatial Durbin fixed effects model is found to be more appropriate, and the elasticity in non-spatial and random effects SDM consider are biased (due to reject the null hypothesis of Hausman test).

We are using bias corrected estimates for interpretation and the reason to chosen the bias correction estimates have been given in section of revenue decentralization. In the second column of the estimation results of SDM, the elasticity of expenditure decentralization is -0.472 which is insignificant, it is overestimate if we compare it to the elasticity coefficient of non-spatial two way-fixed effects model.

Table 4.2.3 Direct and indirect (spillover) effects estimates based on the parameter estimates of the spatial Durbin model reported in Table 4.2.2.

Determinants	(1)	(2)	(3)
	Spatial and Time-period Fixed effects	Spatial and Time-period Fixed effects bias-corrected	Random spatial effects, fixed time-period effects
Direct effect Log(*ed*)	-0.440	-0.423	0.216
	(-1.731)	(-1.506)	(2.89)
Indirect effect Log(*ed*)	-0.132	-0.133	0.989
	(-0.267)	(-0.232)	4.036)
Total effect Log(*ed*)	- -0.572	-0.556	1.206
	(-1.234)	(-0.930)	(4.578)
Direct effect Log(*h*)	0.143	0.149	0.059
	(2.113)	(1.961)	(0.882)
Indirect effect Log(*h*)	0.144	0.174	0.050
	(1.224)	(1.276)	(0.404)
Total effect Log(*h*)	0.288	0.323	0.109
	(2.348)	(2.054)	(0.781)
Direct effect Log(*k*)	0.101	0.109	0.308
	(1.357)	(1.338)	(4.959)
Indirect effect Log(*k*)	0.063	0.071	0.279
	(0.415)	(0.400)	(2.383)
Total effect Log(*k*)	0.165	0.181	0.587
	(1.040)	(0.850)	(4.571)

Notes: t-values in parentheses. Direct and indirect (spillover) effects: $(I-\delta W)^{-1} = I + \delta W + \delta^2 W^2 + \delta^3 W^3 . . .$ are calculated.

In addition to find the direct and indirect effects we only concern the expenditure decentralization variable. In expenditure decentralization, the direct (feedback) and indirect effects (see table 4.2.3) are not exist, because the t-value are insignificant respectively. The reason of insignificant direct and spillover effects is weak institutions and less administrative and political autonomy among the government of the provinces, and that is also a reason of negative effect of expenditure decentralization (RODRÍGUEZ-POSE, *et al.*, 2009 and Iqbal, 2013).

Chapter 5

Conclusion and Policy Recommendations

Given study analyzed the spatial (correlation) interaction effects, the effect of fiscal decentralization on the provinces economic growth and also analyzed the direct and spillover effects. The estimated result in case of revenue decentralization showed that there exist spatial interaction effects, positive effect of revenue decentralization on provincial economic growth and found significant direct (feedback) and indirect (spillover) effects, due to heterogeneous governments in the provinces[1] (from 1990 to 2011), because revenue decentralization generates positive externalities[2] and further in case of human capital and capital labor ratio have positive association to provincial economic growth respectively. On the other hand, the result indicates (in case of expenditure decentralization) that there exist spatial interaction effects, but has negative association with the provincial economic growth. In addition there exist no direct (feedback) and indirect (spillover) effects due to weak institutions[3] and lack of intra governmental competition which may increase the level of corruption, less accountability and lack of political vision of the people. In expenditure decentralization human capital and capital labor ratio have positive association to provincial economic growth. The coefficient of spatial lag of dependent variable has negative association to economic growth (due to boarder effect), when one province income increase it may affect the income of other provinces negatively because investment and business activity move to that province which is economically grow and in this case economic growth in other provinces may fall.

[1] Not concern either there is democratic or dictatorship in centre.
[2] Iqbal, *et al*. (2013): "Decentralisation of revenue generation responsibilities generates positive externalities which increase the per capita income of the country".
[3] Findings of RODRÍGUEZ-POSE, *et al.*, 2009 and Iqbal, 2013.

There are few policy implications which construct from this study:

1. As our empirical results reveal that revenue decentralization have positive direct and spillover effect on economic growth due to competition among the provincial government in given circumstances. Because by giving discretion to provincial government (in revenue generation) will increase the pace of economic growth in their region.

   Unfortunately, in 18th constitutional amendment many funds are move to provincial government but they are still in control of federal government. The Punjab government complaint against the federal government in Supreme Court that federal government is unwilling to handover its share[4]. 18th amendment gives the more autonomy to the provinces, which will leads to competition among the sub-national governments and this competition will leads to positive spillovers. Therefore, it is the responsibility of federal government to move the resources to provinces, as determined under 18th amendment.

2. In case of expenditure decentralization, it will be only effective when provinces have strong institutions, in which they have more administrative and accountability authority which leads to transparency, as a result, expenditure decentralization can contribute positively to economic growth. Hence, Provinces government should take steps to teach and giving the training to public officials in professional ethics, technical and administrative skills by different programs in order to get the significant positive impact of expenditure decentralization on their economic growth.

[4] Dawn News (02/April/2015) News link: http://www.dawn.com/news/1173391

Limitation and way forward of the study:

Due to unavailability of data we are not able to extend our study at district level, in which more spatial variation can be captured and results would be become more versatile. In this study we used fiscal decentralization as a proxy of decentralization by ignoring the political and administrative decentralization. In addition, data of provincial GDP is not collected officially at the provincial government[5] level, which is again an issue of reliability of data.

The research can be extended to find the spatial effect of fiscal decentralization on health sector, poverty and income inequality.

[5] Dawn News (04/Aug/2013) News link: http://www.dawn.com/news/1033968

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