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STARMA Models Estimation with Kalman Filter: The Case of Regional Bank Deposits

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Abstract

In this study, STARMA Models' performances and advantages on analysis of variables based on time and space are addressed. Even though the history of STARMA Models starts from 1980's, these models remained in the shadows because of both lack of variable sets and its estimation difficulties. When the literature is examined, it's seen that STARMA Models can be estimated by linear and non-linear estimators. It's seen that the non-linear estimators are producing more efficient results because of the variable's structure. For this reason, in this study, Kalman Filters and maximum likelihood estimator has been used. The calculation of spatial weight matrix is done with software "Kure" which is developing by our team. As the case study, regional deposits of commercial banks operating in Turkey were analysed. Statistically significant and robust results revealed that STARMA Model has high estimation performance.

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Keywords: Kalman Filter; Space-time Models; Spatial Dependence; STARMA Models; VARMA Models.

1. Introduction

Although many variables compiled from specific geographical areas, in the analysis, usually their time dimensions are taken into account. But there are significant interdependencies between each of these geographical

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regions. If these interdependencies are not taken into account, it's obvious that the analyses will be correct but incomplete because of neglecting the spatial dependencies of the data. In modelling the data sets which have both space and time dimensions; it is crucial to specify the space-time interdependencies of the variables. Most important problem in the space-time modelling is to define these interdependencies accurately.

The spatial behaviour of the variables can change at different moments in time. On the other hand, causes and effects of time may also vary in different locations in the space. Additionally, there may be other problems due to the effect of the neighbourhood relationships of the regions where the variables are compiled from. Although the neighbourhood relationships between the close geographic regions are computable, to calculate the size and the strength of this effect is not so easy. Nowadays, the increase in data sets with these features makes the methods which can make modelling and estimation based on space-time concept popular. In recent years, numerous alternative statistical methods have been developed like dynamic space-time models (Elhorst, 2001), dynamic space-time panel data models (Elhorst, 2005). But even though it has been developed quite long ago, space-time autoregressive moving average / STARMA has important advantages compared to alternatives. The STARMA Models developed by Pfeifer and Deutsch in the beginning of the 1980's, (1980a, 1980b, 1981a, 1981b and 1981c) couldn't have reached the integrated theoretical structure like Box-Jenkins method used in conventional time series analysis. But, it offers opportunities for the successful estimation and forecast at least as Box-Jenkins models in terms of space-time modelling.

By having studied the relevant literature, it is seen that linear and non-linear estimators are used in these models' estimations. For the efficient and robust estimation, it is more appropriate to use non-linear estimators because of the nature of the analysed variables as well as their non-linear spatial dependencies. In this regard, space-time models and Kalman filter are successful alternatives. In our study, estimations will be based on Kalman Filters by the example of regional deposits of the commercial banks operating in Turkey. Since the banks have high spatial dependencies because of their branches and ATM networks, in the decision making process, it is important to analyse them not only by their time dimensions but also their spatial dimensions. Therefore, it is aimed to reveal the superiority of STARMA models on analysis of time and space dependent data. In the study, we use the software named Küre that we're developing, for the calculation of spatial weight matrix. This software that calculates the geographical distance between the regions by their coordinates, determines the weight as w_{ij} = 1/ distance and constitutes the spatial weight matrix according to order of spatial dependence.

2. Methodology

A space-time model is a special time series model which is used for the calculation of linear dependencies between the variables in both time and space. Let's assume that y_{it} is is an economic variable obtained from k amount of constant region, (i=1,2,…,k) and consisting of the observations from multiple periods (t=1,2,…,T). Region can be: provinces, states or countries. The design of the space-time model is based on the assumption that there are relationships between the data obtained from several regions under the acceptance of there is a systematic dependency to the proportional distance between the regions. Thus, the conditional average of variable y_{it} , can be modelled by i and a linear function of the past values of the subject variables obtained from its neighbor regions. Therefore, it is necessary to explain spatial lag idea, for the variable in one region to be associated with the observations of the same variable in other regions. However, spatial lag idea cannot be easily defined as time lag or the temporal lag. (Giacomini and Granger, 2004: 10).

2.1. Description of Spatial Lags

When temporal lag operator leads observed variables to be displaced in one direction for one or more time period, there is not just one direction for the displacement of the same variable in space. Therefore, the definition of spatial lag will vary depending on the spatial layout of the data. First step of the definition of spatial lags is to identify each neighbour region according to some prior selection criteria and group them into neighbourhood sets. In other words, at first the boundaries of the region will be determined then first, second and higher-order neighbours will be defined. Theoretically, if the data is a first and higher order neighbours of the region i, it's considered as two dimension systems (Lee, 2004: 18; Dai and Billard, 1998; Dazelios and Adamowski, 1995).

When each neighbourhood set of each region is once defined, spatial lag operator can be calculated as a weighted average of the all observations of the neighbourhood set where data received from. If y_i is the observation of region i and J_s is the s'th order neighbour set; s'th order spatial lag can be defined as below (Giacomini and Granger, 2004, 10; Di Giacinto, 2006; Zhou and Buongiorno, 2006; Dazelios and Adamowski, 1995):

$$L^{(s)} y_i = \sum_{j \in J^s} w_{ij}^{(s)} x_j \qquad s = 1, 2, ... \tag{1}$$

In the implementation, spatial lags are similar to distributed lags. But spatial lags are not in one direction like the distributed lag structure used in time series analysis. In equation (1), weights selection of $w_{ij}^{(s)}$ is highly important in spatial econometrics. It's assumed that these weights are usually external, not stochastic, and they show the following features (Giacomini and Granger, 2004: 10-11; Zhou and Buongiorno, 2006):

$$\begin{aligned} & w_{ij}^{(s)} \geq 0, \\ & w_{ii}^{(s)} = 0, \\ & \sum\nolimits_{j \in J_s} w_{ij}^{(s)} = 1 \end{aligned} \tag{2}$$

Each elements (w_{ij}) of spatial weight matrix (W) reflects the spatial relationship between two regions (regions i and j). In distance based matrix calculation; since it's considered that an observation collected from one region doesn't affect its own estimation process per unit time, the diagonal elements of the spatial weight matrix will consist of zeros and the other elements will consist of positive numbers (Dubin, 1998). One of the most commonly used methods in this respect is the nearest neighbours method developed by Cliff and Ord (1981). According to this approach, when observations collected from region i and j are in the distance data determined by the researcher e.g.($d_{ij} \leq 100$ Km) or observation from j region is in between the closest observations to i region in the all observations w_{ij}=1; otherwise it will be $w_{ij} = 0$. Defining weight (w_{ij}) as an inverse polynomial of the distance between the each observation pair (ij) is another common practise (Militino, v.d. 2004:197). However, this application is used in a number of different ways. The most basic way of operation is to inverse the distance between the two regions (d_{ij}).

$$w_{ij} = 1 / d_{ij} \tag{3}$$

Another method frequently used in practice is to inverse the distance between the two regions as exponential. In this approach, α is included in the equation as an additional parameter to regulate the relation and increase the performance of the model:

$$w_{ij} = 1 / d_{ij}^{\alpha} \tag{4}$$

In this context, it should be emphasized that; regardless of which method used, incorrect determination of the weight matrix in the space-time models is an important problem creating inconsistencies in the coefficient estimates and reducing forecasting power of the models (Anselin, 1999: 5-6). Spatial weights are selected priori to reflect the geographical features of the regions dealt by the researchers such as distance of the regions, length of their boundaries and number of ways. However, alternative methods are also used such as approaches based on definition of the economic distance.

In this study, spatial weight matrixes (W) were created by adopting an understanding based on the geographical distance between the regions. But there are some differences from the methods used by Cliff and Ord (1981), Militano v.d.(2004:197). It is based on the nearest neighbourhood approach developed by Cliff and Ord but for each neighbourhood level, a separate matrix is formed in a similar way that Giacomini and Granger (2004) and Lee (2004) put in the work. In this sense, we can say that our approach is a mixed approach combining the advantages of both methods. The process consists of four steps. The first step is to calculate the average distance between the examined regions. The second step is to identification of the first order neighbours based on this distance. The third step is to define higher order neighbourly relations with the same concept. The most practical way to define the second and higher-order neighbours is to make the calculation in terms of the distance obtained from multiplying the average distance between the regions with the neighbourhood order to be defined. In the fourth step, separate weight matrices for each neighbourhood level ($W^{(s)}$) are formed. These matrices of size $N \times N$ are the basis for the calculation of the spatial lag and their each elements are defined by the ratio $1/\kappa$. Here, N is the number of region, κ is s'th order neighbours.

2.2. Analysis Method: STARMA Models

To explain estimation and forecast on the data which shows spatial dependence, it could be exploited from the space-time AR(1,1) process which can be considered as the simplest form of space-time model. Assuming that y_{it} is a variable with the zero average and in both time and space it has no dependence beyond the first delays; space-time AR (1,1) or STAR(1,1) process can be expressed as follows:

$$y_{it} = \phi y_{it-1} + \psi \sum_{j=1}^{k} w_{ij}^{(s)} y_{jt-1} + \varepsilon_{it} \qquad i = 1,2,...,k \qquad t = 1,2,...,T \tag{5}$$

In equation (1); $w_{ij}^{(s)}$ are spatial weights which their sum for each i region is 1 and having different values from zero for the i's first order neighbours. By covering $w_{ij}^{(s)}$ weights in a $W^{(s)} = (w_{ij}^{(s)})$ formed $N \times N$ spatial weights matrix, equation number (1) can also be written as a vector as follows:

$$\mathrm{y}_t = \phi \mathrm{y}_{t-1} + \psi W^{(s)} \mathrm{y}_{t-1} + \varepsilon_t \qquad t = 1,2,...,T \tag{6}$$

First term on the right side of the equation (2), is the first time lag of the variable vector $\mathbf{y}_t$, and second term symbolizes the vector's first space lag in t-1 time. In equation (2), space-time autoregressive model doesn't overlap with the spatial autoregressive model. While spatial autoregressive models include dependent variable's simultaneous spatial lags, the space-time autoregressive models include both space and time lags. Space-time autoregressive models are more like vector autoregressive models / VAR. For example, STAR(1,1) model we have mentioned above is a special form of VAR(1). In this regard, autoregressive coefficients matrix was restricted to be equal to $\phi I_k + \psi W$. For a higher spatial and temporal order, it can be made linear generalization. (Giacomini and Granger, 2004: 12; Epperson, 2000: 64):

$$\mathrm{y}_t = \sum_{\ell=1}^{p} \sum_{s=0}^{k_\ell} \phi_{\ell s} W^{(s)} \mathrm{y}_{t-\ell} + \varepsilon_t \tag{7}$$

In the model above, ℓ symbolizes time lag, s symbolizes spatial lag. Therefore, if p is temporal and k is spatial order, the equation (3) is a STAR(p,k) process. Like classical Box-Jenkins models, space-time models have also sub-species including moving average process. This can be expressed in generalized form as follows: (Epperson, 1993: 714; Lee, 2004: 20; Lee, 2005: 14-15):

$$\mathrm{y}_t = \varepsilon_t - \sum_{\ell=1}^{q}\sum_{s=0}^{m_\ell}\theta_{\ell s}W^{(s)}\varepsilon_{t-\ell} \tag{8}$$

In equation (4), ℓ symbolizes the time lag and s symbolizes the spatial lag. Then there is q temporal and m spatial order space-time moving average process or simply STMA (q, m) process

Again, as with classical Box-Jenkins models, variables that both autoregressive and which have moving average features can be modelled by space-time models. Accordingly, space-time autoregressive moving average / STARMA can be defined as follows (Dai and Billard, 1998; Epperson, 2000: 64; Lee, 2004: 19, Lee, 2005: 14-15):

$$\mathrm{y}_t = \sum_{\ell=1}^{p}\sum_{s=0}^{k_\ell}\phi_{\ell s}W^{(s)}\mathrm{y}_{t-\ell} - \sum_{\ell=1}^{q}\sum_{s=0}^{m_\ell}\theta_{\ell s}W^{(s)}\varepsilon_{t-\ell} + \varepsilon_t \tag{9}$$

Equation (5) is a STARMA(p,q,k,m) process. In this context, equation (2) refers to a STARMA(1,0,1,0) process.

3. Dataset

In this study, annual regional deposits data covering the 1988-2013 period of the Turkish commercial banking sector and publicly announced by The Banks Association of Turkey are used. When creating the data sets, regional classification also used by Turkish Statistical Institute is taken into account. In this context, twelve regions; West Marmara, Istanbul, East Marmara, West Black Sea, East Black Sea, Northeast Anatolia, Aegean, West Anatolia, Middle Anatolia, Middle east Anatolia, Mediterranean and Southeast Anatolia are considered. Series of regional deposits has both cross-section and time dimensions. Undoubtedly, this is the most basic feature of space-time models. Since the deposit data doesn't exhibit a stationary structure as well as in a lot of other time series, it is subjected to transformation by taking first their natural logarithm then their first differences. As a result of this transformation, an observation loss occurred in the cross-section related to each region and the total number of observations 312 was reduced to 300.

Since the annual data is used in the study, in the pre-processing, there was no need for procedures such as purging of seasonality and trend. It is known that the seasonal effects are not concerned in the annual data. The Trend movement covers 15 to 18 years. In this study, despite the use of 25 observations as cross section, there was no significant trend effect and so, trend purging process wasn't made.

4. Results

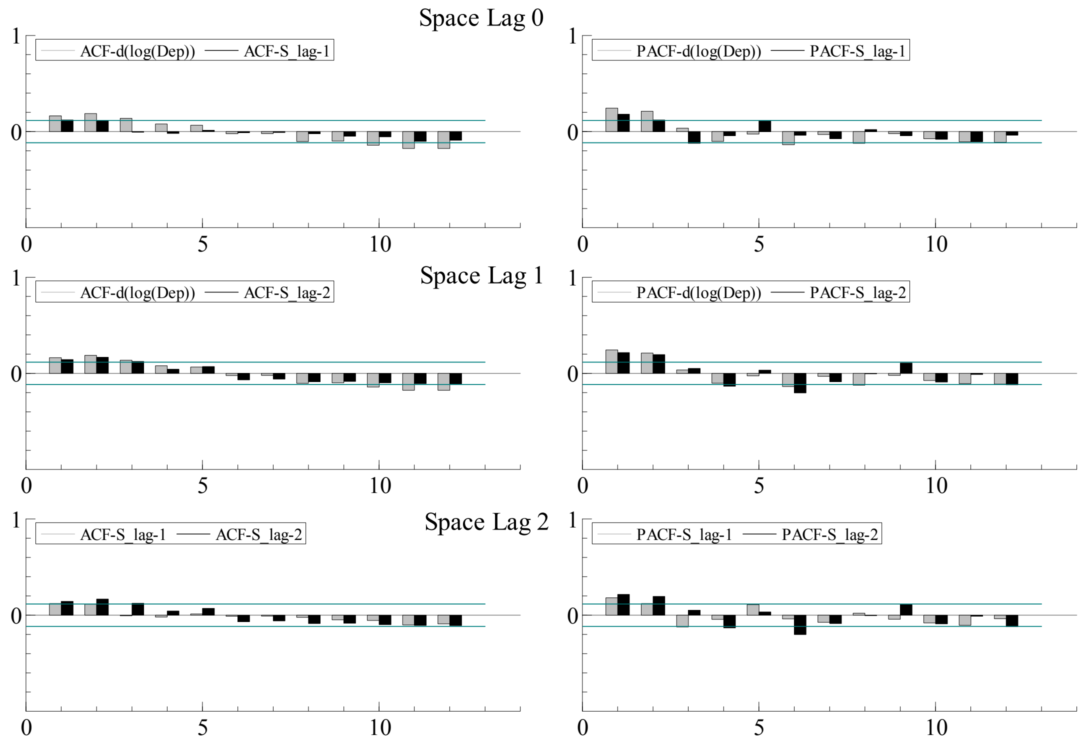
Before proceeding to the analysis, stationary of transformation applied deposit series has been analysed. Since the data obtained from different geographical regions are collected in different sections, spatial relations can be analysed by the logic of cross-sectional dependence or spatial dependence. In this context, it was used panel unit root tests developed by Levin, Lin and Chu (2002), Im, Pesaran and Shin (2003), Pesaran (2007). The findings are presented in Table 1 and reveal that the deposit series is stationary in terms of three different panel unit root tests.

Table 1. Panel Unit Root Tests

	Dep			Space-Time Lag(1)			Space-Time Lag(2)		
	t Stat.	Prob.	Lag	t Stat.	Prob.	Lag	t Stat.	Prob.	Lag
Levin, Lin & Chu	-3.0905	0.0010	1	-3.4553	0.0003	2	-1.8624	0.0313	5
Im, Pesaran and Shin	-2.2020	0.0138	1	-6.2566	0.0000	2	-2.0345	0.0210	5
ADF - Fisher Chi-square	43.7466	0.0082	1	81.5697	0.0000	2	41.2395	0.0157	5

Autocorrelation and partial autocorrelation functions of the regional deposit series were calculated and these are presented in Graph 1. Because the analysis covers twelve regions, the optimal number of spatial lag was envisaged as two. Parallel with the panel unit root tests, the correlograms are also showed that the regional deposit series is stationary.

Graph 1. Autocorrelation and Partial Autocorrelation Functions of Variables



As a result of the analyses of autocorrelation and partial autocorrelation functions presented in Graph 1, it has concluded that appropriate model should be STARMA(2,1,2,1). This model can be represented as follows:

$$\begin{aligned} Dep_t = {} & \phi_1 Dep_{t-1} + \phi_2 Dep_{t-2} + \phi_3 W^{(1)} Dep_{t-1} + \phi_4 W^{(1)} Dep_{t-2} \\ & + \phi_5 W^{(2)} Dep_{t-1} + \phi_6 W^{(2)} Dep_{t-2} + \theta_1 \varepsilon_{t-1} + \theta_2 W^{(1)} \varepsilon_{t-1} + \theta_3 W^{(2)} \varepsilon_{t-1} \end{aligned} \tag{10}$$

Model (6) as a VARMA (p,q) model, was estimated by converted into state space model. In this context, the following equation system is used:

$$z_t = A z_{t-1} + B u_t \quad (7) \quad ; \quad \mathrm{y}_t = C z_t \tag{11}$$

Equation (7) is referred as the state or the transition equation and it defines the behaviour of z_t state variables in time. Equation (8) is referred as the signal or the observation equation and from the observed y_t variables, it allows the determination of the unobservable state variables.

Unobservable state vector is assumed to act as a first order VAB in time. In this equation system, u_t is the error terms vector assumed that serially independent in the simultaneous variance structure (Lütkepohl, 2006, Aksu and Narayan, 1991; Ippoliti, 2001; De Jong and Penzer, 2004; Mauricio, 2005).

As a result of the state-space model estimation, AB coefficients were obtained from the state equations and HO coefficients were obtained from the observation equations (Brincker and Andersen, 1999; De Jong and Penzer, 2004; Hamaker, 2006). State-space estimates were made by the Kalman filter. Unknown elements of the system matrixes are determined by using Kalman filter and fixed-interval smoother and the estimation process is based on a assumption that u_t is Gaussian. Log likelihood function of the sampling as follows:

$$\begin{aligned}\log L(\Phi,\Theta) = -\frac{nT}{2}\log 2\pi - \frac{1}{2}\sum_t \log\left|\tilde{F}_t(\Phi,\Theta)\right| \\ -\frac{1}{2}\sum_t \tilde{u}_t'(\Phi,\Theta)\tilde{F}_t(\Phi,\Theta)^{-1}\tilde{u}_t(\Phi,\Theta)\end{aligned} \quad (12)$$

In this context, maximizing the likelihood function in terms of the unknown parameters Φ and Θ meaning, maximum likelihood method was used. Nonlinear estimates of the model coefficients are made by Marquardt optimization algorithm model. Coefficient estimates are presented in Table 2

In the results in Table 2, it's seen that all coefficients are significant at the level of 1%, except one and the one coefficient is significant at the level of 10%. Residuals of estimated VARMA (p,q) model were analysed and the results are presented in Table 3. These findings show that the structure of the residuals is consistent with the basic assumptions of the model. Autocorrelation and partial autocorrelation functions of the residuals presented in Graph 2 are also support these findings. The estimated model is robust in terms of statistics. The whole samplings and regional estimations of STARMA model are presented in Graph 3 and Graph 4. When analysed, it's seen that the model reflects the regional deposits in a great success.

Table 2. Coefficient Estimates with Kalman Filter and MLE

$$\begin{aligned}Dep_t = \phi_1 Dep_{t-1} + \phi_2 Dep_{t-2} + \phi_3 W^{(1)} Dep_{t-1} + \phi_4 W^{(1)} Dep_{t-2} \\ + \phi_5 W^{(2)} Dep_{t-1} + \phi_6 W^{(2)} Dep_{t-2} + \theta_1 \varepsilon_{t-1} + \theta_2 W^{(1)} \varepsilon_{t-1} + \theta_3 W^{(2)} \varepsilon_{t-1}\end{aligned}$$

	ϕ_1	ϕ_2	ϕ_3	ϕ_4	ϕ_5	ϕ_6	θ_1	θ_2	θ_3
Coefficients	2.0001	-0.9999	1.3062	-0.3071	0.3979	0.4210	-1.0050	-0.9986	-8.0036
z Tests	24.1635	-12.1106	28.9159	-6.7897	5.1472	9.1875	-16.8527	-1146.7230	-1.6363
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.101)
Log. Likelihood	133.5245								
AIC	-0.8101								
BIC	-0.6620								
HQ	-0.7508								

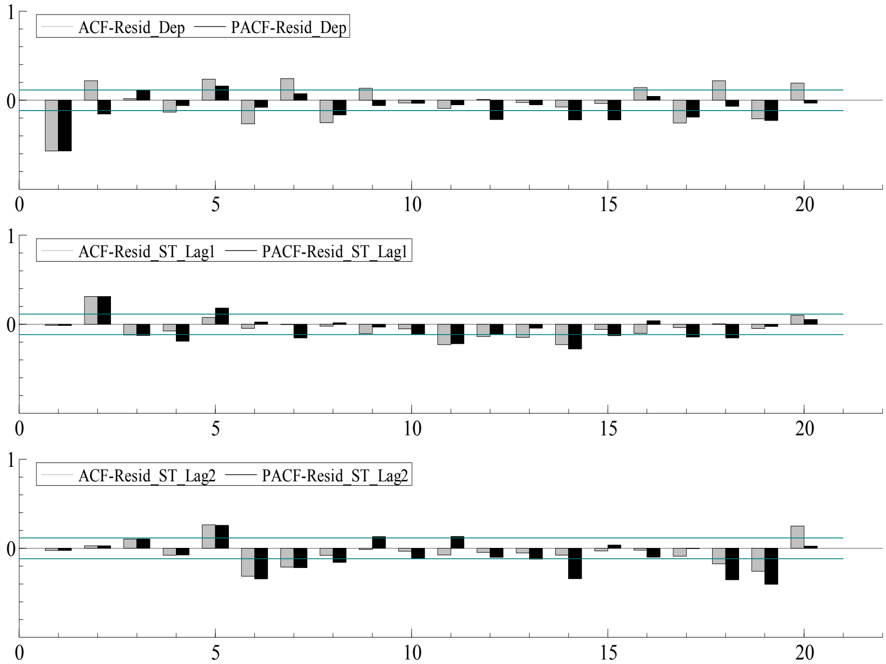
$$\hat{\Sigma} = \begin{bmatrix} 1.1222 & & \\ -0.0309 & 1.6266 & \\ -0.0680 & 0.5159 & 1.1700 \end{bmatrix}$$

Table 3. Residuals Tests

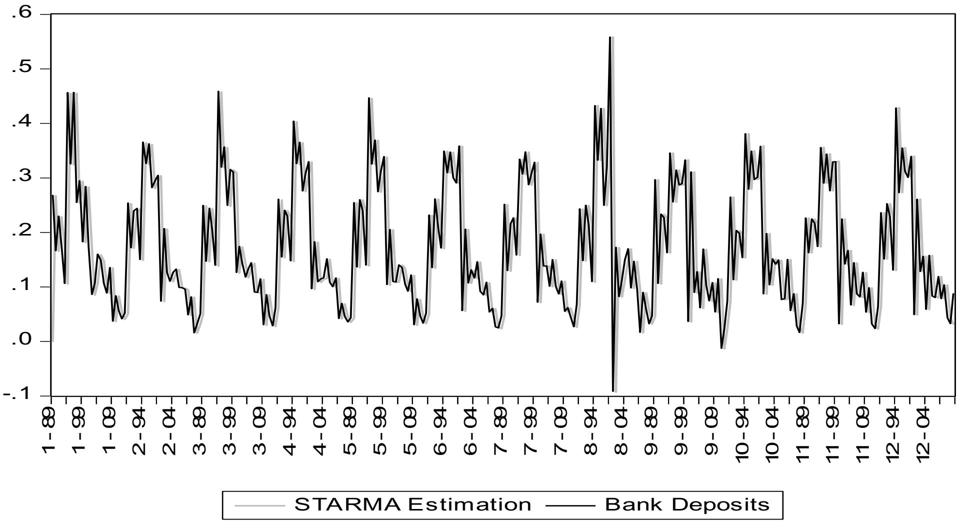
	Residuals		
	Dep	S.T. Lag(1)	S.T. Lag(2)
Mean	0.0010	0.0248	0.0668

Median	-0.0021	-0.0475	0.0079
Maximum	0.3506	1.1306	1.2434
Minimum	-0.6499	-0.4066	-0.6925
Std. Dev.	0.1141	0.2183	0.2896
Skewness	-0.2790	2.4479	1.6121
Kurtosis	6.9862	10.1242	7.7623
Jarque-Bera	202.5125	934.0391	413.4463
	(0.0000)	(0.0000)	(0.0000)
Normality	96.6300	542.9300	103.9300
	(0.0000)	(0.0000)	(0.0000)

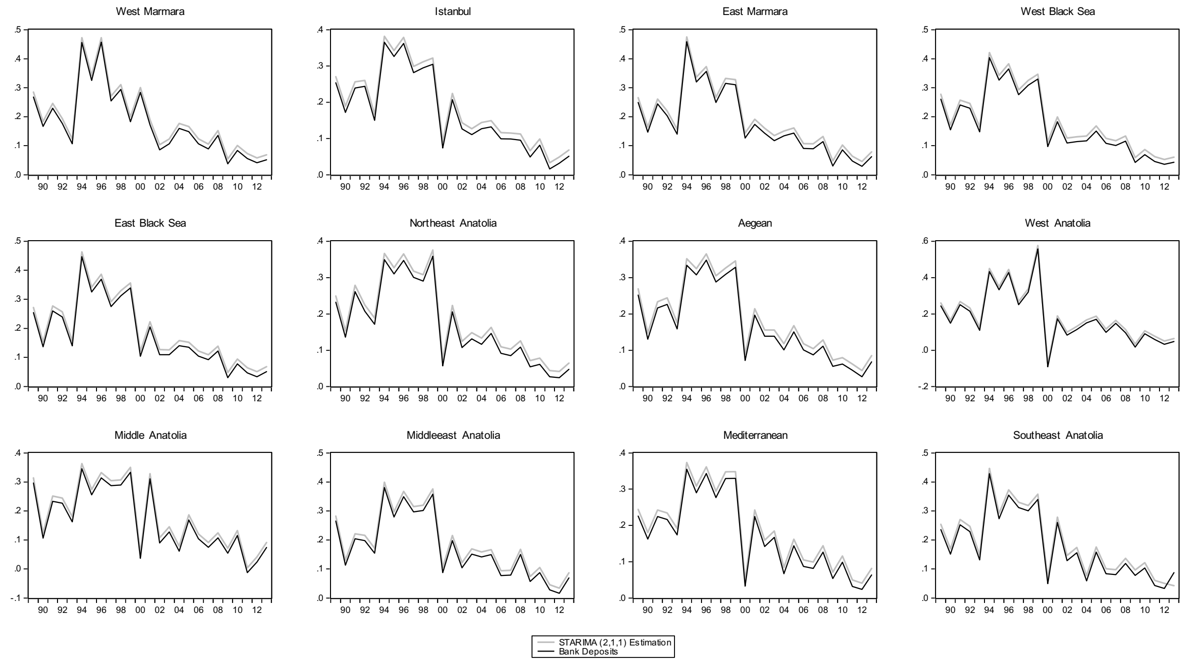
Graph 2. Autocorrelation and Partial Autocorrelation Functions of Residuals



Graph 3. Regional Bank Deposits in Turkey and Its STARMA (2,1,2,1) Estimation (All Sample)



Graph 4. Regional Bank Deposits in Turkey and Its STARMA (2,1,2,1) Estimation (All Sample)



5. Conclusion

Most of the data shows not only time dependence but also geographical dependence according to where they compiled. Therefore, modelling the several variables based on time and space raises the success of the analysis results. STARMA models are very convenient methods for the analysis of such data. In the study, it is attempted to reveal the high estimation performances of STARMA models by using the regional deposit data of the commercial banks. Especially if non-linear estimators are used, these models show more successful results. When results based on Kalman filters and ML estimator are analysed, it is seen that the bank deposits are estimated very successfully.

In decision making process of the national and/or international firms such as banks which spread over a wide geographical area with theirs distribution network, geographical-based data has a critical importance. Analysing the data of production, sales, revenue, cost, performance etc by addressing the understanding of space and time together instead of aggregating them according to time, will increase the efficiency in the decision making process. More robust estimates will form the basis for better decisions. This study has clearly demonstrated that STARMA models show both significant and robust results in terms of the regional deposits. This method can be applied easily and successfully to similar data sets, and can be a serious contribution to decision-making process of researchers and managers.

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