RECONSIDERING THE REGIONAL EMPLOYMENT CONVERGENCE PROBLEM IN TURKEY: SPATIAL PANEL DATA ESTIMATION IN AN SUR FRAMEWORK

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Abstract

Even though convergence in regional employment has been a highly debated issue in the literature, the discussion still remains incomplete as far as sectoral and spatial interactions are concerned. This paper is an attempt to uncover the employment convergence problem in Turkey via incorporating time, space and sectoral heterogeneity under the same framework. For comparison purposes, standard absolute convergence model as well as an interaction model which accounts for the sectoral connections is utilized. The model without any spatial, time and sectoral interaction effects indicates convergence in the agriculture and industry sectors whereas no significant divergence and convergence are recorded in the services sector. We argue that exclusion of the relevant factors causes a bias in the estimated effect of initial employment on the growth rate. Hence, for each sectoral equation, the neighborhood and time effects are included via spatial panel data framework. The feasible generalized three stage least squares estimation of random effects panel data model with spatial error components yields similar outcomes as to the simple pooled OLS model. Subsequently, we further allow for the existence of correlation between the estimated spatial panel data models and employ a spatial panel seemingly unrelated regression model, in which each sectoral employment convergence equation is related through the contemporaneous correlation in the disturbances. The estimation results point out a divergent pattern in the agriculture sector and a convergent trend in the services sector, which is in line with the preliminary data analysis and the expectations. Moreover, the interaction model estimated in a spatial panel SUR framework posits that a lower level of agricultural employment in the initial year has ended up with higher levels of employment in services sector.

Keywords: Sectoral employment dynamics, spatial panel, spatial panel SUR, Turkey.

JEL Codes: C33; E24; R12

1. INTRODUCTION

The persistent disparities in aggregate growth and the large differences in the wealth of Eastern and Western regions has been the main concern of policy makers in Turkey. Even though the issue of regional differences and economic development of Turkish economy have been widely investigated, there is still limited empirical evidence regarding the dynamics of regional employment. Empirical research on employment in Turkey has been mainly focusing on female labor force participation (Tunali (1997), Özar and Senesen (1998) and Tansel (2002)). Quite recently there is a rising interest in the sectoral and regional employment problem as well. Temel et.al. (2005) uses Markov chain model to show that in the long run convergence clubs are likely to occur in the agriculture and industry sectors whereas in the services sector global convergence is expected in Turkey. Öcal and Yıldırım (2008) perform a geographically weighted regression (GWR) model and observe that there is divergence in the employment rates of provinces for the 1985-2000 period. Filiztekin (2009) uses spatial and nonparametric techniques to show that over 1980-2000 period the gap between the provincial unemployment rates are widening with the emergence of spatial clusters across Turkey. Berument et. al. (2009) examines the responses of unemployment rates to various macroeconomic shocks in the economy. They find that unemployment in agriculture and manufacturing responds in different ways.

This paper is an attempt to uncover the employment convergence problem in Turkey via incorporating time, space and sectoral heterogeneity under the same framework; focusing on how the concentration of sectoral employment across 26 Turkish regions has changed over the period 2004-2011. First, a beta convergence analysis of the regional employment rates for manufacturing, agriculture and services sectors are performed by employing a seemingly unrelated regression model (SUR). Then this model is extended in order to capture the spatial aspects of employment dynamics, where spatial dependence is handled in alternative ways. Spatial variations in the sectoral relationships are examined by means of panel data with spatial error components and random effects as well as panel SUR model with spatial error components and random effects. Feasible generalized spatial three stage least squares estimations point out that the outcomes of the spatial panel SUR model are in line with the preliminary data analysis and the expectations.

In the literature, it is a common practice to use growth equations in order to investigate the employment dynamics across regions. However, the discussion would remain incomplete if the sectoral and especially the spatial connections are not taken into account. Across the regions, there are close economic linkages caused by the interdependencies through the access to the common markets. First of all, these regions often have similar industrial composition and production technologies. Hence, employment in any region may depend to some extent on the employment in another region. Any possible shock that could affect one region may possibly affect other regions that produce similar goods for the consumption at the common marketplace. A shock to a producer in one region may affect suppliers of intermediate goods in the neighboring area. Therefore, it can be argued that if there is substantial spatial correlation among regions, its ignorance may result in biased and inconsistent estimates of the employment dynamics. Thus, incorporating spatial effects into the analysis may have a significant impact on the estimated convergence parameters.[1]

To account for this effect, some scholars employ spatial SUR models as a tool for integrating limited heterogeneity in the model. These models present spatial equations for different time periods and allow for correlation between their disturbances, in line with the SUR setting (see Anselin (1988) for a theoretical discussion; Fingleton (2001), LeGallo & Dall'erba (2006) for empirical models). In another strand of the literature, panel SUR models are discussed which include both time and individual effects for each equation and further, a correlation between the error components of these SUR equations (Avery(1977), Baltagi (1980)). Recently, some studies consider the spatial extension of this panel SUR system. Wang and Kockelman (2007) employ a spatial panel SUR model to analyze the crash rates in the transportation of Chinese cities. Baltagi & Pirotte (2011) make an important contribution by considering various estimators for panel SUR model with spatial error correlation. Baltagi & Bresson (2011) extend this work by incorporating spatially lagged dependent variable and proposing Lagrange multiplier tests.

As for the regional employment problem, previous studies mostly handle the issue by forming an SUR system in which each equation represents different time periods. Hence, they build a space-time system with variations on time T and cross-section N. On the other hand, this paper aims to constitute a framework which incorporates an additional dimension: key sectors in the economy. In this sense it would be an (NTxG) system where G stands for the number of equations in the system, i.e. three sectors: agriculture, industry and services. The contemporaneous correlation in

[1] See for example Glendon and Vigdor (2003), Desmet and Fafchamps (2006) for the importance of spatiality in employment dynamics.

the disturbances of each equation will give an idea about the movements of employment across different sectors.

The paper is composed of five sections: In section 2, we present a brief overview of the labor market developments in Turkey for the time period under consideration. Econometric methodology is summarized in section 3. Section 4 presents the empirical results for the employment convergence problem of Turkey and section 5 concludes.

2. LABOUR MARKET DEVELOPMENTS IN TURKEY

Even though the Turkish population growth rate declined over the last decade, Turkey still has one of the highest values among the OECD countries. With an average of 1.286 per cent over the 2001-2011 period, the population growth reached the level of 1.343 per cent in 2009 and 1.323 per cent in 2010 (whereas OECD averages are 0.565 and 0.883 per cent respectively)[2]. In early 1970s Turkey had one of the highest employment rates among the OECD countries, whereas in 2000 the employment rate fell below 50 per cent and under the OECD averages. Employment rate as a percentage of working age population was 46.3 per cent in 2010 and 48.4 per cent in 2011, as compared to the OECD average of 64.8%. Employment growth over the last two years has relatively been high, however still lacking behind compensating for high unemployment rates. Taken as a percentage change from the previous year, employment growth was reported to be 6.1 per cent in 2010 and 5.9 per cent in 2011 whereas the OECD average was 1.2%. On the other hand, unemployment rates were recorded as 12.1 per cent and 10.0 per cent in 2010 and 2011 respectively. The historically low participation and employment rates can be attributed not only to demographic issues and entry problems in the labor market but also to recessions and structural shifts.

The Turkish labor market has experienced significant changes parallel to the macroeconomic environment in the country. Until 1980s, Turkey has implemented an import substitution policy for economic growth. From the early 1980s onwards there has been a change in the industrialization strategy towards an export-led growth regime via an orthodox structural adjustment program, aiming the integration of the country into the global economy. Even though

[2] The values are derived from various issues of OECD Employment Outlook and OECD Historical Statistics. 2011 values for population growth rate are not announced for some OECD countries; hence for the sake of comparison 2010 values are reported here. However, the descriptive analysis of this study covers the period 2001-2011 in general.

export growth increased in post-1980 period, there has been a decrease in the growth rate of employment compared to the import-substitution period, with a drastic decline in real wages.[3] Before 1980 both wages and employment generally moved together. However this parallel movement has been reversed after 1980s without any significant improvement in the employment growth. In 1989, following the liberalization of capital movements, government was able to increase its spending with the help of foreign capital entries. Thus after 1990, increases in real wages were recorded. Onaran (1999) argues that wage demands of the trade unions were found acceptable by the employers for two reasons: First, an increase in public spending indicated an increase in domestic demand. Second, there has been a decline in non-labor input costs due to the appreciation of the domestic currency so that wages could be increased without undermining profits. However, with the 1994 financial crisis exchange rate has depreciated sharply with large interest rate rises, reducing the real wage gains of post-1989 period.

Overall, the suppressed real wages and increased labor market flexibility have not encouraged high employment growth rates in the post-1980 period. Compared to the import-substitution period, a lower rate of growth in employment was recorded even though there has been an increase in export growth. The strategy of export promotion that is based on wage suppression has not been successful in stimulating new investments which may be due to the volatility of growth and, consequently, employment growth has been weak in the absence of industrial restructuring.

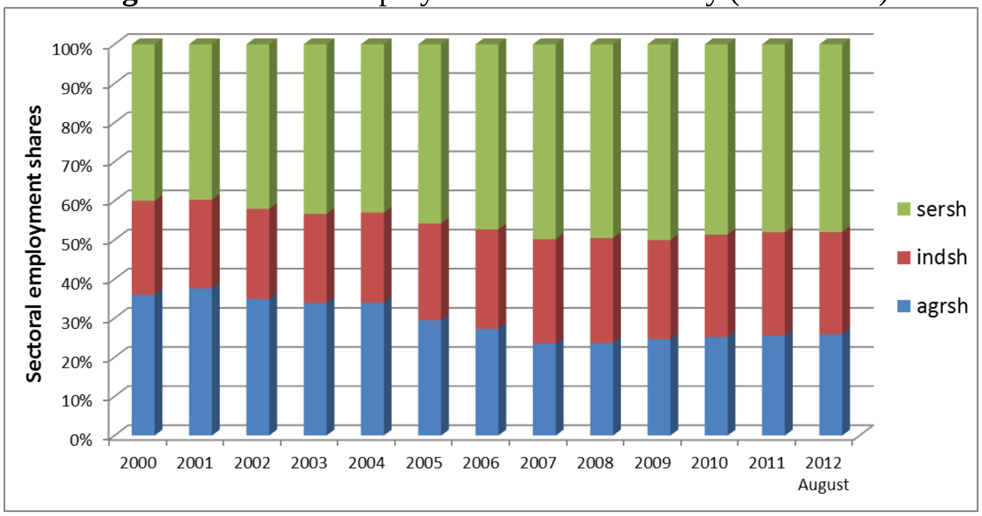
During 2000s, this trend of high unemployment rates and low employment generation capacity persisted, even deteriorated further. The macroeconomic environment of the country had significantly worsened following the 2001 crisis. In 2001 real GNP fell by 7.4 per cent, consumer price inflation increased up to 54.9 per cent and Turkish lira (TL) has lost 51% of its value against foreign currencies. As a result, unemployment rate rose to levels higher than 10 percent and real wages were reduced by 20 per cent (Yeldan, 2011). In the post-2001 crisis period, poor job creation, high interest rates, huge appreciation of TL and expanding current account deficits became the basic patterns of the economy. The elasticity of employment, i.e. percentage gain in employment with respect to percentage change in GDP growth, was relatively low. International Labor Organization employment report (Yeldan, 2011) shows that, for the 1989-2008 period,

[3] See Onaran and Stockhammer (2005), Voyvoda and Yeldan (2001), Onaran (2000) and Taymaz (1999) for a review of labor market developments in Turkey.

employment elasticity is found to be 0.25. But considering two sub-periods, we observe that during 1989-2000, elasticity was 0.39 whereas between 2002 and 2008, it fell down to 0.14. At the sectoral level, the effects were far from being homogeneous: the structure of the labor force has been transforming together with movements out of rural areas to urban areas, resulting a decrease in agricultural employment and an increase in services employment.

There has been a considerable increase in the employment share of services sector since the beginning of 2000s. In 2000 even half of the employed people were located in services sector and this climbed up until 2010 (Figure 1). The agriculture sector, on the other hand has been losing its significance especially after 2004, holding an employment share within the range of 23 to 30 per cent. Based on these figures, it can be argued that unemployed labor in the agricultural sector might have found employment opportunities in the services sector during 2000s. Employment share in industry sector had a relatively smooth pattern, varying from 23 to 27 per cent over 2004-2011.

Figure 1: Sectoral employment shares in Turkey (2000-2012)



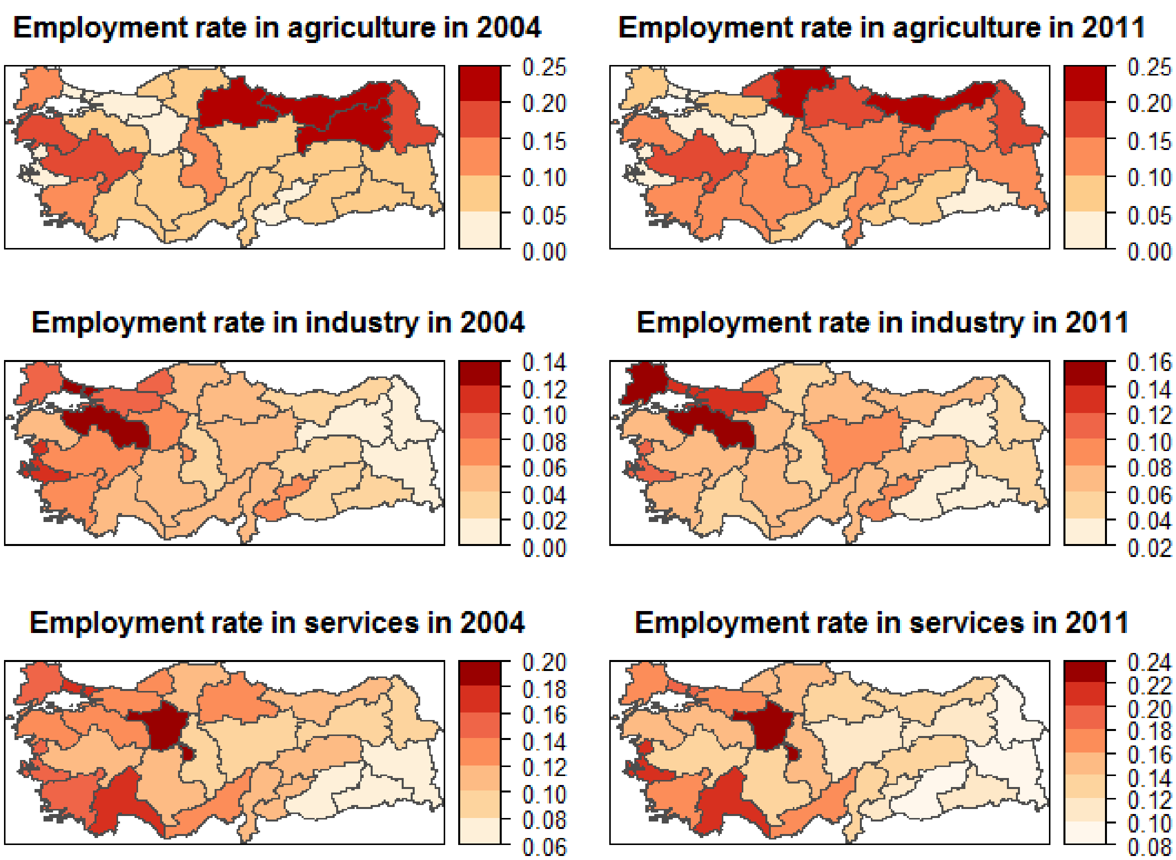
Notes: sersh, indsh and agrsh stand for the employment rates in services sector, industry and agriculture respectively.
Source: Authors' calculations from Turkish Statistical Institute database.

In this period employment rates at the sectoral level were also non-homogeneous across the regions. Two immediate observations follow from Figure 2, which presents the regional sectoral employment rates in 2004 and 2011[4]. First, in both years welfare disparities among regions of Turkey exhibit themselves in sectoral employment rates as well. Eastern regions and Central

[4] Because of the limitations in data availability, the period under investigation is constrained to be 2004-2011. Before this period, there is lack of data both at regional and sectoral level.

Anatolia have relatively high employment rates in agriculture, whereas Western regions have been more specialized in industry and services sectors both in 2004 and 2011. Second, services employment has become more intensive in the non-agricultural regions of Turkey. This shift may have occurred mostly together with informalization in services sector and increase in the family-owned businesses.

Figure 2: Sectoral Employment Rates in 2004 and 2011

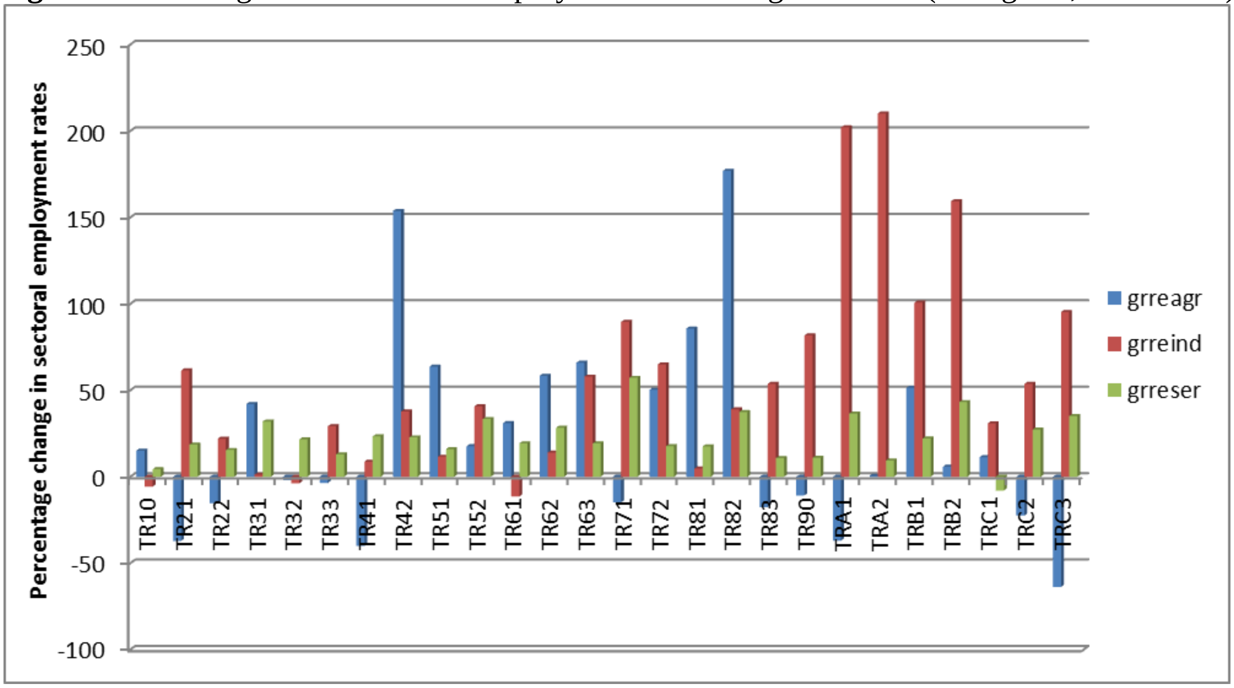


From 2004 to 2011, total number of employed people in agriculture increased by 7.54 per cent, whereas 30.54 per cent in industry and 28.26 per cent in services. Controlling for the drastic rise in the population growth and focusing on the employment in per capita terms, we observe that there is a 0.34 per cent fall in the agricultural employment rates, 20.98 per cent increase in the industrial employment rates and 18.86 per cent increase in the services sector employment rates[5]. At the regional level, negative growth in agriculture is recorded for nine regions in this period

[5] Authors' calculations using the Turkish Statistical Institution database.

(Figure 3). Growth in industrial employment shows significant variability whereas growth in services sector employment rate has a relatively smooth positive pattern over the regions.

Figure 3: Overall growth in sectoral employment rates at regional level (26 regions, 2004-2011)



Notes: Names of the corresponding 26 NUTS-2 level regions can be found in the Appendix. grreagr, grreind and grreser represent growth in agricultural employment rate, growth in industrial employment rate and growth in services sector employment rates respectively.
Source: Authors' calculations from Turkish Statistical Institute database.

In light of the descriptive analysis of Turkish labor market, it can be argued that the employment rates over 2004-2011 period exhibit both sectoral and regional variations. Hence to take all these effects into account in an integrated framework, spatial panel and SUR spatial panel models are utilized in this paper. The underlying methodology is presented in the next section.

3. METHODOLOGY

3.1. Spatial Analysis in Employment Convergence Problem

Neoclassical theory claims that in a constant returns to scale framework without spatial externalities, inter-regional mobility of capital and labor is expected to bring an even distribution of economic activity, and hence employment. The issue of employment dynamics at sub-national level has attracted a great attention in recent years. A large number of studies have been devoted to investigating the determinants of employment at different territorial levels especially for the European Union countries and for the USA (among others, see for example Marelli (2000, 2004), Boeri and Terrel (2002), Perugini and Signorelli (2004), Desmet and Fafchamps, (2005, 2006)). Beta convergence analysis has generally been employed in order to investigate convergence across economies or regions using cross-sectional data, implementing the following equation:

$$\log\left(\frac{E_{it}}{E_{i0}}\right) = \alpha + \beta \log E_{i0} + u_i \qquad \textbf{(1)}$$

where E_{it} denotes employment rate at time t, E_{i0} denotes employment rate at some initial time 0; α is the intercept term, which may incorporate any rate of technological progress; u is random error term distributed i.i.d.$(0,\sigma^2)$, which may represent random shocks to technology or tastes. A negative value of β signifies the beta convergence. However, this approach assumes that all regions or economies under consideration have the same steady state income path. This is a highly restrictive assumption and may induce significant heterogeneity bias in estimates of convergence coefficient. Thus, to control for these effects, panel data counterparts to the employment convergence problem have been employed. Besides controlling for individual heterogeneity, panel data models are superior to cross-section models also in the sense that it allows more informative data, more variability, more degrees of freedom and more efficiency (Baltagi, 2010a).

Another dimension of the convergence analysis is that regional employment growth may follow a spatial pattern. Even though the neoclassical model assumes perfect mobility of factors of production between economies, there may be significant adjustment costs or barriers to mobility of labor and possibly of capital. When regions pursue their own growth promoting policies, there may be spillover effects from those regions to the adjacent regions which may affect employment. Cheshire and Gordon (1998) point that economic rents from research and development and other sources may more likely to accrue locally, where regions are more self-contained. Moreover, Fagerberg *et al*. (1996) claim that rates of technological diffusion may follow a spatial pattern as regions may have different capacities to create or absorb new technologies. Thus, incorporating spatial effects into the analysis may have a significant impact on the estimated convergence parameters.

Hence for the employment convergence problem given in equation (1), the spatial panel data alternatives are offered for each employment equation. This can be handled in a number of ways. First, the panel data model can be specified either as fixed effects, where the individual effects are constant; or random effects, where the individual effects are allowed to change across cross-sections. The shortcoming of fixed effects model is that time-invariant variables are wiped out from the model during the within transformation[6]. Moreover, there is a great loss in the degrees of freedom as it needs introducing dummy variables and hence there are too many parameters to estimate. In this paper, the initial employment rate variable is fixed at 2004 level (time- invariant) in the original convergence model. Also, as there are data limitations, in order not to lose any degrees of freedom, a random effects specification has been utilized.

The spatiality can also be introduced into the model in different ways. First, the spatial error model denotes that the spatial dependence operates through the error process, where any random shock follows a spatial pattern, so that shocks are correlated across adjacent regions. In this case the spatial correlation is brought in the error terms of equation (1) through the multiplication of the spatial weight matrix. Second, the spatial lag (or spatial autoregressive) model examines the extent to which regional growth rates depend on the growth rates of adjacent regions, conditioning on the level of initial employment. This model necessitates direct enforcement of the spatial weight matrix multiplied by the dependent variable as a regressor term. Third, spatial cross-regressive (or spatial Durbin) model allows any spatial spillovers to be reflected in the initial levels of employment. In other words, whereas the spatial autoregressive model only takes the spatial lag of the dependent variable, the spatial Durbin model also takes the spatial lag of the independent variable. Lastly, a spatial autoregressive model with autoregressive disturbances (SARAR, or alternatively SAC model as Le Sage (2009) puts it) can be formed. In this case, the model contains both the spatial error and the spatially lagged dependent variable term. For our purposes, the spatial dimension is introduced into the model by means of spatial error terms. Intuitively, this makes much sense regarding the characteristics of the employment problem mentioned above. A shock to a producer in one region may affect suppliers of intermediate goods in the surrounding regions (Glendon & Vigdor, 2003). Further, in cases where regions produce similar goods for consumption in the global market, when the demand for the certain product changes due to a shock, employment changes tend to occur in several neighboring regions. Therefore, due to the nature of the employment problem, taking spatial dependence through the error components of the employment model is found to be convenient.

[6] See Elhorst (2003, 2010) and Baltagi (2010b) for a discussion on fixed effects spatial panel data models.

3.2. Spatial Panel Data Model

The spatial autocorrelation can be introduced into the error component in different ways. Baltagi et.al. (2003) specifies a SAR process for $\varepsilon_{t,i}$ whereas Kapoor et.al. (2007) applies the SAR process to $u_{t,i}$ first and then take the error components specification to its remainder error term $\varepsilon_{t,i}$. In terms of the error component structure, this paper follows the Kapoor et.al.(2007) method. The random effects spatial error model for employment convergence equation of each sector can be written as follows:

$$
\begin{aligned}
& y_{t,i} = \alpha_i + \beta X_{t,i} + u_{t,i} \\
& u_{t,i} = \rho \sum_{j=1}^{n} w_{i,j} u_{t,i} + \varepsilon_{t,i} \qquad i = 1,\ldots,N \qquad t = 1,\ldots,T \qquad \textbf{(2)} \\
& \varepsilon_{t,i} = \mu_i + v_{t,i}
\end{aligned}
$$

where $y_{t,i} = \ln(\frac{E_{t,i}}{E_{0,i}})$ is the growth of employment rate, $X_{t,i} = \ln(E_{0,i})$ is the initial employment rate for the given sector. $\sum_{j=1}^{n} w_{i,j}$ correspond to each element of the W_{NxN} spatial weights matrix; $u_{t,i}$ is the spatially autocorrelated error component; $\mu_i \sim i.i.d(0,\sigma_\mu^2)$ is the unobservable individual specific effect, $\varepsilon_{t,i} \sim i.i.d(0,\sigma_\varepsilon^2)$ is specified as a one-way error component model and $v_{t,i} \sim i.i.d(0,\sigma_v^2)$ vary over both cross-sections and time periods. In line with the random effects specification, we assume that the individual effects μ_i are uncorrelated with the other explanatory variables. Note that the spatial autoregressive parameter ρ satisfies $|\rho| < 1$.

In stacked form this model can be re-written as:

$$
\begin{aligned}
& y = X\beta + u && (3.1) \\
& u = \rho(I_T \otimes W)u + \varepsilon && (3.2) \qquad \textbf{(3)} \\
& \varepsilon = (\iota_T \otimes I_N)\mu + v && (3.3)
\end{aligned}
$$

where y denotes the (NTx1) vector of dependent variable, X denotes the (NTxk) vector of independent variables including the constant term, W denotes the (NxN) spatial weight matrix,

I_N and I_T correspond to the identity matrix of order (NxN) and (TxT) respectively; ι_T is the (Tx1) column matrix of ones and $\otimes$ denotes the usual Kronecker product . Hence, from (3.2)

$$u = [I_T \otimes (I_N - \rho W)^{-1}]\varepsilon \quad \textbf{(4)}$$

and the variance-covariance matrix of u is,

$$\Omega_u = [I_T \otimes (I_N - \rho W)^{-1}]\Omega_\varepsilon [I_T \otimes (I_N - \rho W^T)^{-1}] \quad \textbf{(5)}$$

where W^T is the transpose of the spatial weight matrix. The variance-covariance matrix of the one-way error component model is,

$$\Omega_\varepsilon = \sigma_v^2 Q_0 + \sigma_1^2 Q_1 \quad \textbf{(6)}$$

where the usual transformation is applied[7]:

$$\sigma_1^2 = \sigma_v^2 + T\sigma_\mu^2$$
$$Q_0 = (I_T - \frac{\iota_T \iota_T^T}{T}) \otimes I_N \quad \textbf{(7)}^{\textbf{8}}$$
$$Q_1 = (\frac{\iota_T \iota_T^T}{T}) \otimes I_N$$

Kapoor et. al. (2007) show that for $T \geq 2$, the following moment conditions can be used for the GMM estimation of the parameters:

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[7] Note that the model is adopted to the different ordering of the data. Contrary to the usual panel data literature, in spatial panel data the observations are sorted so that time t is the slow running index and cross-section i is the fast running index; i.e. the spatial panel data are stacked first by time period, and then by cross-section (see Millo & Piras (2012) for details).

[8] The term $\iota_T \iota_T^T$ is usually referred to as J_T in the literature which is in fact a (TxT) matrix of ones.

$$E\begin{bmatrix} \frac{1}{N(T-1)}\varepsilon^T Q_0 \varepsilon \\ \frac{1}{N(T-1)}\bar{\varepsilon}^T Q_0 \bar{\varepsilon} \\ \frac{1}{N(T-1)}\bar{\varepsilon}^T Q_0 \varepsilon \\ \frac{1}{N}\varepsilon^T Q_1 \varepsilon \\ \frac{1}{N}\bar{\varepsilon}^T Q_1 \bar{\varepsilon} \\ \frac{1}{N}\bar{\varepsilon}^T Q_1 \varepsilon \end{bmatrix} = \begin{bmatrix} \sigma_v^2 \\ \sigma_v^2 \frac{1}{N} tr(W^T W) \\ 0 \\ \sigma_1^2 \\ \sigma_1^2 \frac{1}{N} tr(W^T W) \\ 0 \end{bmatrix} \qquad \textbf{(8)}$$

where $\bar{u} = (I_T \otimes W_N)u$; $\bar{\bar{u}} = (I_T \otimes W_N)\bar{u}$; $\varepsilon = u - \rho\bar{u}$ and $\bar{\varepsilon} = \bar{u} - \rho\bar{\bar{u}}$. The first three moment conditions can be used to compute the initial estimators $\tilde{\rho}$ and $\tilde{\sigma}_v^2$. Based on these initial estimators and the fourth moment condition, $\tilde{\sigma}_1^2$ can be estimated. As a second step one can re-estimate the parameters using the other set of moment conditions to obtain $\hat{\rho}$, $\hat{\sigma}_v^2$ and $\hat{\sigma}_1^2$. In the third step the spatial feasible generalized least square estimator for β can be obtained, after transforming the model twice. Initially, the spatial Cochrane-Orcutt transformation is carried out such that

$$\begin{aligned} y^*(\rho) &= [I_T \otimes (I_N - \rho W)^{-1}]y \\ X^*(\rho) &= [I_T \otimes (I_N - \rho W)^{-1}]X \end{aligned} \qquad \textbf{(9)}$$

Then, the model in (9) is further transformed via premultiplying it by $I_{NT} - \theta Q_1$ where $\theta = 1 - \frac{\sigma_v}{\sigma_1}$.

Applying OLS to this transformed model yields the estimator of the final parameter β.

For the application, rather than using the full set of moments; the initial estimators based on the first three moment conditions or the simplified weighting schemes, in which each sample moment is given equal weights, can also be used. In this paper, though computationally it complicates the model, using the full set of moment conditions is preferred. Based on this GMM procedure (or equivalently feasible generalized spatial three stage least squares estimation in our case), each employment equation is estimated separately for each sector. In other words; for agriculture, industry and services sectors random effects spatial error models are estimated one by one using the described methodology. In the next section, these three estimated sectoral equations are further allowed to be related via contemporaneous correlation among disturbances. Hence, it will be possible to observe sectoral interactions through the heterogeneity described by the error terms of each model.

3.3. Spatial Panel SUR Model

Suppose that the spatial panel data models estimated in section 3.2. for each sector are further correlated with each other through their disturbance terms. Hence we have the following (NTxG) system of equations:

$$\begin{aligned} y_{g,ti} &= \alpha_{g,i} + \beta_g X_{g,ti} + u_{g,ti} \\ u_{g,ti} &= \rho_g \sum_{j=1}^{n} w_{g,ij} u_{g,ti} + \varepsilon_{g,ti} \qquad i = 1,\ldots,N \quad t = 1,\ldots,T \quad g = 1,\ldots,G \\ \varepsilon_{g,ti} &= \mu_{g,i} + v_{g,ti} \end{aligned} \qquad \textbf{(10)}$$

where g=1,…,G is the number of equations (G=3 corresponding to three sectors in our empirical model, but we solve for the general case in this part); the other variables and estimators described as before. For an SUR model, the correlations between the disturbances of equations should be specified. For the error components of this system, we have

$$\begin{aligned} E[\mu_{g,i}\mu_{h,i}] &= \sigma_{\mu_{gh}} \quad \forall i \quad and \;\; g \neq h \\ E[v_{g,it} v_{h,it}] &= \sigma_{v_{gh}} \quad \forall i,t \;\; and \;\; g \neq h \end{aligned} \qquad \textbf{(11)}$$

In order to have an analogous expression to model in (3) we stack the observations over time and cross sections:

$$y = X\beta + u \qquad (12.1)$$

$$u_g = \rho_g (I_{TG} \otimes W) u_g + \varepsilon_g \qquad (12.2) \qquad \textbf{(12)}$$

$$\varepsilon_g = (\iota_T \otimes I_{NG})\mu_g + v_g \qquad (12.3)$$

Note that the subscript "g" is not used for the weight matrix W since the neighborhood relation does not change over the equations. This can be generalized as W_g for different empirical problems, but for our specific purposes the assumption $W_g = W \;\; for \;\; g = 1.,..,G$ holds, i.e. for each employment equation we use the same regions whose neighbors are specified by the same weight matrix.

The model in (12) is different from Wang & Kockelman (2007) model in the sense that the spatial autocorrelation exists in u_{ti} rather than ε_{ti}. It is more like Kapoor et.al. (2007) spatial panel model, but revised for an SUR setting. A similar error component structure has been considered by Baltagi & Bresson (2011); but unlike the one specified here, their model includes a spatial lag term. The spatially autocorrelated error component in (12.2) can be re-written as:

$$u_g = \underbrace{[I_{TG} \otimes (I_{NG} - \rho_g W)^{-1}]}_{B} \varepsilon_g \tag{13}$$

with $B = \begin{pmatrix} I_T \otimes B_1 & & & \\ & . & & \\ & & . & \\ & & & I_T \otimes B_G \end{pmatrix}$ and $B_g = I_N - \rho_g W$

The variance-covariance matrix of u would be

$$\Omega_u = B^{-1} \Omega_\varepsilon (B^T)^{-1} \tag{14}$$

And the variance-covariance matrix of the error component ε is

$$\Omega_\varepsilon = \Omega_v Q_0 + \Omega_1 Q_1 \qquad \text{with}$$

$$\begin{aligned} \Omega_1 &= \Omega_v + T\Omega_\mu \\ Q_0 &= \left(I_T - \frac{\iota_T \iota_T^T}{T} \right) \otimes I_N \\ Q_1 &= \left(\frac{\iota_T \iota_T^T}{T} \right) \otimes I_N \end{aligned} \tag{15}$$

and $\Omega_\mu = \begin{pmatrix} \sigma^2_{\mu_1} & \sigma_{\mu_{12}} & \dots & \sigma_{\mu_{1G}} \\ \sigma_{\mu_{21}} & \sigma^2_{\mu_2} & \dots & \sigma_{\mu_{2G}} \\ . & . & . & . \\ . & . & . & . \\ \sigma_{\mu_{G1}} & \sigma_{\mu_{G2}} & \dots & \sigma^2_{\mu_G} \end{pmatrix}$ $\qquad \Omega_v = \begin{pmatrix} \sigma^2_{v_1} & \sigma_{v_{12}} & \dots & \sigma_{v_{1G}} \\ \sigma_{v_{21}} & \sigma^2_{v_2} & \dots & \sigma_{v_{2G}} \\ . & . & . & . \\ . & . & . & . \\ \sigma_{v_{G1}} & \sigma_{v_{G2}} & \dots & \sigma^2_{v_G} \end{pmatrix}$

The estimation of this system requires the estimation of the spatial panel data model. More concretely, for each equation in the system, the spatial panel data estimation described above will be applied. Subsequently, the residuals of these estimated equations will be further correlated as they belong to an SUR system at this time. Hence, after applying GMM estimation for every equation (as we did above in part 3.2), we take the estimated disturbances and apply FGLS. The resulting estimators will be quite informative as it comes from the model that allows for time, cross-section and equation (i.e. sector) heterogeneity at the same time.

4. EMPIRICAL RESULTS

In this section sectoral employment dynamics are considered for three sectors, namely agriculture, industry[9] and services. These three main sectors are investigated as they constitute the largest employment shares with their sum giving the total employment in the country (see Figure 1). Data on the employment levels for the agriculture, industry, services sectors and non-institutional working age population are obtained from the Turkish Statistical Institute (TurkStat, 2012). We collect data at NUTS-2 level for 26 regions of Turkey over 2004-2011. All variables are taken as thousand person and sectoral employment rates are calculated based on non-institutional working age population of each region[10]. The empirical analysis incorporates the sectoral employment rates rather than levels, in order to control for the drastic changes in population.

The random effects model with spatial error components and its SUR counterpart are estimated as described in Section 3. For the sake of comparison, the pooled OLS and pooled SUR results are also provided. The system estimation approach, i.e. seemingly unrelated regression (SUR), is suggested on the grounds that error terms might be correlated across equations due to the omission of variables. SUR provides parameter estimates that are asymptotically more efficient than ordinary least squares estimates when there is contemporaneous correlation between disturbances of different equations[11]. Accordingly, a three equation system is estimated by SUR in which each equation represents one of the key sectors in the economy:

$$\log\left(\frac{EAGR_{i,t}}{EAGR_{i,t-1}}\right) = \alpha_{10} + \beta_{11}\log EAGR_{i0} + u_{1i}$$

$$\log\left(\frac{EIND_{i,t}}{EIND_{i,t-1}}\right) = \alpha_{20} + \beta_{21}\log EIND_{i0} + u_{2i} \qquad \textbf{(16)}$$

[9] Construction is included in the industry sector, during the analysis.
[10] Note that the employment rate is the ratio of employed persons to the non-institutional working age population (the population 15 years of age and over within the non-institutional population, i.e. the population excluding the residents of dormitories of universities, orphanage, rest homes for elderly persons, special hospitals, prisons and military barracks etc).
[11] See Zellner (1962).

$$\log\left(\frac{ESER_{i,t}}{ESER_{i,t-1}}\right) = \alpha_{30} + \beta_{31}\log ESER_{i0} + u_{3i}$$

where EAGR, EIND and ESER denote employment rates in agriculture, industry and services sectors, respectively. Moreover, in order to capture any interaction effects among the sectors, an alternative model has also been considered for each of the specifications:

$$\log\left(\frac{EAGR_{i,t}}{EAGR_{i,t-1}}\right) = \alpha_{10} + \beta_{11}\log EAGR_{i0} + \beta_{12}\log EIND_{i0} + \beta_{13}\log ESER_{i0} + u_{1i}$$

$$\log\left(\frac{EIND_{i,t}}{EIND_{i,t-1}}\right) = \alpha_{20} + \beta_{21}\log EAGR_{i0} + \beta_{22}\log EIND_{i0} + \beta_{23}\log ESER_{i0} + u_{2i} \qquad \textbf{(17)}$$

$$\log\left(\frac{ESER_{i,t}}{ESER_{i,t-1}}\right) = \alpha_{30} + \beta_{31}\log EAGR_{i0} + \beta_{32}\log EIND_{i0} + \beta_{33}\log ESER_{i0} + u_{3i}$$

where changes in employment dynamics in each sector are conditioned not only on that sector's initial employment rate, but also on other sectors' initial employment rates.

For the base model introduced in (16) and the interaction model presented in (17), the pooled OLS and pooled SUR estimation results are presented in Table 1 and Table 2.

Table 1: Pooled OLS estimation results of employment rate convergence model (with initial employment rates)

	Agriculture		**Industry**		**Services**	
Coefficients	Base	Interaction	Base	Interaction	Base	Interaction
Intercept	-0.050 (0.146)	-0.015 (0.943)	-0.128*** (0.001)	-0.272** (0.016)	-0.005 (0.928)	-0.029 (0.685)
log(reagr04)	-0.024* (0.083)	-0.021 (0.270)		-0.007 (0.481)		-0.003 (0.635)
log(reind04)		0.016 (0.654)	-0.065*** (0.000)	-0.058*** (0.002)		-0.001 (0.936)
log(reser04)		-0.009 (0.938)		-0.084 (0.153)	-0.013 (0.659)	-0.022 (0.568)
Residual standard error	0.206	0.208	0.107	0.107	0.068	0.068
N	182	182	182	182	182	182
DF	180	178	180	178	180	178
SSR	7.673	7.664	2.058	2.034	0.833	0.832
MSE	0.043	0.043	0.011	0.011	0.005	0.005
RMSE	0.206	0.208	0.107	0.107	0.068	0.068

Multiple R-squared	0.017	0.018	0.106	0.116	0.001	0.002

Note: Dependent variables are the logarithms of the yearly growth in employment rates, for each sector. The values reported in parentheses are p-values. (*), (**), (***) denote significance at 10%, 5% and 1% respectively.

Table 2: Pooled SUR estimation results of employment rate convergence model (with initial employment rates)

	Agriculture		**Industry**		**Services**	
Coefficients	Base	Interaction	Base	Interaction	Base	Interaction
Intercept	-0.052 (0.123)	-0.015 (0.943)	-0.128*** (0.001)	-0.272** (0.015)	0.008 (0.868)	-0.029 (0.681)
log(reagr04)	-0.025* (0.066)	-0.021 (0.265)		-0.007 (0.476)		-0.003 (0.631)
log(reind04)		0.016 (0.651)	-0.065*** (0.000)	-0.058*** (0.002)		-0.001 (0.935)
log(reser04)		-0.009 (0.937)		-0.084 (0.148)	-0.005 (0.841)	-0.022 (0.564)
Residual standard error	0.206	0.208	0.107	0.107	0.068	0.068
N	182	182	182	182	182	182
DF	180	178	180	178	180	178
SSR	7.673	7.664	2.058	2.034	0.833	0.832
MSE	0.043	0.043	0.011	0.011	0.005	0.005
RMSE	0.206	0.208	0.107	0.107	0.068	0.068
Multiple R-squared	0.017	0.018	0.106	0.116	0.001	0.002

Note: Dependent variables are the logarithms of the yearly growth in employment rates, for each sector. The values reported in parentheses are p-values. (*), (**), (***) denote significance at 10%, 5% and 1% respectively.

The pooled OLS results indicate that in agriculture sector, the employment rates have been converging over 2004 – 2011 period. However, when the sectoral interaction effects are taken into account, no significant convergence can be recorded. Considering the omitted variables, it is known that the exclusion of regional effects causes a bias in the estimated effect of initial rates on the growth rate, and hence in the estimated convergence rate (Barro, 2012). Therefore it is not surprising to observe a high convergence in the base model in which no regional and no interaction effects are included. For the industry sector, both in the base model and the model that allows for the sectoral interactions, we observe a convergence in the employment rates. No convergence or divergence trends are apparent for the services sector model estimated by pooled OLS. The pooled SUR results provide a similar tableau with smaller standard errors, as expected. In the presence of correlation among the disturbances of each equation, SUR is meant to offer more efficient results than the OLS outcome. However, these outcomes are still far from being sufficient as they ignore the time effects as well as neighborhood effects in the model.

Therefore the spatial panel alternative is presented in Table 3. The neighborhood between the regions is introduced into the model using the binary contiguity weight matrix[12]. FGS3SLS results are obtained using the methodology described in section 3.2.

Table 3: Spatial panel estimation results of employment rate convergence model (with initial employment rates)

	Agriculture		**Industry**		**Services**	
Coefficients	Base	Interaction	Base	Interaction	Base	Interaction
Intercept	-0.048*	-0.028	-0.125***	-0.278***	-0.004	-0.026
	(0.063)	(0.870)	(0.000)	(0.000)	(0.860)	(0.450)
log(reagr04)	-0.023**	-0.021		-0.007		-0.003
	(0.031)	(0.150)		(0.173)		(0.380)
log(reind04)		0.013	-0.064***	-0.057***		-0.0005
		(0.630)	(0.000)	(0.000)		(0.930)
log(reser04)		-0.011		-0.089***	-0.012	-0.021
		(0.900)		(0.006)	(0.370)	(0.240)
Spatial error component (rho)	-0.125	-0.118	0.122	0.147	0.093	0.084

Note: Dependent variables are the logarithms of the yearly growth in employment rates, for each sector. Random effects model with spatial error components is estimated by feasible generalized spatial three stage least squares; full set of moments are used in the estimation. The values reported in parentheses are p-values. (*), (**), (***) denote significance at 10%, 5% and 1% respectively.

The estimated random effects spatial error model shows that in the agriculture sector there are convergence dynamics across the regions. Nonetheless, when the initial employment rates in the other sectors are taken into account, the model indicates neither convergence nor divergence in the agriculture sector. The effects of other sectors' initial employment on the agriculture sector are not significant either. For the industry sector, there is evidence of convergence: the regions that start over with lower levels of industrial employment show higher rates of growth in employment rates, i.e. less industrial-labor-endowed regions are catching up the others. The interaction model shows that agriculture and services sector employment rates in 2004 have a negative impact on the industrial employment changes in 2004-2011. In the services sector no

[12] The neighboring regions take the value of one, whereas the non-neighboring regions take the value zero in the matrix. The diagonal elements are zero since a region cannot be a neighbor of itself. The weight matrix is row-standardized so that sum of the elements in each row will add up to one.

clear evidence of convergence or divergence can be reported as a result of spatial panel model estimation.

Subsequently, we further allow for the existence of correlation between the estimated spatial panel data models and estimate a spatial panel SUR model as described before. The SUR estimation outcomes with random effects and spatial error components are presented in Table 4. We observe substantial changes in the employment convergence model estimation results of each sector.

Table 4: Spatial panel SUR estimation results of industrial employment rate convergence model (with initial employment rates)

	Agriculture		**Industry**		**Services**	
Coefficients	Base	Interaction	Base	Interaction	Base	Interaction
Intercept	0.008	1.326***	-0.027	-0.120	0.038	-0.250***
	(0.820)	(0.000)	(0.660)	(0.405)	(0.440)	(0.007)
log(reagr04)	0.003	0.104***		0.035**		-0.022**
	(0.880)	(0.000)		(0.012)		(0.011)
log(reind04)		0.202*	-0.027	0.341***		-0.019
		(0.054)	(0.240)	(0.000)		(0.575)
log(reser04)		0.323*		-0.649***	0.012	-0.096*
		(0.065)		(0.000)	(0.680)	(0.068)
Spatial error component (rho)	-0.125	-0.118	0.123	0.147	0.093	0.084

Note: Dependent variables are the logarithms of the yearly growth in employment rates, for each sector. SUR model with random effects and spatial error components is estimated by feasible generalized spatial three stage least squares; full set of moments are used in the estimation. The values reported in parentheses are p-values. (*), (**), (***) denote significance at 10%, 5% and 1% respectively.

For each sector, base models do not provide any evidence of convergence or divergence in the employment rates. On the other hand, when the interactions among sectors are introduced, significant dynamics are documented. In the agriculture sector, the employment rates in the regions follow a divergent pattern. Likewise, the initial employment rates in industry and services sectors have a positive impact on the growth of agricultural employment rates. In the industry sector, also, the model indicates divergence in the employment rates. In fact, these results are in line with the preliminary data analysis and the descriptive information provided before. What is more, the spatial autocorrelation in the agricultural equation is negative, which implies that the regions are conversely affecting each other. This can be regarded as a trend towards clustering in agricultural employment rather than a homogenization among the regions.

In the services sector, on the other hand, employment rates show evidence of convergence across the regions. The agricultural employment rate in the initial year has a negative effect on the growth in services sector employment rate. This implies that regions with a lower level of agricultural employment in the initial year has ended up with higher levels of employment in services over 2004-2011. The results are parallel with the initial observations: the agriculture sector is more clustered in interior regions and the eastern provinces. The services employment on the other hand is increasing as a general trend in all regions -though with more concentration in the western parts of the country. Hence the agriculture and services sectors seem like being on different sides of the coin.

As a further step, we investigate whether taking the initial employment rate variable in a dynamic manner would affect the results. To this end, we take the lagged initial employment rate as a regressor and consider the following two specifications which are analogous to equations (16) and (17):

$$\begin{aligned}
&\log\left(\frac{EAGR_{i,t}}{EAGR_{i,t-1}}\right) = \alpha_{10} + \beta_{11}\log EAGR_{i,t-1} + u_{1i} \\
&\log\left(\frac{EIND_{i,t}}{EIND_{i,t-1}}\right) = \alpha_{20} + \beta_{21}\log EIND_{i,t-1} + u_{2i} \qquad \textbf{(18)} \\
&\log\left(\frac{ESER_{i,t}}{ESER_{i,t-1}}\right) = \alpha_{30} + \beta_{31}\log ESER_{i,t-1} + u_{3i}
\end{aligned}$$

And the interaction model becomes:

$$\begin{aligned}
&\log\left(\frac{EAGR_{i,t}}{EAGR_{i,t-1}}\right) = \alpha_{10} + \beta_{11}\log EAGR_{i,t-1} + \beta_{12}\log EIND_{i,t-1} + \beta_{13}\log ESER_{i,t-1} + u_{1i} \\
&\log\left(\frac{EIND_{i,t}}{EIND_{i,t-1}}\right) = \alpha_{20} + \beta_{21}\log EAGR_{i,t-1} + \beta_{22}\log EIND_{i,t-1} + \beta_{23}\log ESER_{i,t-1} + u_{2i} \qquad \textbf{(19)} \\
&\log\left(\frac{ESER_{i,t}}{ESER_{i,t-1}}\right) = \alpha_{30} + \beta_{31}\log EAGR_{i,t-1} + \beta_{32}\log EIND_{i,t-1} + \beta_{33}\log ESER_{i,t-1} + u_{3i}
\end{aligned}$$

The modified base and interaction models have a dynamic initial employment rate variable. The beta convergence parameters show also the short-run response of the growth rates to the employment rates, i.e. the effect from one year to the next can be controlled. The estimation results of these alternative models are given in Tables 5-8.

Table 5: Pooled OLS estimation results of employment rate convergence model (with lagged employment rates)

	Agriculture		**Industry**		**Services**	
Coefficients	Base	Interaction	Base	Interaction	Base	Interaction
Intercept	-0.062*	0.113	-0.156***	-0.267***	-0.090**	-0.118*
	(0.081)	(0.545)	(0.000)	(0.006)	(0.042)	(0.053)
log(lagreagr)	-0.028**	-0.020		-0.004		-0.004
	(0.041)	(0.248)		(0.676)		(0.474)
log(lagreind)		0.010	-0.079***	-0.070***		0.001
		(0.780)	(0.000)	(0.000)		(0.963)
log(lagreser)		0.076		-0.075	-0.064**	-0.076**
		(0.433)		(0.130)	(0.015)	(0.017)
Residual standard error	0.206	0.206	0.106	0.106	0.067	0.067
N	182	182	182	182	182	182
DF	180	178	180	178	180	178
SSR	7.623	7.585	2.020	1.994	0.807	0.804
MSE	0.042	0.043	0.011	0.011	0.004	0.005
RMSE	0.206	0.206	0.106	0.106	0.067	0.067
Multiple R-squared	0.023	0.028	0.123	0.134	0.032	0.036

Note: Dependent variables are the logarithms of the yearly growth in employment rates, for each sector. The values reported in parentheses are p-values. (*), (**), (***) denote significance at 10%, 5% and 1% respectively.

In the agriculture and industry sectors, pooled OLS and pooled SUR estimations suggest similar outcomes to the model with time-invariant initial employment rates. However, in the services sector, the previously insignificant convergence parameters now turn out to be significantly negative, implying employment convergence in the services sector.

Table 6: Pooled SUR estimation results of employment rate convergence model (with lagged employment rates)

	Agriculture		**Industry**		**Services**	
Coefficients	Base	Interaction	Base	Interaction	Base	Interaction
Intercept	-0.065*	0.113	-0.157***	-0.267***	-0.071*	-0.118*
	(0.059)	(0.541)	(0.000)	(0.005)	(0.093)	(0.050)
log(lagreagr)	-0.030**	-0.020		-0.004		-0.004
	(0.027)	(0.243)		(0.672)		(0.469)
log(lagreind)		0.010	-0.080***	-0.070***		0.001
		(0.778)	(0.000)	(0.000)		(0.963)

log(lagreser)		0.076 (0.428)		-0.075 (0.126)	-0.053** (0.036)	-0.076** (0.016)
Residual standard error	0.206	0.206	0.106	0.106	0.067	0.067
N	182	182	182	182	182	182
DF	180	178	180	178	180	178
SSR	7.624	7.585	2.020	1.994	0.808	0.804
MSE	0.042	0.043	0.011	0.011	0.004	0.005
RMSE	0.206	0.206	0.106	0.106	0.067	0.067
Multiple R-squared	0.023	0.028	0.123	0.134	0.031	0.036

Note: Dependent variables are the logarithms of the yearly growth in employment rates, for each sector. The values reported in parentheses are p-values. (*), (**), (***) denote significance at 10%, 5% and 1% respectively.

The modified random effects model with spatial error components imply similar results as before: convergence in the base model of agriculture sector, convergence in the base and interaction models of the industry sector and no evidence of convergence or divergence pattern in the services sector (Table 7).

Table 7: Spatial panel estimation results of employment rate convergence model (with lagged employment rates)

	Agriculture		**Industry**		**Services**	
Coefficients	Base	Interaction	Base	Interaction	Base	Interaction
Intercept	-0.049 (0.100)	0.127 (0.440)	-0.140*** (0.000)	-0.260*** (0.000)	-0.030 (0.360)	-0.051 (0.260)
log(lagreagr)	-0.023* (0.058)	-0.013 (0.350)		-0.004 (0.487)		-0.003 (0.550)
log(lagreind)		0.012 (0.700)	-0.073*** (0.000)	-0.062*** (0.000)		-0.002 (0.840)
log(lagreser)		0.073 (0.390)		-0.081** (0.022)	-0.028 (0.140)	-0.035 (0.150)
Spatial error component (rho)	-0.115	-0.111	0.110	0.115	0.087	0.081

Note: Dependent variables are the logarithms of the yearly growth in employment rates, for each sector. Random effects model with spatial error components is estimated by feasible generalized spatial three stage least squares; full set of moments are used in the estimation. The values reported in parentheses are p-values. (*), (**), (***) denote significance at 10%, 5% and 1% respectively.

On the other hand, spatial panel SUR estimation results with lagged employment rates differ from the one with time-invariant initial employment rates. Contrary to the previous case, now the base model estimations for all sectors imply convergence in the employment rates. However, keeping in mind that these models show only absolute convergence and disregard the presence of any conditional variable, they may still be suffering from omitted variable bias. The interaction models are expected to give more precise outcomes not only because of this reason, but also as they are capable of demonstrating the transition between sectors.

Table 8: Spatial panel SUR estimation results of industrial employment rate convergence model (with lagged employment rates)

	Agriculture		**Industry**		**Services**	
Coefficients	Base	Interaction	Base	Interaction	Base	Interaction
Intercept	-0.068*	1.091***	-0.072	-0.252	-0.153***	-0.711***
	(0.097)	(0.001)	(0.224)	(0.151)	(0.001)	(0.000)
log(lagreagr)	-0.031*	0.069**		0.001		-0.055***
	(0.081)	(0.032)		(0.939)		(0.000)
log(lagreind)		0.099	-0.046**	0.061		-0.051*
		(0.227)	(0.049)	(0.134)		(0.051)
log(lagreser)		0.404***		-0.267***	-0.101***	-0.281***
		(0.008)		(0.000)	(0.000)	(0.000)
Spatial error component (rho)	-0.115	-0.111	0.110	0.115	0.087	0.081

Note: Dependent variables are the logarithms of the yearly growth in employment rates, for each sector. SUR model with random effects and spatial error components is estimated by feasible generalized spatial three stage least squares; full set of moments are used in the estimation. The values reported in parentheses are p-values. (*), (**), (***) denote significance at 10%, 5% and 1% respectively.

The interaction models estimated by spatial panel SUR shows again the divergence in the agricultural employment and convergence in the services employment. In the industry sector, the modified model does not show a significant divergent pattern as before. Hence, industrial employment at the regional level may have diverged from its value of 2004, but this pattern is not obvious when yearly changes in the employment rates are accounted for. The effect of services sector employment in 2004 on the growth rate of industrial employment is found to be significantly negative.

5. CONCLUSION

This study investigates the regional convergence dynamics of sectoral employment rates in Turkey over 2004-2011. First, the effects of initial employment rates on the yearly growth in employment rates are estimated by random effects model with spatial error components, for each sector. Then, considering the possible contemporaneous correlation between these sectoral models, a spatial panel SUR regression is employed. As a further exercise, the initial employment rates are taken to be dynamic in a modified model with lagged employment rates. For all specifications, the base model in which the growth in sectoral employment is explained only by its own initial employment rate and the interaction model in which it is explained also by the other sectors' employment rates are compared to the pooled OLS and pooled SUR results.

It is observed that the panel seemingly unrelated regression model with spatial error components model represents the observed changes in the sectoral employment shares better than the alternatives. This result is in line with expectations since it offers a comprehensive framework where time, cross-section and sectoral relations are mutually incorporated. The feasible generalized spatial three stage least squares estimation outcomes indicate that even though beta divergent trend is observed in agricultural sector employment for 2004-2011 period, mixed results are obtained for industry sector employment. In the services sector, there exists evidence of convergence, which is in line with expectations. The descriptive analyses as well as the econometric estimations suggest that over the last decade Turkey has experienced a shift towards services sector, which affects its employment rates positively in all regions. On the other hand, the agriculture sector is losing its significance and over time it has become more concentrated in particular regions.

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APPENDIX
NUTS-2 Level Regions and Provinces in Turkey (2004-2011)

NUTS-2 regions	Provinces
TR10	İstanbul
TR21	Tekirdağ, Edirne, Kırklareli
TR22	Balıkesir, Çanakkale
TR31	İzmir
TR32	Aydın, Denizli, Muğla
TR33	Manisa, Afyon, Kütahya, Uşak
TR41	Bursa, Eskişehir, Bilecik
TR42	Kocaeli, Sakarya, Düzce, Bolu, Yalova
TR51	Ankara
TR52	Konya, Karaman
TR61	Antalya, Isparta, Burdur
TR62	Adana, Mersin
TR63	Hatay, Kahramanmaraş, Osmaniye
TR71	Kırıkkale, Aksaray, Niğde, Nevşehir, Kırşehir
TR72	Kayseri, Sivas, Yozgat
TR81	Zonguldak, Karabük, Bartın
TR82	Kastamonu, Çankırı, Sinop
TR83	Samsun, Tokat, Çorum, Amasya
TR90	Trabzon, Ordu, Giresun, Rize, Artvin, Gümüşhane
TRA1	Erzurum, Erzincan, Bayburt
TRA2	Ağrı, Kars, Iğdır, Ardahan
TRB1	Malatya, Elazığ, Bingöl, Tunceli
TRB2	Van, Muş, Bitlis, Hakkari
TRC1	Gaziantep, Adıyaman, Kilis
TRC2	Şanlıurfa, Diyarbakır
TRC3	Mardin, Batman, Şırnak, Siirt
Total number: 26	*Total number: 81*