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ORIGINAL PAPER

Regional income convergence and conditioning factors in Turkey: revisiting the role of spatial dependence and neighbor effects

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Abstract

This paper studies regional income convergence and its conditioning factors across 81 provinces of Turkey over the 2007–2019 period. Through the lens of a nonlinear dynamic factor model, we first test the hypothesis that all provinces would eventually converge to a common long-run equilibrium. We reject this hypothesis and find that the provincial dynamics of income per capita are characterized by 6 convergence clubs. Next, we evaluate the conditioning factors behind club formation. Our results suggest that spatial dependence across provinces plays an essential role in the formation of convergence clubs. The spatial distribution of the convergence clubs has a clear spatial pattern, and the dynamics of the provincial income distribution are spatially integrated. We also find that geographical neighbors are more important for middle and high-income provinces. Finally, we show that the performance of geographical neighbors affects the probability of club membership through spillovers in capital accumulation and structural change.

JEL Classification O47 · R10 · R11

1 Introduction

Regional inequality is a major concern for the Turkish economy (Celebioglu and Dall'erba 2010; Gezici and Hewings 2004, 2007; Karahasan 2020a; Yildirim et al. 2009). The existence of large and persistent disparities in economic development

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between eastern and western regions has long been a central issue for researchers and policy makers. Identifying and explaining the sources of regional inequality in Turkey may help the design and monitoring of policies that aim to foster sustainable regional development.

Motivated by this context, we study the dynamics of regional inequality across provinces of Turkey and analyze the driving forces of regional convergence over the 2007–2019 period. To do so, we follow a two-step procedure. First, we test the overall convergence in income per capita across provinces and identify possible convergence clubs by using the nonlinear dynamic factor model developed by Phillips and Sul (2007). In the next step, we use an ordered probit model to analyze the factors conditioning club membership and the effect of neighboring regions.

The literature on regional convergence in Turkey is mainly based on the classical convergence framework of Barro and Sala-i Martin (1991), which only describes the behavior of an average or representative economy. However, it ignores important factors such as technological heterogeneity, nonlinear dynamics, and local convergence clubs (Durlauf and Quah 1999; Galor 1996; Johnson and Papageorgiou 2020; Phillips and Sul 2007). In this context, this paper aims to contribute to this literature by providing an alternative perspective that extends beyond the average behavior of a representative economy.

Our main findings are threefold. First, we reject the hypothesis that all provinces would eventually converge to a common long-run equilibrium and find that provincial income dynamics are characterized by six local convergence clubs. Second, when we evaluate the conditioning factors behind club formation—without accounting for spatial dependence across provinces—we find that only initial GDP per capita and investment per capita are significant predictors of club membership. Third, we find that spatial dependence across provinces plays an important role in the club membership, particularly for middle- and high-income provinces. Moreover, the performance of geographical neighbors affects the probability of club membership through spillovers in capital accumulation and structural change.

This study contributes to the existing literature on regional convergence in Turkey in three fronts. First, the convergence framework used in this study is based on provincial heterogeneity and the formation of multiple convergence clubs. Second, there is only one study done by Aksoy et al. (2019) that analyzes regional convergence and conditioning factors in Turkey by applying the Phillips and Sul (2007) methodology. However, the study of Aksoy et al. (2019) abstracts from the role of spatial dynamics in the process of convergence. To the best of our knowledge, this paper is the first study that studies regional convergence, spatial dependence, and neighbors' effects in the context of the framework of Phillips and Sul (2007).

The rest of this paper is organized as follows. Section 2 provides an overview of the related literature. Section 3 presents the data and methodological approach of the paper. Section 4 presents the empirical results. Finally, Sect. 5 offers some concluding remarks.

2 Related literature

2.1 Regional development and policies in Turkey

Regional disparities have been a major issue and policy concern in Turkey for many decades. To reduce the disparities between the eastern and western regions and promote the economic development of less developed regions, especially after the planned development period starting from the 1960s, various regional development strategies and policies have been implemented by the government. There are three major policies to reduce disparities across regions: Priority Provinces in Development (PPD) program, Regional Development Projects (RDP), and Regional Development Agencies (RDA). These regional development strategies and policies have been supported by 5-year development plans, the first implemented in 1963, and the last (Eleventh Development Plan) published for the 2019–2023 period (Akçagün 2017, p. 274).

One of the main policies to decrease regional disparities in Turkey is the PPD program. In 1968, 22 provinces located in the east and southeast of Turkey were determined as PPDs. As of 1998, the number of PPDs increased to 51 (49 provinces and two districts). PPDs have some typical characteristics: higher agricultural employment, lower industrial employment, a lower urbanization rate, and lower GDP per capita (Gezici and Hewings 2004, p. 119). Different government assistance programs, such as those that increase the wages of workers or provide agricultural credits, have been implemented in the context of the PPD program (DPT 2003, p. 50). In 1999, after Turkey was admitted as a candidate for the European Union membership, the first two regional development agencies were founded in the regions of Izmir and Mersin-Adana. The RDA program is a regionally based initiative of publicly financed institutions outside the central and local government administration that aims to promote economic development (Danson et al. 2017, p. 17). By the year 2009, 26 RDA programs were established in 26 NUTS-II regions. In addition to these large development programs, there are several stand-alone regional development projects that have specific objectives of promoting regional development. Some of them include the Southeastern Anatolia Project (GAP), Eastern Anatolia Project (DAP), Eastern Black Sea Project (DOKAP), and the Konya Plain Project (KOP).

2.2 Non-spatial studies

In recent years, numerous studies have studied regional convergence and inequalities across regions in Turkey. Early studies mainly focused on absolute and conditional convergence and reported mixed results. Tansel and Güngör (1999) show the existence of absolute and conditional convergence across 67 provinces in Turkey over 1975–1995. Filiztekin (1998) finds evidence of conditional convergence across provinces in Turkey over 1975–1995. Karaca (2004) shows a divergence in income across provinces in Turkey over the 1975–2000 period. Erlat and Ozkan (2006) show that 13 provinces converge conditionally in Turkey. Kırdar and Saracoğlu (2008) test convergence in real per capita income across provinces in Turkey over 1975–2000, and found absolute divergence and conditional convergence.

After the seminal papers of Phillips and Sul (2007), Phillips and Sul (2009), many papers have adopted a nonlinear dynamic factor model to analyze the convergence in income both across countries (Anoruo et al. 2019; Apergis et al. 2010; Barrios et al. 2019b; Martin and Vazquez 2015; Tam 2018) and across regions and provinces (Aksoy et al. 2019; Bartkowska and Riedl 2012; Mazzola and Pizzuto 2020; Montañés et al. 2018; Von Lyncker and Thoennessen 2017; Zhang et al. 2019).[1] These papers usually follow a two-step procedure. First, they identify possible convergence clubs using the club convergence methodology developed by Phillips and Sul (2007, 2009). Second, they analyze the factors affecting the probability of joining club membership using mainly ordered logit or probit models. Bartkowska and Riedl (2012) analyze convergence across 206 European NUTS-II regions over 1990–2002 and assessed the factors determining the formation of convergence clubs. The club clustering algorithm identifies multiple convergence clubs, and ordered logit regressions indicate that per capita income, labor force, high-tech production, and human capital significantly affect the probability of joining a particular club. Von Lyncker and Thoennessen (2017) analyze the convergence across 194 European NUTS-II regions over the period 1980–2011 and identified multiple convergence clubs similar to Bartkowska and Riedl (2012). According to the results of ordered logit regressions, income per capita, labor force participation rate, human capital, physical capital, population growth, industry, and service share are important factors in explaining the club membership. Zhang et al. (2019) analyze the convergence in income across 329 prefecture-level city regions in China over 1990–2014. The club clustering test identifies four convergence clubs, each converging to a different constant. Furthermore, the results of ordered logit regressions indicate that initial income per capita, physical capital, human capital, service share, government spending, and foreign direct investment significantly affect the probability of joining a particular convergence club. Aksoy et al. (2019) test the convergence in GDP per capita across 81 NUTS-III regions in Turkey over two periods, 1987–2001 and 2004–2017, and identified multiple convergence clubs across provinces for the two intervals. The ordered logit model estimates indicate that initial per capita income, human capital, and total credits are the driving forces of club membership. Cutrini (2019) tests the convergence across 274 NUTS-II regions over the period 2003–2016, and identifies multiple convergence clubs. Furthermore, the ordered logit model results indicate that while an increase in the share of manufacturing sector and knowledge-intensive services increase the probability of joining higher-income clubs, an increase in the share of routine services increases the probability of joining lower-income clubs.

[1] The club convergence methodology has been used in different concepts beyond per capita income, such as convergence in carbon dioxide emissions (Panopoulou and Pantelidis 2009), ecological footprint (Apaydin et al. 2021), labor productivity (Mendez 2020), happiness (Apergis and Georgellis 2015), house prices (Churchill et al. 2018), patents (Barrios et al. 2019a), institutional quality (Glawe and Wagner 2021), etc.

Zhang et al. (2020) investigate the convergence in income per capita and factors affecting club membership across 108 counties of Henan province in China over the period 1995–2014. The club cluster analysis identifies four convergence clubs across regions, and the ordered logit models indicate that initial per capita income, physical capital, geographical agglomeration, and local fiscal expenditure are important drivers of club membership.

2.3 Spatial studies

The second group of studies considers the spatial dynamics of regional convergence and regional disparities. Gezici and Hewings (2004) find no evidence of convergence across both provinces and functional regions in Turkey. Furthermore, their spatial analysis indicates that GDP per capita is spatially dependent. Gezici and Hewings (2007) show that while inter-regional inequalities are increasing, intra-regional inequalities are declining for all spatial partitions over 1980–1997 in Turkey. Their results also indicate a strong spatial autocorrelation in GDP per capita for the initial and final years. Celebioglu and Dall'erba (2010) use an exploratory spatial data analysis to study regional disparities across 76 provinces in Turkey over the 1995–2001 period. Their results show a statistically positive spatial autocorrelation in GDP per capita, total public investment, and human capital. Taking into account the role of spatial heterogeneity, Akçagün (2017) study regional convergence across provinces in Turkey over two periods: 1991–2001 and 2002–2009. The results confirm that conditional convergence exists across provinces for both sub-periods. Dogan and Kındap (2019) find evidence of absolute convergence in gross value added per capita across NUTS-II regions in Turkey over 2004–2011. Furthermore, the Moran's I statistic reveals a statistically significant positive spatial autocorrelation for GVA per capita. Karahasan (2020a) tests the convergence across regions in Turkey over 1975–2017 by considering spatial effects. The results indicate that although average regional income increases and standard deviation falls, there is still spatial clustering measured by Moran's I. Furthermore, the study reveals the existence of a club convergence process which is affected by the income level of neighboring regions. Karahasan (2020b) studies the spatial variability of convergence across NUTS-III regions in Turkey over the 2004–2017 period. Although the findings support the existence of convergence across regions, regional convergence is spatially heterogeneous. Less developed eastern regions show higher convergence compared to western regions; however, the speed of convergence differs across less developed regions.

3 Data and methodology

3.1 Data

The dataset covers the 2007–2019 period for 81 provinces (NUTS-III level) in Turkey. We use the regional GDP per capita (chain-linked volume, 2009) for the

Table 1 Descriptive statistics

	Mean			Standard deviation		
	2007	2019	2007/2019	2007	2019	2007/2019
GDP per capita	11126	16027	0.69	4496	5495	0.82
Real investment per capita	1223	3523	0.35	814	2435	0.33
Human capital	43.32	126.64	0.34	104.70	283.47	0.37
Agriculture, share	14.94	14.15	1.06	7.06	7.30	0.97
Routine services, share	17.99	17.59	1.02	5.80	6.10	0.95
Knowledge-intensive services, share	3.46	3.73	0.93	1.53	1.97	0.78
Population density	111.09	132.20	0.84	268.63	333.35	0.81

Data on human capital is from 2008 instead of 2007

analysis. The other explanatory variables used in the empirical analysis are total credits per capita as a proxy for investment in physical capital, the total number of higher education graduates (in thousands) as a proxy for human capital, the share of agriculture (% of GDP), the share of routine services (% of GDP), the share of knowledge-intensive services (% of GDP), and the population density. Following Cutrini (2019), routine services include wholesale and retail trade, transportation and storage, accommodation, and food service activities. Knowledge-intensive services include information and communication, professional, scientific, and technical activities, administrative, and support activities. We use the regional consumer price index (2003 = 100) to deflate total credit data. Since the regional CPI data are only available at the NUTS-II level (26 regions), following Aksoy et al. (2019), we apply the same CPI for all provinces in a specific region. We compiled data from the Turkish Statistical Institute (TurkStat), except for total credit which is compiled from the Banks Association of Turkey.

The factors that condition club membership are organized into three groups of variables. First, based on standard growth theory, measures of investment in physical capital and human capital are included under the heading "growth fundamentals". Next, to control for the structural characteristics of the economy, the output shares of agriculture, routine services, and knowledge-intensive services are included under the heading "structural change". Finally, to control for initial conditions and agglomeration effects, the initial level of GDP and population density are included under the heading "other control variables". The descriptive statistics and spatial distributions of these variables are presented in Table 1, and Figs. 1 and 2, respectively. Figure 1 clearly shows an east–west divide, and we also observe that disparities across regions are persistent over time. Similar to GDP per capita, the spatial distribution of investment per capita in Fig. 2 shows that investment in the east side of Turkey is lower than the west side. However, we do not observe a similar east–west divide for the other variables.

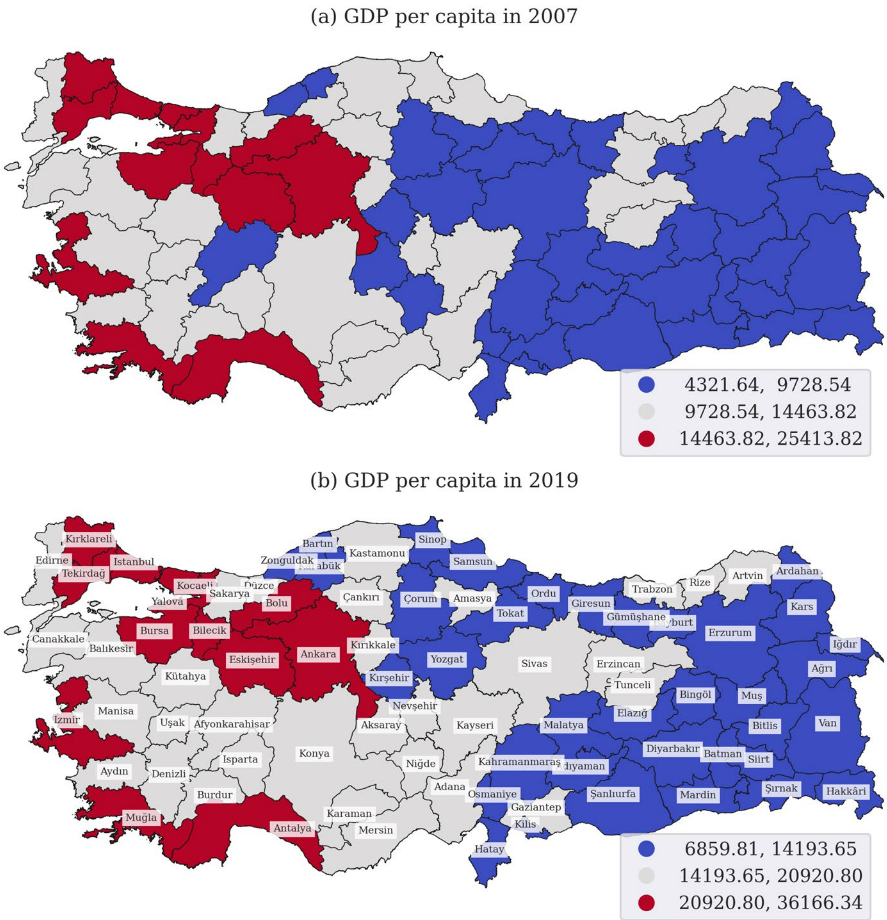

Fig. 1 Spatial distribution of GDP per capita in 2007 and 2019. In the maps, regions are classified into three categories based on the Fisher–Jenks optimization algorithm

3.2 Convergence test and club identification

In this paper, we employ the econometric methodology proposed by Phillips and Sul (2007) to test the hypothesis that all provinces in Turkey would eventually converge to a common long-run equilibrium. Log-t convergence test developed by Phillips and Sul (2007) is based on a nonlinear time' varying factor model. The starting point of the model is the decomposition of panel data for GDP per capita, (X_{it}), into two components:

$$X_{it} = g_{it} + a_{it}, \tag{1}$$

where g_{it} is a systematic component and a_{it} is a transitory component.

To separate common components from idiosyncratic components, Eq. (1) can be transformed as:

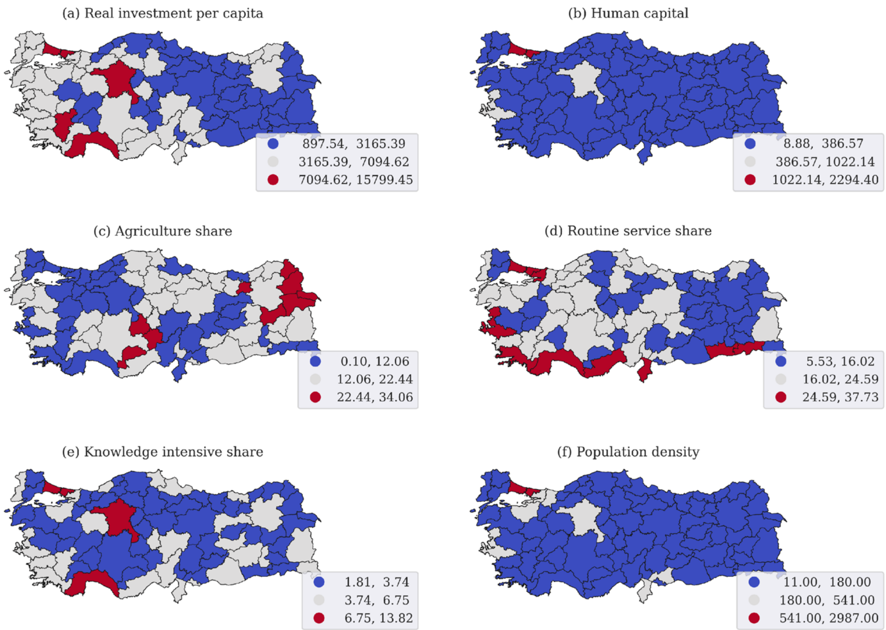

Fig. 2 Spatial distribution of main variables in 2019. In the maps, regions are classified into three categories based on the Fisher–Jenks optimization algorithm

$$X_{it} = \left(\frac{g_{it} + a_{it}}{\mu_t} \right) \mu_t = \delta_{it} \mu_t, \tag{2}$$

where μ_t and δ_{it} represent a common component and an idiosyncratic component, respectively. δ_{it} is a measure of the distance between the common trend component μ_t and X_{it}. As it is impossible to directly estimate the loading coefficients, δ_{it}, without imposing some structure δ_{it} and μ_t, the common factor may be removed by constructing the following relative transition paths:

$$h_{it} = \frac{X_{it}}{N^{-1} \sum_{i=1}^{N} X_{it}} = \frac{\delta_{it}}{N^{-1} \sum_{i=1}^{N} \delta_{it}}, \tag{3}$$

where h_{it} indicates the relative transition parameter which measures the loading coefficient δ_{it} to the panel average at time t.

Equation (3) shows the two properties of h_{it}. First, the cross-sectional mean of h_{it} is equal to one and second, if the factor loading coefficients δ_{it} converge to δ_i, the relative transition parameter h_{it} converges to one. In this case, as shown in Eq. (4), the cross-sectional variance of the relative transition parameter, H_t, converges to zero asymptotically. The property $H_t \rightarrow 0$ is used to test the null hypothesis of income convergence and to group provinces into convergence clubs.

$$H_t = N^{-1} \sum_{i=1}^{N} \left(h_{it} - 1\right)^2 \rightarrow 0 \text{ as } t \rightarrow \infty \tag{4}$$

To empirically test hypothesis of regional convergence, Phillips and Sul (2007) propose the following log-t regression model:

$$\begin{gathered} \log\left(H_1/H_t\right) - 2\log(\log(t)) = a + b\log(t) + u_t \\ \text{for } t = [rT], [rT]+1, \dots, T \text{ with } r > 0, \end{gathered} \tag{5}$$

where $[rT]$ is the initial observation in the regression, which implies that the first fraction of the data (i.e., r) is discarded. Based on Monte Carlo simulations, Phillips and Sul (2007) suggest to set $r = 0.3$ when the sample is small ($T \leq 50$). Phillips and Sul (2007) propose a conventional inferential procedure for Eq. (5). Specifically, they recommend a one-sided t-test with heteroskedasticity and autocorrelation-consistent standard errors. The null hypothesis of convergence is rejected if $t_b < -1.65$.

If convergence is not found for the whole sample, a local clustering procedure is suggested by Phillips and Sul (2007), Phillips and Sul (2009) to identify local convergence clubs. The procedure has five steps and is presented in Appendix 1.

3.3 Spatial dependence across regional units

An analysis of global spatial dependence evaluates the hypothesis of spatial randomness and the presence of an overall pattern of clustering. The most commonly used statistic to evaluate the existence of global spatial dependence is the Moran's I. In the context of regional income studies, the Moran's I statistic describes the association between income values at one location and those at neighboring locations (Anselin 1995; Anselin et al. 2007). If the Moran's I is statistically different from $-1(N-1)$, where N is the number of regions, then the null hypothesis of spatial randomness can be rejected.[2] The numerical values of the Moran's I usually range between -1 and $+1$. When its value is close to one (minus one), it indicates positive (negative) spatial autocorrelation. While the positive spatial autocorrelation indicates spatial similarity and an overall pattern of clustering, negative spatial autocorrelation indicates spatial dissimilarity and a checkerboard pattern.

An analysis of local spatial dependence allows us to identify the location of spatial clusters and spatial outliers (Anselin 1995; Anselin et al. 2007). From a measurement standpoint, it is commonly based on the breaking up of a global statistic of spatial dependence. Specifically, a local analysis of the Moran's I helps us to classify regions into four groups. The first two groups describe the location of spatial clusters. The first type of spatial cluster indicates regions with high-income values surrounded by neighbors with high-income values (that is, a high-high cluster). The second type of spatial cluster indicates regions with low-income values surrounded by neighbors with low-income values (that is, a low-low cluster). The third and forth groups describe the location of spatial outliers. The first type of

[2] Appendix 3 presents the equations for measuring global and local spatial dependence.

spatial outlier indicates regions with high-income values surrounded by neighbors with low-income values (that is, a high–low group). The second type of spatial outlier indicates regions with low-income values surrounded by neighbors with high-income values (that is, a low–high group).

To study the temporal dynamics of local spatial dependence, Rey et al. (2011) use recent advances in geovisualization and directional statistics to propose a dynamic local indicator of spatial association. This dynamic approach allows us to study the role of spatial dependence in the evolution of the regional income distribution. In its most simple form, the framework of Rey et al. (2011) can be understood as a dynamic Moran scatter plot. Specifically, it evaluates the co-evolution of a region and its neighbors using directional vectors within a Moran scatter plot.

3.4 Factors conditioning club membership

We also analyze the factors conditioning club membership using the ordered regression model introduced by McKelvey and Zavoina (1975). Our dependent variable, denoted by c represents the club to which a region belongs according to the clustering procedure described in Appendix 1. This variable can be classified as an ordinal variable since the identified clubs are ranked. Assuming that the membership to a certain club is driven by a continuous latent variable, y_i^*, represents the individual steady-state income level. Thus, our model can be expressed as follows:

$$y_i^* = \beta X_i + \varepsilon_i, \tag{6}$$

where X_i includes explanatory variables and ε_i has a standard normal distribution. Since the dependent variable y_i^* is unobserved, in order to compute the probabilities of observing values of c given X, we use a maximum likelihood (ML) estimation framework. To determine the effect of a single variable on the probability of joining a particular convergence club, we report the marginal effects on the probabilities of each variable.

When studying the determinants of club membership and regional convergence, a growing literature has been interested in evaluating the role of spatial spillovers from neighboring regions (Bartkowska and Riedl 2012; Fischer 2011; Li et al. 2018). For that purpose, we identify each province's geographical neighbors based on geographical proximity. That is, two provinces are considered neighbors if they share a common border or corner. Next, we compute the mean neighbor performance for all explanatory variables. These new variables, known as spatial lags in the spatial econometrics literature, are proxies for the performance of each province's geographical neighbors.[3]

[3] More specifically, we estimate a SLX spatial model. See Elhorst (2014) for further details.

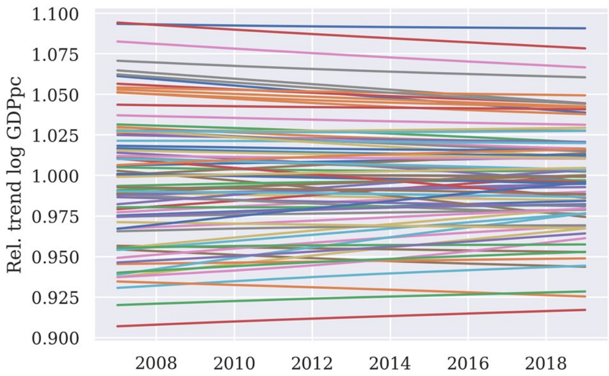

Fig. 3 Evolution of relative trends of (log) GDP per capita. For each province, the value of its long-run trend of GDP per capita is normalized by the cross-sectional mean of each year

Table 2 Log-*t* convergence test

	Coeff	SE	*T*-stat
log(*t*)	− 0.71	0.03	− 20.52

The null hypothesis of convergence is rejected with the *T*-statistic is smaller than − 1.65

Table 3 Initial convergence clubs (before merge tests)

	Club1	Club2	Club3	Club4	Club5	Club6	Club7	Club8	Club9	Club10
Coeff	0.07	0.13	0.03	0.13	0.05	0.09	0.19	0.29	0.19	0.91
T-stat	0.56	1.65	0.32	1.23	0.53	0.89	1.54	2.24	1.97	4.04

The null hypothesis of convergence is rejected with the *T*-statistic is smaller than − 1.65. Non-convergent regions are Istanbul and Kocaeli

4 Results

4.1 Convergence test and club identification

Figure 3 shows the transition paths of GDP per capita for the provinces in Turkey. In this figure, for each province, the value of the long-run trend of GDP per capita is normalized by the cross-sectional mean of each year. Figure 3 indicates that there is no unique convergence tendency among provinces. Furthermore, we observe a high degree of heterogeneity in the evolution of the relative trends of (log) GDP per capita.

To analyze the overall pattern of convergence across 81 provinces in Turkey, we apply the log-*t* convergence test of Phillips and Sul (2007). As expected, given patterns of Fig. 3, the results of log-*t* tests in Table 2 show that the null hypothesis of overall convergence is rejected at the 5% (− 20.52 < −1.65), which indicates that

Table 4 Final convergence clubs (after merge tests)

Final clubs	Merged clubs	Number of regions	Coefficient	T-statistic
Club 1	Club: 1	2	0.07	0.56
Club 2	Clubs: 2, 3	17	− 0.06	− 0.66
Club 3	Clubs: 4, 5, 6	31	− 0.05	− 0.55
Club 4	Club: 7	18	0.19	1.54
Club 5	Clubs: 8, 9	9	− 0.11	− 1.35
Club 6	Club: 10	2	0.91	4.04

The null hypothesis of convergence is rejected with the T-statistic is smaller than − 1.65. Non-convergent regions are Istanbul and Kocaeli

provinces in Turkey do not converge to the same long-run equilibrium in terms of GDP per capita.

Since the null hypothesis of overall convergence is rejected, we test the existence of local convergence clubs. In Table 3, the results of the clustering algorithm show that there are ten convergence clubs. With the exception of Istanbul and Kocaeli, 79 out of the 81 Turkish provinces are converging to multiple local equilibria. In contrast with Table 2, Table 3 shows that the null hypothesis of (local) convergence is not rejected as the T-statistic of the log-t test is greater than − 1.65 for all clubs.

After identifying an initial convergence club classification, Phillips and Sul (2009) argue that sequential club merging tests are needed to avoid overestimating the actual number of clubs.[4] Several studies have now applied these merging tests as an essential part of the club identification procedure (Schnurbus et al. 2017; Von Lyncker and Thoennessen 2017; Gunawan et al. 2021, among others). Based on these arguments, we apply sequential club merging tests to evaluate whether any of the initially identified clubs can be merged into larger clubs. Table 4 shows the results of these tests.

Sequential merge testing of adjacent clubs has three notable implications for the final club classification of the Turkish provinces. First, the number of convergence clubs has been reduced from ten to six. For each of these final clubs, the T-statistic is greater than − 1.65, thus the null hypothesis of (within) convergence is not rejected. Second, the provincial composition of some clubs has largely increased. For instance, Club 3 is now composed by the initially found Club 4, Club 5, and Club 6.[5] Third, the club merging procedure has generated some weak

[4] Specifically, Phillips and Sul (2009, p. 1171) argue that the third step of their clustering algorithm is highly conservative when setting the sieve criterion to zero for short time series. However, one negative consequence of this setting is that it increases the probability of finding more convergent clubs than the actual true number. Thus, they recommend implementing a sequential club merging procedure as the fifth step of their clustering algorithm. From a computational implementation standpoint, Du (2017) and Schnurbus et al. (2017) have supported this argument and included this fifth step in their Stata and R routines, respectively.

[5] As explain by Gunawan et al. (2021), having large clubs is methodologically desirable for the next stage of the analysis in which the conditioning factors of club membership will be evaluated.

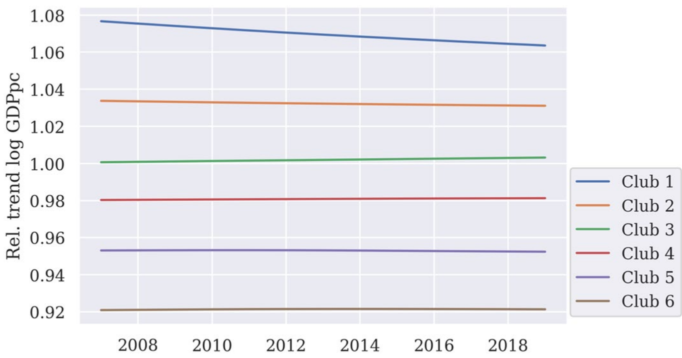

Fig. 4 Evolution of relative trends of (log) GDP per capita across clubs. For each province, the value of its long-run trend of GDP per capita is normalized by the cross-sectional mean of each year

convergence clubs. Specifically, the convergence coefficient has become negative for Club 2, Club 3, and Club 5.

The existence of weak convergence clubs deserves further clarification. A convergence club is considered weak when the convergence coefficient is negative, but its *T*-statistic is greater than − 1.65. The primary criterion for evaluating convergence in the framework of Phillips and Sul (2007) is the *T*-statistic of the log-*t* test. As such, all clubs in Table 4 are interpreted as convergence clubs. The negative sign of the convergence coefficient, however, casts some doubts on the strength of regional convergence within these clubs. These clubs usually appear after merging clubs (Phillips and Sul 2009; Bartkowska and Riedl 2012; Cutrini 2019). In the case of Turkey, the study of Aksoy et al. (2019) also reports weak convergence clubs after the merge procedure. Despite the limitation, having fewer and larger clubs helps us reduce overestimation concerns in the number of clubs as well as data variation concerns within clubs. Having enough observations within each club is particularly important when analyzing the conditioning factors of club membership.

By taking the cross-provincial average within each club, Fig. 4 illustrates the summary transition paths of each club. We observe that the relative transition paths show a smooth trend, and there is a lack of convergence among clubs. The relative transition paths of Club 1 and Club 2, which may be classified as high-income clubs, are largely above the panel average. Since they are close to the panel average, Club 3 and Club 4 may be classified as upper-middle-income and lower-middle-income clubs, respectively. Club 5 and Club 6 may be classified as low-income clubs as they are systematically below the panel mean.

Based on the transition paths of each individual province in the sample, Fig. 5 illustrates a graphical summary of the final club classification. Appendix (Table 8) provides a list of province names with their respective club classification. Figure 5 shows that per-capita income differences within each club are decreasing over time. Based on the convergence coefficient of Table 4, which is proportional to the within-club convergence speed, we observe that the provinces of club 6 are converging at the fastest speed. This result is in part due to the fact that Club 6 includes only two

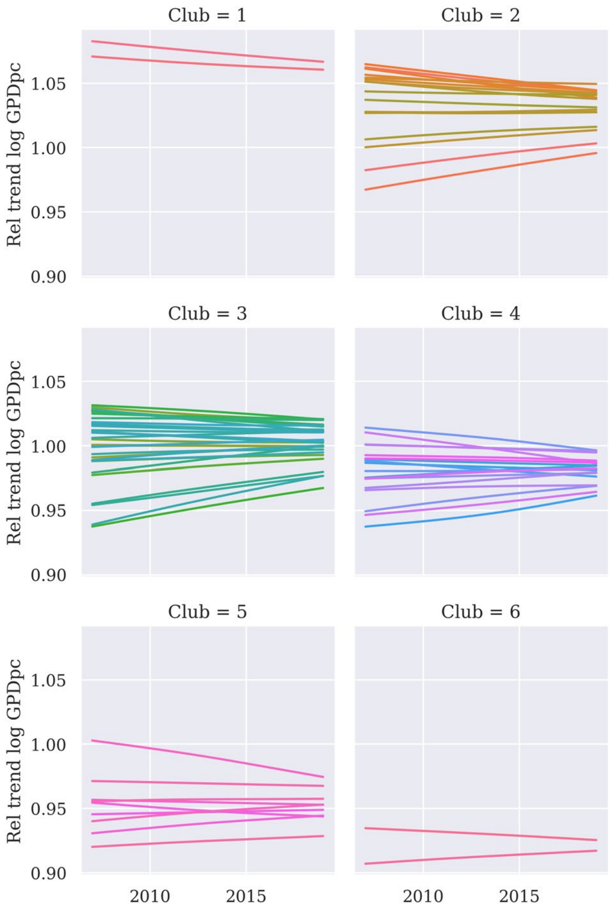

Fig. 5 Convergence clubs. Since two regions, Istanbul and Kocaeli, are diverging, they are not shown in this figure

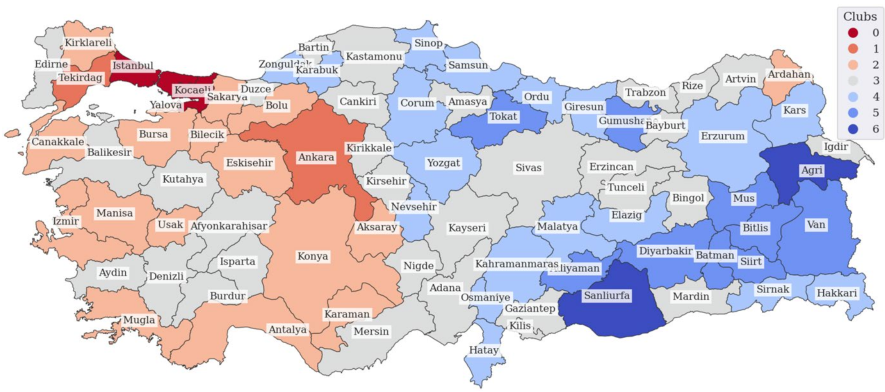

Fig. 6 Spatial distribution of the convergence clubs. Club 0 indicates non-convergent regions

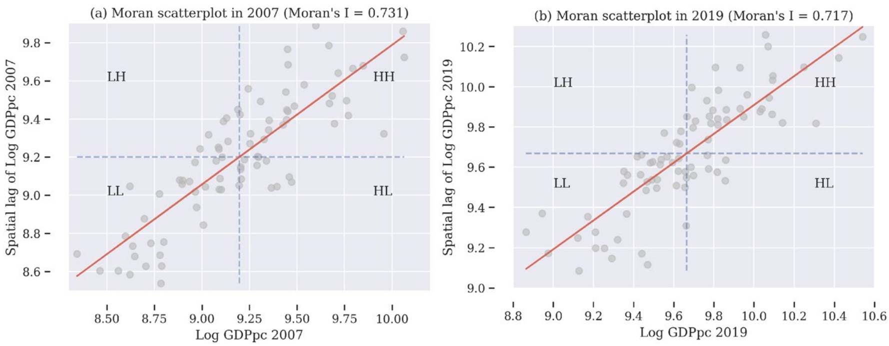

Fig. 7 Global spatial dependence in 2007 and 2019. HH stands for high-income regions surrounded by other high-income regions. LL stands for low-income regions surrounded by other low-income regions. HL stands for high-income regions surrounded by low-income regions. LH stands for low-income regions surrounded by high-income regions. A region is identified as high (low) income when is above (below) the average

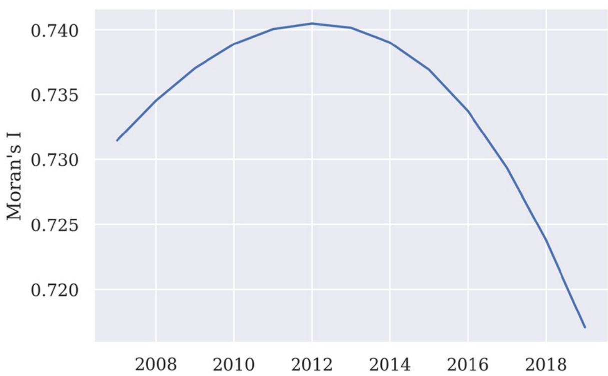

Fig. 8 Nonlinear evolution of global spatial dependence

provinces. In contrast, Club 4 is not only the second largest club, with 18 provinces, but also the second club that is converging at the fastest speed.

4.2 Spatial dependence across regional units

Figure 6 illustrates the spatial distribution of the convergence clubs in Turkey. As expected, the map clearly shows an east-west divide. The two provinces with the highest income per capita, the members of the divergent group, are İstanbul and Kocaeli. They are the two major metropolitan and industrial cities, and they are located in the Marmara region. Club 1 includes Ankara, the capital city of Turkey, and Tekirdag. We observe that provinces in high-income clubs (Club 1 and Club 2) are mostly located in the west part of the country. Club 3, the upper-middle-income club, is the largest convergence club with 31 provinces. The members of Club 3 are located more sparsely, from Marmara (Edirne province) to the

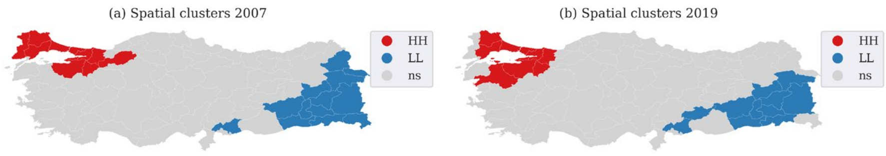

Fig. 9 Local spatial dependence. Based on the Moran scatter plot, HH (LL) stands high (low) income regions surrounded by other high (low) income regions. ns stands for non-statistically significant region

easternmost of Turkey (Igdir province). The provinces of Club 4, the lower-middle-income club, are mostly located in the central and east parts of Turkey. As expected, the provinces in low-income clubs, Clubs 5 and 6, are mostly located in the eastern and southeastern parts of Turkey.

Taken together, Figs. 7 and 8 show the direction, magnitude, and dynamics of global spatial dependence. Panel (a) of Fig. 7 indicates that there is a high spatial correlation (Moran's $I = 0.731$) in GDP per capita in 2007. In the same figure, panel (b) shows a slight decrease in spatial dependence (Moran's $I = 0.717$) in 2019. In both cases, the null hypothesis of spatial randomness in the distribution of GDP per capita is rejected by the data. The positive slope of the Moran scatter plot indicates that there is an overall pattern of clustering. Specifically, high (low) income regions tend to be located near other high (low) income regions. Figure 8 provides further insights on the evolution of global spatial dependence. Over the 2007–2019 period, the spatial dependence has evolved in a highly nonlinear way. It increased between 2007 and 2012 and has since decreased. Despite these nonlinear dynamics, the degree of spatial dependence remains high by 2019.

Figure 9 illustrates the location and persistence of spatial clusters. Based on the quadrants of the Moran scatter plot, one could map those high (low) income regions and their neighbors. However, based on the inference analysis proposed by Anselin (1995), not all regions are located in the high-high (HH) or low-low (LL) quadrants are statistically significant. Despite this limitation, a clear east-west divide can be observed. In particular, Turkey's northwestern provinces have high income levels, while the southeastern provinces have significantly lower incomes. As indicated by the two panels of Fig. 9, this east-west divide is largely persistent over time.

Taken together, the spatial clusters reported in Fig. 9 and the convergence clubs reported in Fig. 6 provide a complementary perspective on the location of high-, middle-, and low-income clusters of development. Figure 9 reveals persistent and statistically significant clusters of high-income regions in the northwest and low-income regions in the southeast. However, based on the framework of Anselin (1995), regions in between these clusters are not statistically significant. To fill in this informational gap, the framework of Phillips and Sul (2009) can provide a more detailed classification for these regions. From Fig. 6, one can observe a large middle-income cluster (Club 3) running from the middle of the north to the middle of the south. In support of this observation, the Fisher–Jenks classification algorithm, used in panel (b) of Fig. 1, indicates that (besides the center west) middle-income regions are mostly located from north to south.

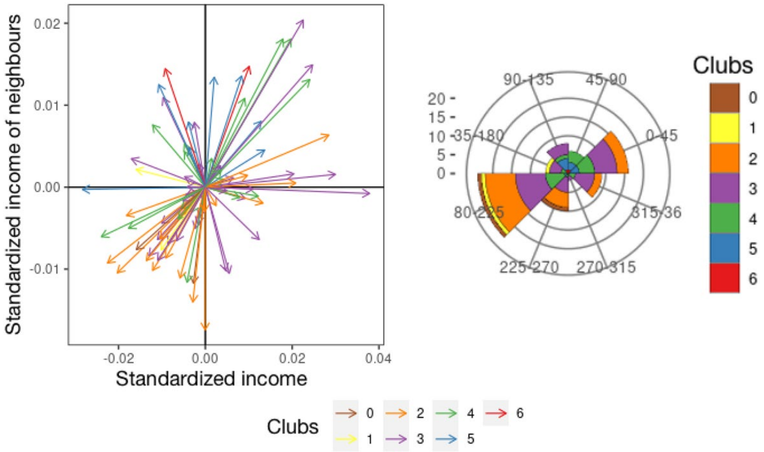

Fig. 10 Dynamics of local spatial dependence and convergence clubs. Standardized income refers to relative log GDP per capita. The arrows indicate the direction and magnitude of the change in log GDP per capita from 2007 to 2019

A dynamic analysis of local spatial dependence is presented in Figure 10.[6] In the scatter plot, the horizontal axis (X) indicates the standardized value of log GDP per capita, while the vertical axis (WX) indicates the average of the standardized value of log GDP per capita of the neighbors of each region. The origin of the scatter plot (O, O) indicates the initial GDP position. In our case, it is the log of GDP per capita in 2007. For each region, the arrows indicate the direction and magnitude of the change in log GDP per capita between 2007 and 2019. At a glance, the predominant shifts are in the northeast and southwest quadrants. Vectors pointing to the northeast indicate a positive co-movement of a region and its neighbors within the regional income distribution. In contrast, vectors pointing to the southwest indicate a worsening of the relative positions of a region and its neighbors. As indicated by Rey (2001), the predominant movement of vectors in these two directions is indicative of space-time integration. In other words, there is evidence of spatial dependence in the—dynamics—of the income distribution.

The colors of the vectors represent the convergence clubs identified in the previous section. Spatial convergence across clubs would occur when the arrows of the higher-income clubs (1, 2, 3) tend to point to the southwest direction and the arrows of the lower-income clubs (4, 5, 6) tend to point to the northeast direction. However, the large number of arrows and colors make it difficult to identify clear patterns in Fig. 10. To solve this problem, Rey et al. (2011) propose using a circular histogram. Using this device, the main finding of Fig. 10 is that the more frequent co-movements are in Clubs 2 and 3. For Club 2, the predominant pattern is a movement to the southwest. This negative co-movement reflects a worsening of the relative

[6] Figure 10 is the standardized directional version of the Moran scatter plot of Figure 7.

Table 5 Marginal effects on probabilities of club membership

Variable	Club 2	Club 3	Club 4	Club 5
Growth fundamentals				
Investment per capita	0.0634	0.0408	− 0.0799*	− 0.0243
	(0.0424)	(0.0315)	(0.0485)	(0.0181)
Human capital	− 0.0379	− 0.0243	0.0477	0.0145
	(0.0580)	(0.0391)	(0.0717)	(0.0235)
Structural change				
Agriculture, share	− 0.0570	− 0.0366	0.0717	0.0218
	(0.1445)	(0.0952)	(0.1821)	(0.0559)
Routine services, share	0.1023	0.0658	− 0.1289	− 0.0392
	(0.2741)	(0.1798)	(0.3418)	(0.1091)
Knowledge-intensive services, share	− 0.0579	− 0.0372	0.0729	0.0222
	(0.1239)	(0.0860)	(0.1608)	(0.0472)
Other control variables				
GDP per capita (2007), in logs	0.7418***	0.4770	− 0.9345***	− 0.2843***
	(0.1882)	(0.2957)	(0.2719)	(0.1043)
Population density	0.1973	0.1268	− 0.2485	− 0.0756
	(0.3481)	(0.2399)	(0.4479)	(0.1321)
Observations	17	31	18	9

Robust standard errors in parentheses. Marginal effects are computed at the mean of all variables. The symbols ***, **, * indicate statistically significance at the 1, 5, and 10 percent, respectively

positions of a region and its neighbors. In terms of within-club convergence, the southwest directions of the arrows indicate that the convergence process of Club 2 is largely driven by a backward movement of the high-income regions and their neighbors. For Club 3, there is no a unique predominant pattern. In this case, within-club convergence appears to be driven by both forward and backward mobility.

4.3 Factors conditioning club membership

To analyze the factors conditioning the club membership, we employ an ordered probit regression model. Only clubs 2, 3, 4, and 5 are included in this analysis as Club 1 and Club 6 contain very few observations. Therefore, our sample consists of 75 out of the 81 provinces of Turkey. The dependent variable is an ordinal indicator of club membership, which varies from 2 to 5.

Table 5 reports the average marginal effect on probabilities for each club. First, the ordered probit results indicate that initial GDP per capita and investment per capita are the most important factors conditioning the club membership. Investment per capita has a significant and negative effect only on the membership of Club 4. In other words, an increase in investment per capita decreases the probability of joining the lower-middle-income club. Although human capital is one of the main drivers of economic growth, our results show that there is no significant relationship between

Table 6 Marginal effects on probabilities of club membership (with the spatial lag of GDP per capita

Variable	Club 2	Club 3	Club 4	Club 5
Growth fundamentals				
Investment per capita	0.0697*	0.0540	– 0.0996**	– 0.0241
	(0.0393)	(0.0378)	(0.0496)	(0.0173)
Human capital	0.0274	0.0213	– 0.0392	– 0.0095
	(0.0540)	(0.0425)	(0.0777)	(0.0176)
Structural change				
Agriculture, share	– 0.0050	– 0.0039	0.0071	0.0017
	(0.1370)	(0.1065)	(0.1961)	(0.0473)
Routine services, share	– 0.0167	– 0.0129	0.0239	0.0058
	(0.2564)	(0.1975)	(0.3662)	(0.0876)
Knowledge-intensive services, share	– 0.0882	– 0.0683	0.126	0.0305
	(0.1075)	(0.0999)	(0.1651)	(0.0375)
Other control variables				
GDP per capita (2007), in logs	0.4578***	0.3549	– 0.6544***	– 0.1583*
	(0.1557)	(0.2357)	(0.2445)	(0.0817)
W GDP per capita (2007), in logs	0.4978**	0.3859*	– 0.7116***	– 0.1721**
	(0.2082)	(0.2268)	(0.2669)	(0.0806)
Population density	0.0269	0.0208	– 0.0384	– 0.0093
	(0.3257)	(0.2547)	(0.4677)	(0.1126)
Observations	17	31	18	9

W is a spatial weights matrix that summarizes the geographic connectivity structure across provinces. A queen contiguity criteria has been used in the construction of this matrix. In this SLX-type model, variables using W as a prefix indicate spatial spillover effects (Elhorst 2014). Robust standard errors in parentheses. Marginal effects are computed at the mean of all variables.

The symbols ***, **, * indicate statistically significance at the 1, 5, and 10 percent, respectively

human capital and club formation. With respect to structural characteristics, the findings indicate that the share of agriculture, routine and knowledge-intensive services have insignificant effects on club formation. As expected, an initially high GDP per capita increases the probability of joining high-income Club 2, and decreases the probability of joining lower-middle-income Club 4 and low-income Club 5. Specifically, a one-unit increase in log initial income in 2007 increases a region's probability of joining Club 2 by 74.2% and decreases the probability of joining Club 5 by 28%. Finally, there is no statistically significant relationship between population density and club formation.

Next, to analyze the effect of neighboring regions in determining the formation of convergence clubs, we add the spatial lags of explanatory variables. Spatial lags are constructed using a Queen contiguity weighting matrix (W) of order one.[7] Following Bartkowska and Riedl (2012), first, we only include the

[7] This matrix indicates that the neighbors of a region are those who share a common border or vertex.

Table 7 Marginal effects on probabilities of club membership (with spatial lags)

Variable	Club 2	Club 3	Club 4	Club 5
Growth fundamentals				
Investment per capita	0.0645*	0.0732	– 0.1227***	– 0.0150
	(0.0343)	(0.0458)	(0.0467)	(0.0105)
W investment per capita	0.1447*	0.1643	– 0.2754**	– 0.0336
	(0.0772)	(0.1239)	(0.1393)	(0.0227)
Human capital	– 0.0121	– 0.0138	0.0231	0.0028
	(0.0490)	(0.0569)	(0.0937)	(0.0117)
W human capital	– 0.1444	– 0.1639	0.2747*	0.0335
	(0.0882)	(0.1256)	(0.1521)	(0.0240)
Structural change				
Agriculture, share	– 0.0263	– 0.0299	0.0501	0.0061
	(0.1047)	(0.1238)	(0.2037)	(0.0238)
W agriculture, share	0.1050	0.1192	– 0.1998	– 0.0244
	(0.2228)	(0.2527)	(0.4156)	(0.0515)
Routine services, share	– 0.3368	– 0.3823	0.6408*	0.0782
	(0.2297)	(0.2965)	(0.3881)	(0.0544)
W routine services, share	– 0.7214*	– 0.8188	1.3726**	0.1676
	(0.4223)	(0.5108)	(0.5750)	(0.1168)
Knowledge-intensive services, share	– 0.0327	– 0.0371	0.0623	0.0076
	(0.0675)	(0.0848)	(0.1344)	(0.0155)
W knowledge-intensive services, share	0.4703*	0.5338*	– 0.8949**	– 0.1092
	(0.2843)	(0.3224)	(0.3567)	(0.0846)
Other control variables				
GDP per capita (2007), in logs	0.3382**	0.3839	– 0.6436**	– 0.0786
	(0.1720)	(0.2545)	(0.2596)	(0.0542)
W GDP per capita (2007), in logs	0.2755	0.3127	– 0.5241	– 0.0640
	(0.2178)	(0.2916)	(0.4000)	(0.0542)
Population density	0.1902	0.2159	– 0.3620	– 0.0442
	(0.2553)	(0.2981)	(0.4691)	(0.0602)
W population density	0.2724	0.3091	– 0.5183	– 0.0633
	(0.5078)	(0.6273)	(0.9884)	(0.1239)
Observations	17	31	18	9

W is a spatial weights matrix that summarizes the geographic connectivity structure across provinces. A queen contiguity criteria has been used in the construction of this matrix. In this SLX-type model, variables using *W* as a prefix indicate spatial spillover effects (Elhorst 2014). Robust standard errors in parentheses. Marginal effects are computed at the mean of all variables.

The symbols ***, **, * indicate statistically significance at the 1, 5, and 10 percent, respectively

spatial lag of GDP per capita. Our results show that the initial income of neighboring regions has a significant effect on the club formation. Table 6 indicates that an increase in neighbors' income increases the probability of joining Club 2 and Club 3, and decreases the probability of joining Club 4 and Club 5. Besides, investment per capita is still significantly related to club membership.

In our final specification (Table 7), we add the spatial lags of all of the explanatory variables. In terms of growth fundamentals, investment per capita in neighboring regions is significantly related to the probability of joining high-income and lower-middle-income clubs. Interestingly, human capital in neighboring regions only increases the probability of joining the lower-middle-income club. At first sight, this result may appear unintuitive as higher human capital in neighboring regions is associated with joining a lower-middle-income category (that is, Club 4). Nevertheless, this negative spatial dependence could be interpreted as a process of spatial competition (Elhorst and Zigova 2014; Griffith 2019; Griffith and Arbia 2010). Regions may compete in terms of attracting skilled workers from other regions. Specifically, the neighbors of a low-income region may increase their human capital by attracting (reducing) the relatively few skilled workers that live in surrounding low-income regions. In that case, the region that loses more skilled workers is more likely to join a lower-income club.

In terms of the structural change variables, let us recall that the baseline model without spatial lags showed that structural characteristics have an insignificant impact on club membership. However, after adding the spatial lags of all variables, some structural characteristics became statistically significant. This result highlights the importance of spatial spillovers in the process of structural change. Consistent with the findings of Cutrini (2019), an increase in the share of routine services increases the probability of joining the lower-middle-income club (that is, Club 4). Furthermore, the share of routine services in neighboring regions has a significant effect on club formation. While an increase in neighbors' routine services decreases the probability of belonging to a high-income club (Club 2), it increases the probability of joining a lower-middle-income club (Club 4). As the marginal effects of routine services and its spatial lag (*W* routine service share) are pointing to the same direction, provinces tend to show a pattern of spatial complementary. That is, when a region increases its routine service share, so do their neighbors, and jointly increase (decrease) their chances of joining a relatively low (high) income group such as Club 4 (Club 2).

In contrast, the share of knowledge-intensive services tends to show a pattern of spatial competition. That is, when both a region increases and its neighbors increase their knowledge-intensive service share, only the neighbors increase their changes of joining a high-income club. Although more detailed analyses of spatial complementary and spatial competition are beyond the scope of this paper, the consideration of spatial dependence enriches both the analysis of structural change and regional convergence. More granular regions, as well as larger time horizons, would favor these types of analyses.

In terms of the other control variables, the results are twofold. First, neither population density nor its spatial spillover (spatial lag) are statistically significant. This result, however, does not imply that economic agglomeration or urbanization are not relevant for the process of regional convergence. As these two conditioning factors are highly correlated with GDP per capita, investment per capita, and human capital; disentangling its specific marginal effect becomes difficult when using a relatively small sample size like ours. Despite this lack of statistical significance, the signs of their marginal effects show the expected direction: higher population density increases the chances of joining high-income clubs.

Second, compared to Table 6, the spatial lag of GDP per capita is not statistically significant. To some extent, this result is expected as some of the spatial lags of the growth fundamentals and structural change variables are already statistically significant. In Table 6, the spatial lag of GDP may act as a proxy for the spatial lag of capital accumulation and economic structure. Once these variables are included in the model, however, the role of the spatial lag of per capita GDP may become less relevant.

Finally, we can compare our results with the studies investigating the factors affecting club membership. In line with the results of Bartkowska and Riedl (2012), Von Lyncker and Thoennessen (2017) Aksoy et al. (2019), Cutrini (2019), Zhang et al. (2019), our results show that a higher initial income per capita increases the probability of joining high-income clubs, as expected. However, in contrast to studies of Bartkowska and Riedl (2012), and Zhang et al. (2020), which find an insignificant relationship for the spatial lag of income and club membership, our results show that the initial income of neighboring regions has a significant effect on the club formation. Regarding the impact of the routine and knowledge-intensive service share on club membership, our results are consistent with those of Cutrini (2019). Our results show that there is no significant relationship between human capital and club formation. This finding is inconsistent with that of Bartkowska and Riedl (2012), Von Lyncker and Thoennessen (2017) and Zhang et al. (2019), which show that higher human capital is significantly related to the probability of joining higher-income clubs. However, they are consistent with those of Aksoy et al. (2019) who report an insignificant relationship between human capital and club membership in Turkey. Lastly, our results are consistent with the findings of Bartkowska and Riedl (2012), Aksoy et al. (2019), Zhang et al. (2020) in the sense that higher capital stock per capita increases the probability of joining high-income clubs.

5 Concluding remarks

This paper studies regional income convergence and its conditioning factors across 81 provinces of Turkey over the 2007–2019 period. Through the lens of the nonlinear dynamic factor model of Phillips and Sul (2007), we first test the hypothesis that all provinces would eventually converge to a common long-run equilibrium. We reject this hypothesis and find that the provincial dynamics of income per capita are characterized by six convergence clubs. The spatial distribution of the convergence clubs strongly indicates an east-west divide. This pattern is also consistent with our analysis of local spatial dependence, which indicates that clusters of high (low) income are located in the northwest (southeast) part of the country.

We next evaluate the conditioning factors behind club formation and the role of spatial dependence. Our results suggest that spatial dependence across provinces plays an important role in the formation of convergence clubs. In particular, the dynamics of the provincial income distribution appear to be spatially integrated. That is, there are significant synchronous co-movements between a region and its neighbors in the evolution of the provincial income distribution. Moreover, these co-movements are more frequent in high-income and upper-middle-income clubs.

When studying the factors conditioning club membership without accounting for the role of spatial dependence, we find that only initial GDP and investment per capita are significant predictors of club membership. Consistent with our previous spatial dependence results, we find that the initial income of neighboring regions has a significant effect on the formation of convergence clubs. Moreover, we find that the performance of geographical neighbors affects the probability of club membership through spillovers in capital accumulation and structural change.

In terms of policy implications, although various policies have been implemented to reduce regional disparities, inequality across provinces is still a matter of concern for policy makers in Turkey. The existence of multiple convergence clubs confirms that disparities in income still exist, which could imply that current policies are still far from promoting a balanced process of regional development. Based on our results, which show the importance of investment for joining income clubs, both public and private investments are required in the eastern provinces. Our results also highlight the importance of investment in knowledge-intensive services. The successful structural change from low-value-added routine services to high-value-added knowledge-intensive services should be prioritized by regional governments. Furthermore, local development policies need to be implemented considering the composition of the local convergence clubs. Regional development agencies should be more effective and cooperate with local companies, universities, and local public authorities. The fact that high-income convergence clubs are generally located in the west while low-income convergence clubs are located in the east confirms a persistent east-west divide in economic development. Thus, policy makers need to consider geographical interactions across regions when forming regional development policies.

Appendix

1. Clustering algorithm for club identification

1. Cross-sectional ordering: Sort the economies in decreasing order based on their last observation.
2. Core group formation: Select the first k highest economies in the panel to form the subgroup G_k for some $2 \leq k < N$ and apply the log-t regression to obtain the

convergence test statistic $t_k = t(G_k)$ for this subgroup. Then, choose the core group size k^* by maximizing t_k over k according to the criterion $k^* = \mathrm{argmax}_k \{t_k\}$ subject to min $\{t_k\}\rangle - 1.65$. t_k indicates the one-side t-statistic that is needed to evaluate the statistical significance of the convergence test. If $t_k > -1.65$ is not valid for $k = 2$, then the highest economy is dropped from the core group and the algorithm can be repeated again for the rest of the sample.

3. Sieving economies for club membership: The remaining economies are added to the core group G_k one by one and the log-*t* test is executed again Eq. (5). When the economy is added, a new group is formed if the *t*-statistic is greater than − 1,65.
4. Recursion and stopping: Form the new group consisting of all economies that could not be selected in Step 3, and apply log-*t* test for this subgroup. If $t_k > -1.65$, it indicates that two convergence subgroups exist. Otherwise, if the null hypothesis of convergence is rejected, Step 1 to 3 are repeated. If no core group is found, then the remaining economies are labeled as divergent and the algorithm stops.
5. Club merging: Run the log-*t* test for all pairs of initial clubs. The merging procedure is iterative. That is, the log-*t* test is applied for the initial clubs 1 and 2, and if they fulfill the convergence test jointly, they should be merged into a new. Repeat this merging procedure for the remaining clubs until the convergence test is rejected.

2. List of convergence clubs

See Table 8

Table 8 List of convergence clubs

Club	Provinces
Club 1 (2)	Ankara , Tekirdag
Club 2 (17)	Aksaray, Antalya, Ardahan, Bilecik, Bolu, Bursa, Canakkale, Eskisehir, Izmir, Karaman, Kirklareli, Konya, Manisa, Mugla, Sakarya, Usak, Yalova
Club 3 (31)	Adana, Afyonkarahisar, Amasya, Artvin, Aydin, Balikesir, Bartin, Bayburt, Bingöl, Burdur, , Cankiri, Denizli, Duzce, Edirne, Erzincan, Gaziantep, Igdir, Isparta, Kastamonu, Kayseri, Kilis, Kirikkale, Kirsehir, Kutahya, Mardin, Mersin, Nigde, Rize, Sivas, Trabzon, Tunceli
Club 4 (18)	Corum, Elazig, Erzurum, Giresun, Hakkari, Hatay, Kahramanmaras, Karabuk, Kars, Malatya, Nevsehir, Ordu, Osmaniye, Samsun, Sinop, Sirnak, Yozgat, Zonguldak
Club 5 (9)	Adiyaman, Batman, Bitlis, Diyarbakir, Gümüshane, Mus, Siirt, Tokat, Van
Club 6 (2)	Agri, Sanliurfa
Non convergent group (2)	Istanbul, Kocaeli

Number of provinces are in the parenthesis

3 Measurement of global and local spatial dependence

3.1 Global spatial dependence

For any period t, the global Moran's I statistic is defined as follows:

$$I_t = \frac{N}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \left[\frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}\left(X_i - \bar{X}\right)\left(X_j - \bar{X}\right)}{\sum_{i=1}^{n} \left(X_i - \bar{X}\right)^2} \right] \tag{7}$$

where N is the number of regions, w_{ij} is an element of a spatial weight matrix (W) that defines the neighborhood structure between each pair of regions, X_i and X_j indicate the income values of regions i and j, respectively; and $\bar{X}$ is the average value of income.

3.2 Local spatial dependence

For any period t, the local Moran's I statistic is defined for each region i as follows:

$$I_{it} = \left(\frac{X_i - \bar{X}}{m_o} \right) \sum_{j=1}^{n} w_{ij}\left(X_j - \bar{X}\right) \text{ with } m_o = \sum_{i=1}^{n} \frac{\left(X_i - \bar{X}\right)^2}{n} \tag{8}$$

where the notation follows that of Eq. 7.

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Declarations

Conflict of interest The authors declare no competing interests.

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