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Regional Inequalities in Greece During a Time of Flux

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Abstract

Following the 2008 global financial crisis Eurozone countries and specifically countries at the periphery suffer severely reminding the rise of depression economics among the region. Originating from its fiscal troubles Greece is one of the countries which has been heavily hit by the adverse effects of the crisis. Keeping discussions on the macroeconomic fundamentals of Greece on one side, this study diverts the attention towards the extent and path of regional inequalities with specific focus on the post 2000 turmoil period in Greece. Our findings indicate the existence of a long convergence episode in Greece from 1980s and onwards with no exception during the crisis. We also find strong evidence for the existence of spatial spillovers with some cyclical behaviour. However, our additional analyses identify that spatial dependence and heterogeneity works together for the Greek case, resulting in sizable spatial variability in the speed of convergence accelerating during the post crisis period. Moreover, we discuss that observed post crisis convergence is a downward one which shifts its geographic extent reminding the possibility of a reshuffling among the Greek regions.

JEL Codes: R10, R11

Keywords: Convergence, Greece, spatial inequalities.

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Kriz Döneminde Yunanistan'da Bölgesel Eşitsizlikler

Öz

2008 küresel krizi sonrası Avrupa bölgesinde çevre ekonomileri olarak tanımlanan ülkelerin krizden daha fazla etkilenmiş olduğu görülmektedir. Bununla birlikte durgunluk ekonomisinin derin etkilerinin bölgede görülmeye başladığı tartışılmaktadır. Yunanistan'ın mali sorunları ile birlikte krizden en çok etkilenen Avrupa ülkelerinin başında geldiği de ayrıca bilinmektedir. Bu çalışma tüm bu tartışmalara ek olarak Yunanistan'da bölgesel eşitsizliklerin ilgili dönemde nasıl ilerlediğine odaklanmaktadır. Bulgular Yunanistan'da 1980'lerde başlayan ve 2000'li yıllarda hızlanan bir yakınsamanın varlığını göstermektedir. Ek olarak tüm dönem boyunca mekânsal dışsallıkların etkin olduğu görülmektedir. Ancak mekânsal bağlar ve heterojenlikler yakınsama hızında yüksek varyasyon oluşmasına neden olmaktadır. Bu yapı içinde yakınsamanın bir kulüp oluşumuna neden olduğu ve bölgelerin yakınsama patikaları ile mekânsal refahları arasında bir ilinti olduğu görülmektedir. Bu etkinin kriz sonrası dönemde daha da şiddetlendiği görülmekte ve yakınsamanın aşağı doğru bir yakınsama olduğu düşünülmektedir.

JEL Kodları: R10, R11

Anahtar kelimeler: Mekânsal eşitsizlikler, yakınsama, Yunanistan

1. Introduction

In recent years Greece has attracted much publicity and policy analysis due to its ongoing fiscal difficulties and the deep economic crisis it has experienced since 2009 – having lost almost a quarter of its GDP in the space of five years. Quite naturally, given the challenges facing Greece in relation to its Eurozone membership, attention in the relevant policy and academic debates has focused predominantly on questions that have to do with national development problems and national growth dynamics. An interesting – if not disconcerting – consequence of this has been that attention to regional evolutions and problems has been at best peripheral – especially outside the regional-scientific community in Greece. In relation to the latter, a body of work has slowly started to emerge looking at the regional economic impact of the crisis in the country (Monastiriotis, 2011; Monastiriotis and Martlelli, 2013; Psycharis et al, 2014a; Psycharis et al, 2014b; Monastiriotis, 2014; Karahasan and Monastirotis, 2017). However, a wider and more extensive study of the regional responses to the crisis and the adjustments that took place across space at the sub-national level during this period, let alone an examination for how these may link to longer-run distributional dynamics and past regional evolutions, is notably missing from the literature.

Our screening of the literature confirms that Greece has been under investigated by the literature on regional disparities in Europe. One battery of the discussions follows the ‘neoclassical convergence’ tradition. For instance, Siriopoulos and Asteriou (1998), Petrakos and Saratsis (2000), Ioannides and Petrakos (2000), Michelis et al (2004), Christopoulos and Tsionas (2004), Benos and Karagiannis (2008) and Lolos (2009) use different versions of the neoclassical convergence model and confirm the existence of a catch up effect across the Greek regions. While these studies carry out a detailed discussion on the path of the regional disparities, a related dimension of the process is examined within the spatial and distributional dynamics of income distribution. Tsionas (2002) and Alexiadis and Tomkins (2004) used different versions of Markov chain analysis and highlighted that despite continuous signs of convergence at global level different episodes from 1970 and onwards witness the formation of convergence clubs thus regional income polarization.

Despite these influential attempts to examine the regional disparities in Greece, there seems to be lack of detailed analysis of the local variations of the regional dynamics. That is both spatial spillovers as well as spatial heterogeneity can be crucial aspects of inequalities and distributional dynamics both of which are possible influences on the formation of local policies. We believe investigating the regional disparity issue and measuring the extent of spatial ties are both complementary analysis that can be even augmented by the inclusion of the examination of local variations.

Originating from this gap, in this paper we seek to make a contribution in this direction by providing a more holistic analysis of regional evolutions and growth dynamics in Greece, within a spatial economic analysis context, for the 1980-2012 period. This we believe will allow us to understand the peculiarity of the post crisis environment in Greece compared to other sub-intervals. We start by an examination of sigma- and beta-convergence, but examine simultaneously the role of space (in the form of proximity and spatial association) in conditioning the pace and extent of convergence. At this stage we aim at incorporating the impact of spatial spillovers through the use of spatial econometrics tools. However, we find it noteworthy to remark that, diverting the attention towards to the spatial variability issue is the central expected contribution of the article. Using the Geographically Weighted Regression (GWR) approach we calculate the spatial variability of the beta convergence and question whether each region of Greece realize the same level of convergence (or divergence) in terms of regional inequalities. Finally, we also examine a spatially augmented version of transition probability analyses to evaluate the extent of club convergence.

Throughout our analysis we look at the issues under study across four separate periods, starting from 1980, the year before Greece's accession to the EU, and going up to 2012, which is reasonable close to the point representing the height of the crisis.[1] This allows us to investigate in depth two issues that we see as interrelated.[2] First, the patterns of regional growth and the spatial dynamics underpinning them over the long-run period, i.e. in the 'good times' before the eruption of the crisis. Second, the regional responses to the crisis and the adjustments that took place across space at the sub-national level during the crisis period.

Our analysis reveals a number of interesting findings that have never before been considered for Greece – and are indeed rather understudied also in the international literature more widely. We find that Greek regions are undergoing a period of convergence since 1980s but also we identify that this speed of convergence has a spatio-temporal pattern that varies among different sub periods and midst different geographies. This we believe complements the previous findings/literature and also sheds new light on the understanding of regional growth processes and dynamics in the country. Additionally, we find spatial dependence as an ingredient part of the regional convergence in Greece. On the other hand, we also find strong empirical evidence on the spatial heterogeneity of regional income differences as well as the speed of convergence. Specifically, in relation to the crisis period, we further find that speed of

[1] At the national level, the rate of decline in real GDP subsided significantly after the first quarter of 2013 and was essentially reversed by the end of that year (indeed, in 2014Q1 Greece registered a positive growth rate for the first time since the start of the crisis).

[2] Our argument here, as we discuss more fully later in the paper, is that the regional responses and adjustment patterns during the crisis should not be seen as independent from the dynamics and evolutions that characterised the pre-crisis period. Studying these two in isolation (i.e., separately for the crisis and pre-crisis periods) thus reduces, in essence, the informational value of the analysis.

convergence accelerates in all parts of the country yet reversed in terms of its relative speed in some specific regions of the country, which suggests that regional problems may persist well beyond the prospective / hoped-for “Grecovery”.

The structure of the paper is as follows. Section 2 starts with a presentation and discussion of our method (with more attention paid to those parts of our approach that have not been too widely applied in the literature), the case at hand (especially talking about the four periods and the Greek political-economic context in each of these) and our data (information about sources and comparability issues – basic descriptives are presented later). Section 3 presents (some descriptives and) our base results on the issue of convergence and evidence on the extent and structure of regional disparities (sigma-convergence and decomposition). Section 4 constructs the traditional beta convergence models and implements two different extensions by incorporating the role played by the spatial ties. First we augment the traditional convergence models by controlling for spatial dependence, next we aim at using spatial heterogeneity concept in order to question the local instability of the convergence. Section 5 carries out a set of transition probability analyses to understand the extent of club convergence during the period of analysis. We also consider the spatiality of the transitions in order to test whether the club formation has a distinct geographical pattern. The last section concludes with some reflections on the dynamics of regional growth in Greece and the role of the crisis – and of the prospective recovery – in these.

2. Data and Methodology

In order to better apprehend the evolutions for the post 2000 period, we decide to follow a strategy to understand the historical origins of the regional imbalances in Greece. We consider the post 1980 period by investigating the developments in four different sub-intervals. In that sense while 1980-1990 sheds light on the roots of the inequalities during the accession to European Union, 1990-2000 period summarizes the path of inequalities in Greece during its so called good times right before our focus period. 2000-2008 interval will give in-debt overview of the environment with entrance to European Monetary Union (EMU) in 2001; naturally this period will give information on the pre-crisis environment. Finally post 2008 period represents the central focus of the study on the impact of the debt crisis on the regional imbalances in Greece. Data for the pre 2000 period comes from Cambridge Econometrics (CAMECON) and for the post 2000 period we used the official statistical data base of Hellenic Statistical Authority (ELSTAT).

In general, the “convergence” framework relies on the decreasing returns principle of the neoclassic production function (Solow, 1956). Later on Barro and Sala-i Martin (1992) formalize the convergence model; that is cross country as well as regional differences can be explained based on two specific convergence measures. Sigma convergence is a dispersion figure which basically measures the cross section standard deviation. Beta convergence on the other hand constructs a relationship between the initial income level of regions with an average rate of growth for a given time interval. Equation 1 is the traditional beta convergence model, where $y_{i,0}$ is the per capita income of region i in the initial year and T is the time span of the analysis. The left hand side of equation 1 measures the growth rate of per capita income, α is the constant, $\left(1-e^{-\lambda T}\right)$/T is the coefficient of the initial income that we denote by β and finally $u_{i,t}$ is the error term. Model measures the unconditional (absolute) convergence; a negative value for β represents the absolute beta convergence. Note that it is also possible to calculate the speed of convergence and the half –life of convergence by λ and t^{*}.

$$\frac{1}{T}\ln\left(\frac{y_{i,T}}{y_{i,0}}\right)=\alpha+\frac{1}{T}\left(1-e^{-\lambda T}\right)\ln\left(y_{i,0}\right)+u_{i,t}\ ;\ \lambda=-\frac{\ln(1+\beta.T)}{T}\ ;\ t^{*}=-\frac{\ln(1/2)}{\lambda} \qquad [1]$$

While sigma and beta convergence measures are commonly used, another measure that can yield additional on the source on the inequalities is the Theil Index (Bourguignon; 1979). Theil Index (Equation 2) enables us to decompose the inequalities into inter and intra-regional inequalities by implementing a decomposition. y_i and x_i are the relative shares provincial income and population thus measures the between inequalities. Meanwhile Y_g is the region g's share in total national income and T_g is the Theil Index that measures disparities among provinces in region g.

$$T=\sum_{i=1}^{n}y_i\log\left(\frac{y_i}{x_i}\right)+\sum_{g=1}^{n}Y_gT_g \qquad [2]$$

Combes et al. (2008) pin point that spatial concentration measures can be a good proxy to underline agglomeration of economic activity. In a way rising spatial concentration can be treated as a proxy for divergence. Among different measures Moran's I spatial auto-correlation statistics is commonly used (Equation 3). *n* is the number of local units and *s* is the summation of the all elements in the weight matrix (*w*).[3]

[3] In addition to the measurement of the spatial association at the global scale, a further dimension of the spatial dependence is the local decomposition of the spatial dependence. Anselin (1995) proposed the use of Local Indicator of Spatial Association (LISA) in order to observe the local variation of the spatial dependence via; $I_i=\left(x_i-\bar{x}\right)\sum_j w_{ij}\left(x_j-\bar{x}\right)$. LISA analysis gives four major groups for local spatial association. Regions with above and below average income in spatial association forms the High-High and Low-Low clusters while regions with high income in close proximity to low income regions and regions with low income in close proximity to high income regions are represented as High-Low and Low-High outliers respectively.

$$I_i = \frac{n}{s} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum (x_i - \bar{x})^2} \quad [3]$$

While spatial auto-correlation measure contains information on the extent of the spatial inequalities, there are additional motives embedded within spatial ties and spillovers. The neoclassic convergence model presumes that regions are isolated and no spillover among them takes place. Rey and Mountouri (1999) discuss that neglecting the impact of spatial effects may cause in biased estimates of the true speed of convergence. Indeed the convergence model introduced in Equation 1 can be further augmented by including the impact of spatial dependence. Spatial Lag Model (SAR) and Spatial Error Model (SEM) can be estimated in an unconditional way as in Equations 4 and 5 respectively.

$$\frac{1}{T}\ln\left(\frac{y_{i,T}}{y_{i,0}}\right) = \alpha + \rho W \frac{1}{T}\ln\left(\frac{y_{i,T}}{y_{i,0}}\right) + \frac{1}{T}\left(1 - e^{-\lambda T}\right)\ln\left(y_{i,0}\right) + u_{i,t} \quad [4]$$

$$\frac{1}{T}\ln\left(\frac{y_{i,T}}{y_{i,0}}\right) = \alpha + \frac{1}{T}\left(1 - e^{-\lambda T}\right)\ln\left(y_{i,0}\right) + \lambda W \varepsilon + u_{i,t} \quad [5]$$

Even spatially augmented versions of the convergence models earn increasing attention, recent discussions shift towards to the instability of the convergence. That is, even the spatial convergence models incorporate the spatial dependence, they neglect and fail to control for the possibility of the spatial heterogeneities and/or spatial non-stationarity. This may result in over/under representation of convergence as it is possible to observe spatial variation in the measured speed of convergence. The problem of spatial heterogeneity can be best controlled for by the use of the Geographically Weighted Regression (GWR) approach. As discussed by Brunsdon et al. (1998), Fotheringham and Brunsdon (1999), Fotheringham et al. (2002) GWR allows in the estimation of local parameter estimates. Equation 6 is a different way of measuring convergence in a GWR setting allowing for the determination of local beta estimates for each region.

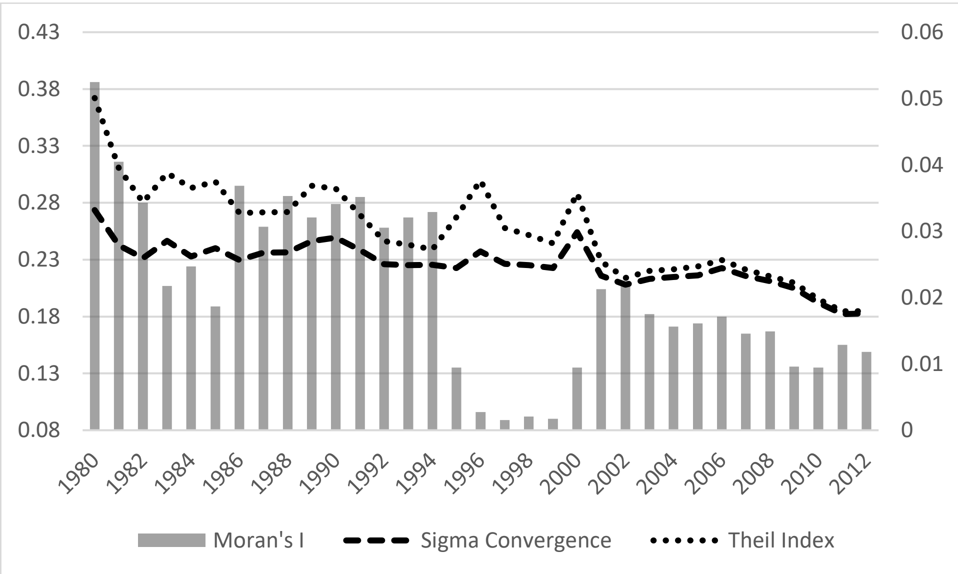
$$\frac{1}{T}\ln\left(\frac{y_{i,T}}{y_{i,0}}\right) = \alpha\left(u_i, v_i\right) + \frac{1}{T}\left(1 - e^{-\lambda T}\right)\left(u_i, v_i\right)\ln\left(y_{i,0}\right) + u_{i,t} \quad [6]$$

GWR is a weighted regression where related weights are determined by the neighbour effects. The crucial item is the determination of the neighbour effects through a bandwidth and a kernel. The bandwidth which is embedded in the kernel defines the units to be considered as neighbours. Note that a kernel can be adaptive and fixed, while an adaptive kernel uses the bandwidth to consider a given number of units as connected, a fixed kernel considers units as interconnected within a fixed distance. The optimal bandwidth is selected by using different criterions such as Akaike Information Criteria (AIC), Bayesian Information Criterion (BIC) and Cross Validation (CV).[4] This recent advance in spatial econometrics finds popularity among regional scholars investigating the convergence issue. For instance, Bivand and Brunstad (2005) for Europe, Paraguas and Dey (2006) for India, Eckey et al. (2007) for Germany, James and Moeller (2013) for United States (US) and Artelaris (2015) for Europe validate sizable spatial instabilities in the speed of convergence.

3. Regional disparities and spatial dynamics: descriptive patterns

Since our study covers a long time-period, we start our analysis with a set of descriptive measures concerning three inter-related issues: the nature and evolution of regional disparities; the distribution of regional incomes and changes therein; and extent of spatial associations (clustering, hotspots) in the country.

Figure 1. Aggregate measures of regional disparity and spatial association



Notes: Moran’s I left axis, Sigma Convergence, Theil Index right axis
Source: CAMECON, ELSTAT, Authors’ own calculations

[4] See Fotheringham et al. (2002) for a detailed discussion on the background of GWR and the use of adaptive and fixed kernel functions. See also Nakaya et al. (2005) and Nakaya (2014) for further discussions on testing the variability of the coefficient estimates.

As is depicted in Figure 1, regional disparities at the NUTS3 level were reasonably high at the start of the 1980s and remained rather stable throughout the decade. Since their peak in 1990s, however, regional disparities followed a declining trend almost uninterruptedly until 2002.[5] The trend appeared to reverse in the early 2000s, but resumed more intensively since 2007, i.e., with the eruption of the crisis in Greece. This pattern is consistent across measures of inequality (standard deviation, showing sigma-convergence and the Theil index, for which the trends appear to be generally steeper) and is also consistent with findings elsewhere in the literature using other measures of regional performance (e.g., Monastiriotis, 2014).

These results are also confronted by the general structure of the distribution given in Table 1. Given a rise in the average per capita income in the pre-crisis period, there tends to evolve an overall tendency of fall in the variation of the distribution. Moreover, the range of the distribution seems to shrink, together with the rise in the min-max ratio indicating an overall improvement in terms of inequalities. Yet the fall in the average income in the post-crisis environment reminds that there is a possible reshuffling of per capita income distribution.

Table 1. Dispersion of per capital GDP (*in ln.*)

	Range	Min/Max	Mean
1980	1.493	0.852	9.037
1990	1.311	0.868	9.083
2000	0.960	0.903	9.279
2008	0.936	0.911	10.016
2012	0.914	0.913	9.891

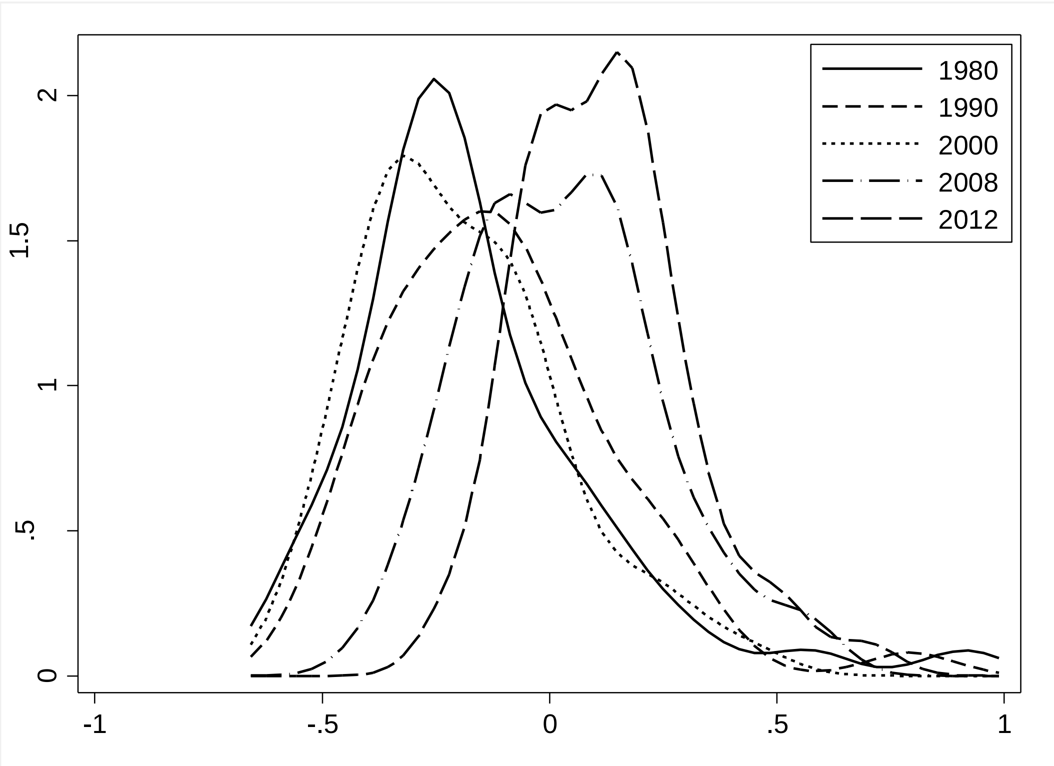
Source: CAMECON, ELSTAT, Authors' own calculations

We can examine further these movements by looking directly at the distribution of regional incomes in the country and its persistence over time / across the four periods under consideration. A convenient way to implement this is with the use of fitted Kernel density functions, as depicted in Figure 2. As can be seen there tends to be a movement towards a bi-model distribution for the post 2000 period. In a way for the pre 2000 period the distribution is rather more uniform with a tighter distribution in 1980. For both 1990 and 2000 there seems to be limited yet significant clustering in the right tails reminding the possibility of the marginalization of some high income regions. On the other hand, two post 2000 era seems to witness a relatively more dispersed pattern realizing a bi-

[5] Note that the peak in 2000 is in part related to the switch in the data sources used and should be read with caution.

modal distribution which becomes even more visible during the crisis period of post 2008. This reminds us the possibility of a club formation in a way expressing different set of regions of converging to different long run states. Additionally, it seems to be also reasonable to link this with the pattern that we detect in the acceleration of the min-max ratio for the post 2000 period. Even usual inequality measures signal possibility of a decline in regional imbalances, it is vital to note that this period of decline in inequalities especially becoming more visible during the crisis period is a way creating a somehow dual structure in Greece in terms of regional differences.

Figure 2. Distribution of regional incomes (Kernel densities)



Source: CAMECON, ELSTAT, Authors’ own calculations

These observations to some extent are consistent with the picture we obtain with regard to the persistence of regional rankings using a simple Spearman rank correlation analysis given in Table 2. We find an overall persistence coefficient of 0.293 for the full 1980-2012 period. In general, between 1980 and 1990 there is sizable persistence which tends to weaken during the 1990-2000 period, yet accelerated once again after the post 2000 period. In terms of the impact of the crisis we report the highest persistence during this period.

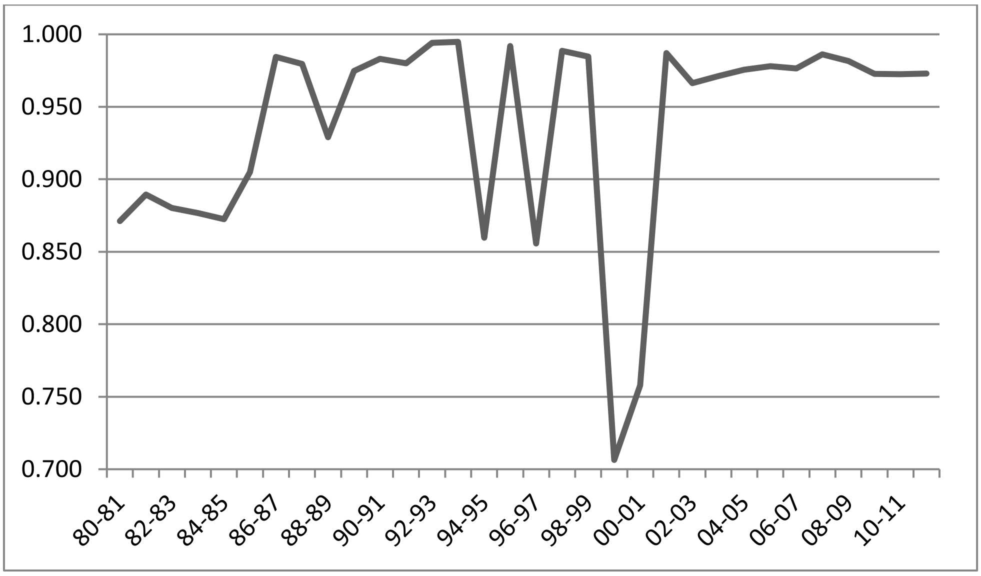
Table 2. Historical Persistence of Regional Inequalities

	1980	1990	2000	2008	2012
1980	1.000				
1990	0.780	1.000			
2000	0.344	0.566	1.000		
2008	0.317	0.507	0.762	1.000	
2012	0.293	0.431	0.747	0.939	1.000

Source: CAMECON, ELSTAT, Authors' own calculations

Year-to-year persistence is of course much higher; ranging between 0.87 and 0.98. In general, the short-run persistence of income distribution accelerates during the early 1990 and thereafter realizes a cyclical period between 1990 and 2000 and then once again a period of high but stable persistence during the 2000-2012 period. Interestingly over the whole period the lowest persistence both in terms of historical persistence (Table 2) as well as year-to-year short term persistence (Figure 3) is observed during the end of 1990s while Greece was accessing to EMU.

Figure 3. Year-to-year Persistence of Regional Inequalities

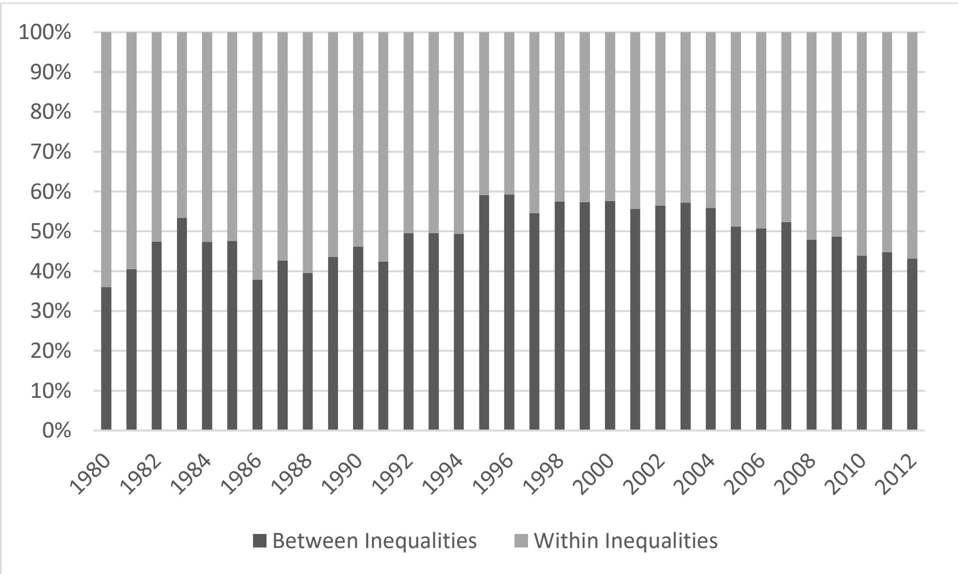


Source: CAMECON, ELSTAT, Authors' own calculations

Besides these questions concerning attributes of the distribution of regional incomes (standard deviation, max/min ratio, persistence, etc), it is also useful to examine the location of regional disparities, both in the sense of whether these concern macro-geographical versus micro-geographical (i.e., localised) patterns and in relation to the wider spatial dynamics underpinning them (i.e., spatial clustering and heterogeneity). As mentioned previously, the use of the Theil index allows us to perform a decomposition of inequalities between their intra-NUTS2 ('within') and extra-NUTS2 ('between') components.

As is shown in Figure 4, intra-NUTS2 inequalities are sizeable (typically, above 50%) and, although declining in the slow convergence period (1986-1996), they have been actually on the rise in the more recent period of fast convergence. This suggests that macro-geographical disparities (across NUTS2 regions) are only a part of the story of regional disparities in Greece – suggesting in turn that the latter is not only a story of spatial heterogeneity but rather of localised inequality. Macro-geographical disparities have further declined faster during the crisis, thus accounting for a larger proportion of the overall decline in regional disparities in this period.

Figure 4. 'Within' and 'between' components of regional disparity



Source: CAMECON, ELSTAT, Authors' own calculations

Another way of looking at the issue of regional heterogeneity is by examining the extent of spatial clustering, or association, by means of the Moran's I statistic (Figure

1).[6] Following the early remarks of Karahasan and Monastirotis (2017) we observe that the behaviour of the spatial clustering has been more cyclical, exhibiting a steep decline and then fast rise around the mid-1980s; relative stability until 1994; a sizeable deep in the years 1995-2001, which coincide with Greece's adjustment period for entry into the Eurozone; and restoration of spatial association in 2002 with a continuous declining trend thereafter. In all cases, and especially in the post-2008 period, the level of spatial association appears very low, suggesting weak and limited spatial clustering in the country – which is consistent with the results of the Theil decomposition.

Table 3. Spatial Auto Correlation Results (Per capita GDP)

	Moran's I (stats.)		**LISA Clusters (count)**				
	N2	**Inv. Dis.^2**	**Not Significant**	**High-High**	**Low-Low**	**High-Low**	**Low-High**
1980	0.462*** (0.109)	0.386*** (0.062)	44	5	2	0	0
1990	0.362*** (0.115)	0.279*** (0.066)	41	7	3	0	0
2000	0.336*** (0.124)	0.200*** (0.071)	45	5	0	0	1
2008	0.334*** (0.125)	0.167*** (0.071)	42	4	4	1	0
2012	0.260** (0.122)	0.149*** (0.070)	43	4	3	1	0

Notes: s.e. in (), ***, ** and * represents significance at 1%, 5% and 10% respectively. N2 and Inv. Dis^2 are k-nearest neighbour weight matrix (order 2) and an inverse distance weight matrix respectively.

This is further supported by more detailed analyses, derived from LISA calculations, which return only a handful (typically 3-5) of statistically significant 'hotspots' and 'spatial clusters' in any year. Table 3 gives the combined results for selected cut-off years. Note that we report the global spatial auto-correlation measure by using two different weight matrix specifications. For both we identify a fall in the spatial

[6] The statistic depicted here is based on an inverse distance spatial weights matrix.

association, yet it should be noted that in each year spatial dependence is observed to be lower for the inverse distance weight matrix with respect to a k-nearest weight matrix. This underlines the level of locality of the spatial association. Meanwhile, we also count the LISA scores of regions based on their significance as well as their magnitude by using inverse distance weight matrix.

Table 4. Persistence across Spatial Regimes

		High-High	Low-Low	High-Low	Low-High
GR113	**Rodopi**	0	1	0	0
GR115	**Kavala**	0	0	4	0
GR126	**Serres**	0	11	0	0
GR133	**Kozani**	0	0	13	0
GR134	**Florina**	0	0	5	0
GR141	**Karditsa**	0	6	0	0
GR144	**Trikala**	0	6	0	0
GR211	**Arta**	0	14	0	0
GR213	**Ioannina**	0	16	0	0
GR214	**Preveza**	0	4	0	0
GR221	**Zakynthos**	0	1	0	0
GR223	**Kefallinia**	0	10	0	0
GR224	**Lefkada**	0	2	0	0
GR231	**Aitoloakarnania**	0	1	0	0
GR233	**Ileia**	0	3	0	2
GR241	**Voiotia**	30	0	0	0
GR242	**Evvoia**	23	0	0	0
GR243	**Evrytania**	0	1	0	0
GR244	**Fthiotida**	12	0	0	0
GR245	**Fokida**	15	0	0	0
GR253	**Korinthia**	3	0	0	0
GR254	**Lakonia**	0	1	0	0
GR255	**Messinia**	0	6	0	0
GR300	**Attiki**	33	0	0	0
GR421	**Dodekanisos**	22	0	0	0
GR422	**Kyklades**	25	0	0	0

Even we detect very low number of significant spatial associations still our findings contain supportive information on the extent of the persistence. In Table 4 we count the number of years that regions are reported in given spatial regimes.[7] This will help in understanding the rigidity within the spatial regimes. In other words, this will contain

[7] We use k-nearest neighbor weight matrix for persistence analyses of the spatial regimes.

information about the possibility for one region to move to another spatial regime during the sample period. For instance, once we focus on the provinces with at least one year of observation with a significant spatial association, we identify that regions do not move within the distribution frequently. Additionally, our findings indicate that high income regions realize higher persistence with respect to low income ones. Note that there are very few cases where regions are locked in outlier geographies.

Thus, overall, our descriptive analysis leads us to a number of interesting observations with regard to regional disparities and spatial dynamics in Greece over the 30-year period under consideration. Regional disparities are relatively small and certainly declining over time. They are however significantly localised: although macro-geographical disparities are also present (and sizeable), the extent of within-NUTS2 inequality is comparatively very high. Moreover, it seems to be a case of a more bi-modal distribution for the post 2000 period, which reminds us the possibility of different spatial regimes. Still, evidence of significant localised polarisation, in the form of significant spatial 'hotspots' and 'outliers', is at best limited – as is the evidence concerning spatial clustering at large (global Moran's I) and in specific localities (LISA analysis). It all points to a pattern of 'spatial randomness', which is if anything intensifying with time / in more recent periods, in the sense that regional incomes do not follow strong distributional (disparities) or spatial (clustering) patterns. This motivates us to examine the issue of (disparities and) convergence more formally – while continuing to take into account spatial dynamics – as we do in the next section.

4. Regional Growth and Convergence

As mentioned previously, evidence on sigma convergence may mark disparate evolution in terms of growth dynamics; for example, the overall variance of the distribution of the regional income may be declining while at the same time specific regions may be experiencing cumulative growth advantage (implying essentially a tendency for club formation). This concern is also apparent via the bi-modality of the distribution during the post 2008 period as well as the high persistence detected in the local spatial association mainly among the already developed regions. Even the beta convergence is not expected to fully handle with the presence of club formation; in a way we believe our extensions for spatial heterogeneity of convergence speeds will contain sizable information on the formation of different regimes of convergence. In order to examine this, we turn to the examination of different variants of beta convergence. Table 5 gives the estimations results for the different time intervals considered in the previous section. We estimate initially the unconditional models which later we augment by controlling for population density, market size and regional accessibility. Results from non-spatial models indicate the presence of significant convergence in the entire sample in general. Only for the 1980-1990 period we report lack of significant convergence for the models conditioning for some geographical factors. Keeping this on one side, our results indicate rising speed of convergence once these regional factors are considered for the remaining intervals. However, it is remarkable that convergence tends to have a rather cyclical pattern that accelerates more during the 1990-2000 and 2008-2012 sub intervals.

As discussed before, the traditional convergence model rules out the possible impact of spatial diffusions. However, given the fall in transportation costs worldwide and based on the fact that physical and non-physical barriers to trade and connectivity diminishes during the last decades, neglecting the possible spatial spillovers may create distortions in evaluating the catch up attempt of the Greek regions. To account for the spatial dependence within convergence modeling we introduce a spatial lag and spatial error components to the convergence framework as outlined in Section 2. Our reasoning is that; spatial diffusion may work over regional growth rates or it can be the omitted factors and/or common shocks that are diffusing geographically creating some sort of a spatial spillover mechanism among Greek regions. Results given in Table 5 indicate that controlling for the impact of spatial ties does not impede the existence of convergence.[8] However, we observe that the speed of convergence is observed to be marginally lower once spatial dependence is controlled for. This is in a way in line with Rey and Montouri (1999) who reports marginal decline for the speed of convergence for US, with Arbia et al. (2005) and Arbia and Piras (2005) who demonstrate a fall in the speed of convergence once spatial lag of regional growth is included for the case of Italy and the European Union.

Even though using spatial variants of the traditional convergence model offers solutions to the spatial diffusion problem, still it does not propose a formal elucidation on the possible spatial instabilities. That is, up to this stage we presume that calculated speed of convergence may vary through time among different sub-intervals, yet we do not consider the possibility of the spatial heterogeneity which may create different convergence regimes among the Greek geography. This has been validated by the geographic variability (spatial variability) test which indicates that convergence speed for Greek regions is not dispersed homogenously. In a way this reminds us that conditioning on the spatial dependence may still underestimate the extent of the local differences. This result is parallel with Eckey et al. (2007) that demonstrates that convergence rates tend to vary geographically in Germany and more recently with Artelaris (2015) who underlines the spatial heterogeneity of convergence across the European Union countries. Inspired by these contemporary discussions and the possibility of observing local variations of convergence we extent our modelling strategy by using the Geographically Weighted Regression (GWR) approach. Our results reported in Table 5 are in supportive of our concerns; that the range between the

[8] Note that we do not report the full estimation results. These results which are available from authors upon request also show the significance of the spatial dependence (over rho and lambda) in the lag and error models. This once more validates the concerns on the existence of spatial diffusion which has been rarely considered formally within the traditional convergence model.

minimum and maximum speed of convergence varies both historically as well as geographically. For instance, during which convergence is observed to be fast there

Table 5. Regional Convergence

	1980-1990			1990-2000		
	β	λ	t^*	β	λ	t^*
Non-Spatial						
Uncd.	-0.022***	2.44%	28.45	-0.038***	4.83%	14.36
Cond.	-0.012	1.29%	53.68	-0.044***	5.78%	11.99
Spatial						
SAR	-0.017**	1.84%	37.74	-0.035***	4.28%	16.18
SEM	-0.018**	2.01%	34.44	-0.038***	4.85%	14.29
GWR						
Mean	-0.022***	2.44%	28.45	-0.039***	4.99%	13.90
1-Min	-0.033	4.01%	17.29	-0.048	6.51%	10.64
2-Max	-0.017	1.85%	37.40	-0.025	2.87%	24.15
3-Lower Quartile	-0.022	2.54%	27.34	-0.046	6.19%	11.20
4-Median	-0.018	1.96%	35.28	-0.043	5.55%	12.49
5-Upper Quartile	-0.017	1.91%	36.37	-0.034	4.18%	16.58
G. Var. Test	-30.409			-54.116		
	2000-2008			**2008-2012**		
	β	λ	t^*	β	λ	t^*
Non-Spatial						
Uncd.	-0.015***	1.64%	42.16	-0.041***	4.51%	15.38
Cond.	-0.030***	3.42%	20.28	-0.048***	5.33%	13.01
Spatial						
SAR	-0.015**	1.64%	42.34	-0.042***	4.62%	14.99
SEM	-0.016**	1.66%	41.65	-0.041***	4.45%	15.56
GWR						
Mean	-0.015***	1.63%	42.55	-0.035***	4.08%	16.99
1-Min	-0.031	3.55%	19.52	-0.044	4.79%	14.47
2-Max	-0.011	1.19%	58.48	-0.020	2.04%	34.05
3-Lower Quartile	-0.016	1.70%	40.71	-0.040	4.31%	16.07
4-Median	-0.013	1.42%	48.97	-0.036	3.89%	17.81
5-Upper Quartile	-0.012	1.28%	54.15	-0.031	3.36%	20.64
G. Var. Test	-205.082			-102.685		

Notes: ***, ** and * indicates the significance of the beta coefficient of the convergence models. For Geographically variability test (G. Var. Test) a positive value of diff-Criterion (AICc, AIC, BIC/MDL or CV) suggests no spatial variability in terms of model selection criteria. β, λ, t^* represents the coefficient of the initial per capita GDP, speed of convergence and half-life of convergence respectively.

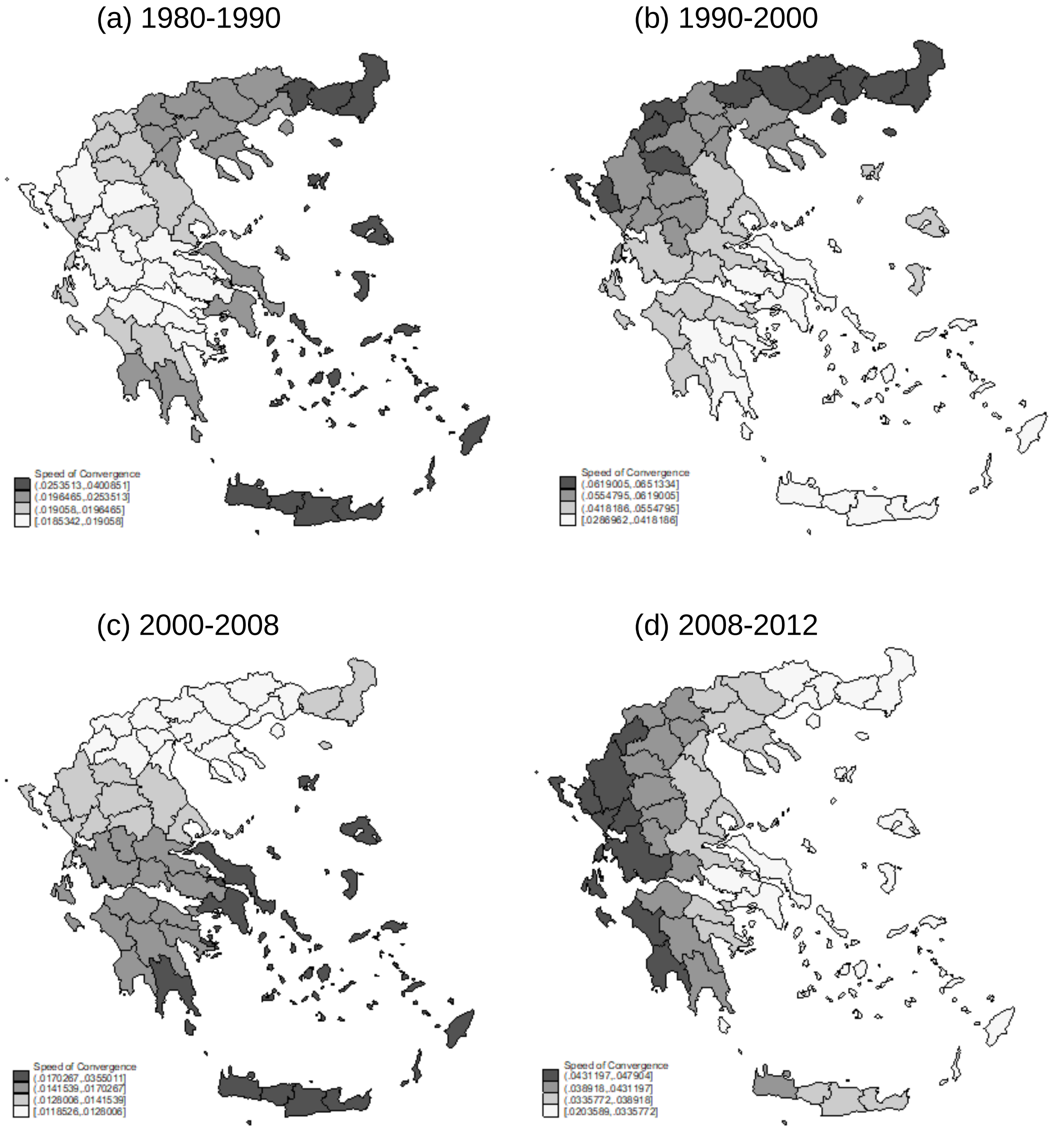
seems to be a range of 3.64% and 2.75% between minimum and maximum convergence speeds for 1990-2000 and 2008-2012 sub periods. The variation seems to be marginally smaller once the relatively slow convergence periods of 1980-1990 and 2000-2008 are considered (2.16% and 2.36% respectively). In a way during the fast convergence years (covering both 1990-2000 and 2008-2012) there are some regions in Greece that are able to close half of their gap with their steady states in 10 years but there are also some that have ability to get closer to their long run income levels by half in 34 years. In that sense our concerns on the spatiotemporal dynamics seems to prevail; not only the change in the speed of convergence through time matters but also it is a matter of fact that there are different local convergence experiences within specific time intervals.

At this stage, focusing on the post 2000 period yields a number of important information. Among the investigated four sub-intervals the pre-crisis period of 2000-2008 has the slowest speed of convergence reminding us a worsening of the distribution even before the start of the debt crisis. Yet for the aftermath of the crisis this time we tend to identify a bounce back of faster convergence. That said, in all cases we continue to identify the spatial variability of the speed of convergence. This suggests that even speed of convergence has a cyclical pattern among different sub-intervals; crisis environment does not have direct influence on the extent of the overall spatial heterogeneities. This brings additional concerns on the spatial distribution of the observed speed of convergence.

In order to understand whether there is a shift in the geography of convergence we compare the spatial variability of the speed of convergence for different time intervals given in Figure 5. Figure 5 identifies the spatial variability of speed of convergence supporting the concerns that geography of convergence moves historically. For instance, considering the relatively fast convergence in sub periods 1990-2000 and 2008-2012, it seems that there exists a north dominant convergence in the late 1990s whereas it turns out to be a clear west oriented convergence during the crisis periods of post 2008. However, note that the low convergence episodes of 1980-1990 and 2000-2008 Greece witness a relatively similar spatial variability in terms of convergence speeds.[9]

[9] In addition to the local variation of the beta coefficient and the speed of convergence, we implement the analysis of the local variation of the intercept and the R^2. Our findings show that like the spatial variability of the speed of convergence, both long run steady state growth rates (intercept) as well as the fit of the relationship (R^2) realizes substantial spatial variability. These results are available upon request.

Figure 5. Spatial Variability of the Speed of Convergence



Source: Authors' own calculations

5. Distributional Dynamics

While the descriptive analysis gives information on the periodical as well as spatial path of inequalities and different variants of the convergence models focuses on the ability for poor regions to catch up with the rich ones, all suffer from giving insufficient information on the distributional dynamics. Even investigating the evolution of the distribution is possible by observing the Kernel type distribution functions; still it is not possible to distinguish regions in terms of their mobility within the distribution. For instance, it would not be possible to identify if a poor/rich region in one year moves to an upper/lower income group in the subsequent year unless transition probabilities are considered. These types of movements within the distribution can be identified by the use of Markov Chain analysis which is offered as an alternative to the traditional convergence models by Quah (1993 and 1996). Quah (1993 and 1996) for a cross section of countries and US; Lopez-Bazo et al. (1999) and Le Gello (2004) for Europe applied the Markov Chain approach and identified the possibility of club formation in a way towards polarization unlike the strong convergence finding of the traditional neoclassical convergence approach.

Quah (1996) discuss that in addition to observing the probability of transition among different income classes, it is possible to identify a long run or ergodic distribution in a way to understand the tendency of the shape of the distribution in the long run. Additionally, as underlined by Quah (1996) different properties of the evolution of the distribution can be studied from the certain properties of the transition matrix. For instance, Ponzio and Di Gennaro (2004) and Monfort (2008) underlines that an indicator of speed can be calculated by using the second eigenvalue obtained from the transition probability matrix. This speed similar to convergence framework can be used to measure half-life of convergence. Finally, stability of the distribution can also be calculated by using the transition probability matrix. As discussed in Monfort (2008) stability index yields information on the stability of the distribution; summation of the all elements of the main diagonal of the matrix is normalized by the number of pre-determined states of the distribution.

While applying the Markov Chain framework a crucial point is the detection of the income classes through which transition are going to be traced. As discussed by Quah (1993) obtaining close number of observations in the initial year can be preferred while determining the cut-off grids. Therefore, we base our income groups by grouping regions based on the 75%, 90%, 100% and 115% of the per capita income of Greece in each year, which gives us the most uniform number of regions among income classes in the initial year.[10] Results are given in Table 6.

Overall, one notable finding is the general path of inequalities which is much or less identical to the one we detect during the convergence analysis. For instance, we continue to identify falling stability during the post crisis episode, with a half-life number more than two times lower than the one detected in 1980s. That said, specific transition probabilities contain some additional findings inhibiting the source of disparities. For example, probability of having any kind of upward mobility from the lowest income group is 28% in 1980s, while same probability jumps to 75% after the crisis. More interestingly considering mobility from middle income groups (income state 3); there is 32% of chance to move to a lower income group during 1980s, while upward mobility

[10] We also try different grids with different number of income classes. As mentioned in Lopez et al. (1999) there are also differences in our transition probabilities with different grids, yet they seem to have negligible influence on the qualitative analysis.

probability is just 14%. That said after the crisis probability for a region in the middle income group to fall to a lower income group is significantly lower and around 5%. On contrary upward mobility to a higher income region group is 20%. Keeping all these in mind it is worth underlining that observing an upward mobility from any income group seems to realize decreasing probability once average income rises. For instance, during the post crisis period, probability of an upward mobility for the lowest income regions are 75% compared to 18% for the regions in the middle income group. Note that during the other sub intervals we do not observe such a divergence between low and middle income regions' upward mobility probabilities. For 1980s there is 26% chance for regions in the lowest income group to move one state upwards within the distribution while same upward mobility probability is 14% for regions in the middle income group. This make us think on the source of higher convergence after the crisis; that the fast jump of the lowest income regions upwards within the distribution, matching with the drastic fall of average income during this period both suggest the possibility of a convergence towards the falling mean of the distribution.

While transition probabilities up to this stage gives sizable information suggestive of an improvement after 2000 (unlike the downgrading of 1980s), they can be developed further by also incorporating the possibility of spatial conditioning. Following Rey (2001) we consider a spatial lag conditioning and aim at measuring the transition probabilities once more, but this time conditioned on the income level of spatial proximity.

Our concern is that any upward mobility for a region can be higher if some other high income regions are in close proximity. We group spatial proximity into three groups (high, mid and low) and test whether locating close to regions with certain income levels affects the chances of transition probabilities and thus convergence. Indeed our findings (Table 7) are supportive of this concern. For instance, in 1980s and 1990s having middle income regions in close proximity decreases half-life to convergence relative to especially having low income regions in surrounding. During the pre-crisis period this time locating spatially linked to high income regions decreases half-life to convergence. That said even more interestingly during the post crisis episode things turn out just the opposite. Regions spatially linked to low income regions have the lowest half-life values suggesting that these regions are observing an even more drastic convergence attempt which once more fits into our concerns on the reshuffling of regional income patterns. Our results from different variants of Markov Chain analyses supports the existence of convergence, partially in the form of a club formation which can be explained by the geographical and economic differences of the spatial proximity.

Table 6. Traditional Markov Chain Analysis

			1980-1990				
	1	**2**	**3**	**4**	**5**		
1	0.72	0.26	0.02	0.00	0.00	Stability	0.73
2	0.14	0.68	0.16	0.01	0.01	Index	
3	0.00	0.32	0.53	0.14	0.01	Convergence	0.23
4	0.00	0.03	0.10	0.79	0.08	Index	
5	0.00	0.00	0.02	0.06	0.92	Half-life to	10.33
Int. Dist	0.208	0.367	0.159	0.139	0.127	Steady State	
Erg. Dist.	0.140	0.286	0.149	0.181	0.243		
			1990-2000				
		1	**2**	**3**	**4**	**5**	
1	0.88	0.10	0.01	0.01	0.00	Stability	0.76
2	0.13	0.77	0.09	0.01	0.00	Index	
3	0.03	0.20	0.63	0.13	0.00	Convergence	0.24
4	0.02	0.02	0.19	0.70	0.06	Index	
5	0.00	0.00	0.07	0.13	0.80	Half-life to	5.56
Int. Dist	0.251	0.296	0.182	0.182	0.088	Steady State	
Erg. Dist.	0.403	0.321	0.143	0.100	0.032		
			2000-2008				
	1	**2**	**3**	**4**	**5**		
1	0.72	0.28	0.00	0.00	0.00	Stability	0.78
2	0.03	0.81	0.16	0.00	0.00	Index	
3	0.00	0.02	0.59	0.39	0.00	Convergence	0.22
4	0.00	0.00	0.03	0.81	0.16	Index	
5	0.00	0.00	0.00	0.03	0.97	Half-life to	5.38
Int. Dist	0.194	0.328	0.137	0.194	0.147	Steady State	
Erg. Dist.	0.000	0.001	0.011	0.166	0.822		
			2008-2012				
	1	**2**	**3**	**4**	**5**		
1	0.25	0.75	0.00	0.00	0.00	Stability	0.66
2	0.03	0.59	0.38	0.00	0.00	Index	
3	0.00	0.05	0.75	0.18	0.02	Convergence	0.39
4	0.00	0.00	0.04	0.75	0.21	Index	
5	0.00	0.00	0.00	0.04	0.96	Half-life to	4.52
Int. Dist	0.020	0.167	0.216	0.260	0.338	Steady State	
Erg. Dist.	0.000	0.004	0.030	0.165	0.801		

Notes: Int. Dist., Erg. Dist. represents initial and ergodic distributions respectively.

Table 7. Spatial Markov Chain Analysis

				1980-1900								1990-2000		
		1	**2**	**3**	**4**	**5**			**1**	**2**	**3**	**4**	**5**
Low	**1**	0.73	0.23	0.03	0.00	0.00	**Low**	**1**	0.93	0.05	0.00	0.01	0.00
	2	0.19	0.70	0.09	0.00	0.01		**2**	0.10	0.81	0.07	0.02	0.00
	3	0.00	0.37	0.53	0.05	0.05		**3**	0.00	0.29	0.71	0.00	0.00
	4	0.00	0.00	0.00	0.80	0.20		**4**	0.07	0.07	0.07	0.80	0.00
	5	0.00	0.00	0.11	0.11	0.78		**5**	0.00	0.00	0.00	0.20	0.80
	Erg.	0.25	0.34	0.12	0.11	0.15		***Erg.***	0.52	0.31	0.09	0.06	0.00
Mid.	**1**	0.68	0.32	0.00	0.00	0.00	**Mid.**	**1**	0.72	0.28	0.00	0.00	0.00
	2	0.14	0.69	0.16	0.01	0.00		**2**	0.14	0.77	0.09	0.00	0.00
	3	0.00	0.32	0.55	0.13	0.00		**3**	0.00	0.19	0.58	0.22	0.00
	4	0.00	0.06	0.13	0.63	0.19		**4**	0.04	0.04	0.30	0.59	0.04
	5	0.00	0.00	0.00	0.18	0.82		**5**	0.00	0.00	0.25	0.00	0.75
	Erg.	0.15	0.37	0.17	0.14	0.15		***Erg.***	0.23	0.40	0.16	0.08	0.01
High	**1**	0.75	0.25	0.00	0.00	0.00	**High**	**1**	0.88	0.00	0.13	0.00	0.00
	2	0.03	0.64	0.31	0.03	0.00		**2**	0.14	0.74	0.09	0.03	0.00
	3	0.00	0.29	0.52	0.19	0.00		**3**	0.08	0.18	0.65	0.10	0.00
	4	0.00	0.02	0.10	0.84	0.04		**4**	0.00	0.00	0.18	0.73	0.10
	5	0.00	0.00	0.00	0.02	0.98		**5**	0.00	0.00	0.06	0.14	0.81
	Erg.	0.01	0.13	0.13	0.25	0.45		***Erg.***	0.35	0.17	0.25	0.14	0.07
				2000-2008							**2008-2102**		
		1	**2**	**3**	**4**	**5**			**1**	**2**	**3**	**4**	**5**
Low	**1**	0.82	0.18	0.00	0.00	0.00	**Low**	**1**	0.33	0.67	0.00	0.00	0.00
	2	0.02	0.88	0.11	0.00	0.00		**2**	0.00	0.64	0.36	0.00	0.00
	3	0.00	0.00	0.54	0.46	0.00		**3**	0.00	0.00	0.76	0.18	0.06
	4	0.00	0.00	0.00	0.82	0.18		**4**	0.00	0.00	0.06	0.67	0.28
	5	0.00	0.00	0.00	0.00	1.00		**5**	0.00	0.00	0.00	0.13	0.88
	Erg.	0.00	0.00	0.00	0.00	1.00		***Erg.***	0.00	0.00	0.06	0.28	0.65
Mid.	**1**	0.68	0.32	0.00	0.00	0.00	**Mid.**	**1**	0.00	1.00	0.00	0.00	0.00
	2	0.05	0.78	0.17	0.00	0.00		**2**	0.06	0.56	0.39	0.00	0.00
	3	0.00	0.00	0.59	0.41	0.00		**3**	0.00	0.11	0.67	0.22	0.00
	4	0.00	0.00	0.05	0.86	0.10		**4**	0.00	0.00	0.06	0.82	0.12
	5	0.00	0.00	0.00	0.06	0.94		**5**	0.00	0.00	0.00	0.00	1.00
		0.00	0.00	0.04	0.37	0.57							
	Erg.	0	0	4	9	7		***Erg.***	0.00	0.00	0.00	0.00	1.00
High	**1**	0.40	0.60	0.00	0.00	0.00	**High**	**1**	0.00	0.00	0.00	0.00	0.00
	2	0.04	0.71	0.25	0.00	0.00		**2**	0.00	0.50	0.50	0.00	0.00
	3	0.00	0.04	0.62	0.35	0.00		**3**	0.00	0.00	0.89	0.11	0.00
	4	0.00	0.00	0.02	0.78	0.20		**4**	0.00	0.00	0.00	0.78	0.22
	5	0.00	0.00	0.00	0.03	0.97		***5***	0.00	0.00	0.00	0.03	0.97
	Erg.	0.00	0.00	0.00	0.12	0.86		***Erg.***	0.00	0.00	0.00	0.10	0.89

Notes: Erg. is the ergodic distribution.

6. Conclusion

Our results from different specifications of the traditional convergence models are crucial. First not the least, it seems precise that even there is a cyclical nature, Greek regions undergo a period of convergence which is fastest at the recent crisis period of post 2008. In a way it is also important to underline that even spatial ties are getting weaker we continue to detect significant and marginally slowing convergence in the spatial convergence models. However, most remarkable finding is the way that the speed of convergence varies among the geography of Greece; this proposes the existence of a spatiotemporal convergence for the Greek regions becoming more peculiar during the crisis period. Additionally, our results from different transition probability analyses confirm the existence of club formation. Remarkably the club formation has a distinct geographical pattern which validated that spatial proximity has influence on the fate of the Greek regions' mobility within the regional income distribution.

Greece experience overall gives a picture for a peripheral European country benefiting from various regional policies of EU considering the overall convergence trend. However, we identify that the fast speed of convergence detected for the 1990-2000 and 2008-2012 periods had different fundamentals. While for the former we identify the good times before the EMU accession with falling regional inequalities and rising average income; for the post 2008 period there seems to be a reshuffling among the Greek regions, which underlines a downward convergence and distinct spatial variability of the speed of convergence. This reminds that spatial regimes of the convergence are quiet divergent before and after the crisis.

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