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Convergence and determinants of young people not in employment, education or training: An European regional analysis

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ABSTRACT

In this paper, we study the convergence in the rates of young people Not in Employment, Education or Training (NEET) across the 274 European regions from 2000 to 2019. First, we apply the club convergence methodology and identify the presence of four important clusters with different trends in NEET rates. The estimated clusters consist of sub-national regions in quite distinct parts of Europe. Then, a spatio-temporal econometric model is used to confirm the presence of a reduction in the disparities (β–convergence) of these rates across the European regions. We identify the main drivers in each cluster and calculate the long-run NEET rates. The unemployment rate and the percentage of early leavers from education and training are the main drivers of NEET rates in all clusters.

1. Introduction

The Not in Employment, Education or Training (NEET) rate is defined as the percentage of young people aged 15–24 years old not employed and not involved in further education or training. This measure offers a useful tool to understand young people's vulnerabilities in terms of labour market participation and social inclusion.[1] It is of paramount importance to analyse the determinants of the NEET rate: knowledge of the determinants, and therefore the risk factors that can predict this phenomenon, can help policymakers to implement measures to tackle the social and economic consequences of young people's social and labour exclusion.

There are several key factors that lead to the NEET phenomenon, which is at the root of observed socioeconomic inequalities in the young population and causes specific groups being left behind. These include gender discrimination, low wages, precarious jobs, vulnerability to the effects of the financial crisis, persistence of unemployment, inefficient school-to-work transition, and poor on-the-job-training. Additionally, the distributive effects of skill biased technological change or the decline in the effectiveness of tax and benefit systems to redistribute market income, non-standard forms of employment, and lack of social protection in between jobs can all potentially lead to an increase in NEET rates.

In the context of the European Union (EU) and the economic integration process, and given that this phenomenon is observed in all EU countries, it is important to ascertain whether there are common causes that explain the evolution of the NEET rates across Europe. It would be misleading to assume that this rate in each country solely responds to its domestic structural (and cyclical) factors without taking into consideration the effect of the endogenous market forces stemming from the economic integration process. The existence and identification of commonalities in these rates across Europe can help policymakers to devise and implement a common EU strategy, as this is a phenomenon that can be more efficiently tackled through EU-wide policy measures.

In this paper, we study the convergence of NEET rates across 274 EU regions between 2000 and 2019 using two complementary tools. First, we apply the Phillips and Sul (2007, 2009) transition modelling and

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[1] The numerator of this indicator refers to individuals aged 15–24 years old who are unemployed or inactive according to the International Labour Organization definition and they have not received any formal or non-formal education or training in the four weeks preceding the survey. The denominator corresponds to the total population of the same age group.

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econometric convergence tests, and identify the presence of four important clusters with different trends in them. The estimated clusters consist of sub-national regions in quite distinct parts of Europe. More in detail, the first two main clusters contain regions located mainly in Eastern Europe, Southern Europe, UK and France, while the other two include regions mainly in Central and Northern Europe. Clusters 1 and 2 show an increase in NEET rates with respect to the observed panel average trend, but at different speeds (cluster 1 shows a higher increase in this rate than cluster 2). The third cluster show relatively constant rates with respect to the panel average. The fourth main cluster presents a decreasing rate compared to the whole panel. Finally, there are two additional clusters comprising eight regions (six of which are in Germany) show a clear reduction in relative NEET rates.

Next, we apply a spatio-temporal econometric model to verify the presence of conditional convergence in each cluster. We also calculate the long-run NEET rates and identify their drivers. The percentage of early leavers from education and training, and the unemployment rate are the main drivers of this rate in all clusters. These two variables explain between 66.1 and 92.4 percent of the long-run NEET rate for clusters 1, 2, 3 and 4.

In this paper, we address certain limitations in the literature. First, we analyse NEET rates using sub-national regional data. National figures alone cannot reveal the complexity of the NEET phenomenon which depends on specific regional and territorial aspects. Regional data is therefore much needed to understand the changing patterns of these rates and their long-run determinants. Also, regional data provide a better framework to assess the effect of policy measures. Second, previous literature analysing convergence with panel data either do not consider the existence of clusters or exogenously assume the existence and composition of the clusters. In contrast, in our paper we do not impose an ad hoc grouping of regions; rather we determine the clusters endogenously. Third, a spatio-temporal dynamic panel model is used to analyse the determinants of the NEET rates and calculate the main drivers and their contribution to this phenomenon. Our paper provides valuable information on the causes of these rates, and observed regional differences, across Europe. This analysis is entirely novel and to the best of our knowledge, has not been performed to date in the empirical literature. Thus, we combine two previously separate strands of the literature, on NEET rates convergence and on their long-run determinants. Our analysis makes it possible to determine not only the fundamental determinants of the long-run NEET rates, but also the relative importance of each of them. Fourth, we explicitly model the spatial effects and account for them when testing the determinants of the identified clusters, since geographical contiguity can explain the characteristics shared by regions in the same cluster. Therefore, we believe that this is the first study to analyse the $\beta^* - convergence$ in NEET rates across the EU regions and the drivers of this convergence, by combining regional cluster analysis and panel data methods.

From a policy perspective, our results suggest that measures aimed at reducing the NEET problem need to take into consideration both the particular patterns of the specific regional clusters and the factors revealed in the analysis of the long-run NEET rates determinants. Thus, policy measures need to be designed that will increase the employability of young people by preventing them from leaving school early and by reintegrating them into education, and to reduce inefficiencies in the process of school-to-work transition by providing good quality apprenticeships and traineeships.

In Section 2, we perform a literature review looking at the convergence in NEET rates while in Section 3 we present the theoretical link between β–convergence and convergence in these rates. Section 4 describes their evolution across EU regions. Section 5 details the methodologies used to calculate the clusters and convergence. Section 6 presents results. Finally, Section 6 sets out the conclusions that can be drawn from this research.

2. Literature review

The concept of convergence, in its most general sense, is the reduction or equalizing of disparities. Convergence is a real, long-term phenomenon observed in economic growth processes, when two or more countries' levels of well-being or development tend towards one another over time (Barro and Sala-i-Martí, 1991). Convergence is also observed in other settings. For example, Ravallion (2012) shows the theoretical link between β–convergence and "poverty convergence" when economic growth reduces poverty (the advantage of growth). Recent analyses have focused on the empirical presence of real convergence or divergence in social and labour market indicators in the EU, on topics such as health, unemployment, inequality and poverty (see for example, Bouvet, 2010; Ravallion, 2012; Maynou et al., 2015; Monfort et al., 2018; Lafuente et al., 2020; Cuestas et al., 2021). It is also important to study the presence of "advantage of growth" for NEET reduction, which together with β–convergence in economic growth may help to explain the observed β*–convergence in NEET rates.

The evolution of youth unemployment and NEET rates across Europe has been analysed in the literature. The NEET rate, however, is considered a better indicator of the 'youth left behind' phenomenon than the youth unemployment rate (O'Higgins, 2011; Scarpetta et al., 2010); the reason is simple, the NEET rate is a more comprehensive measure to the concept of 'lost generation' and predicts better young people's risk of social and labour exclusion (Ruesga-Benito et al., 2018). The literature on youth unemployment and the NEET rates emphasizes that youth unemployment is more sensitive to business cycle oscillations though have also indicated major country-specific variations (Bell and Blanchflower, 2010, 2011; Verick, 2011, Choudhry et al., 2012, Ghoshray et al., 2016). Economic crisis hit young people disproportionately hard intensifying young unemployment and joblessness (Jimeno and Rodriguez-Palenzuela, 2002, OCDE, 2016) since they are more likely to work in temporary and atypical contracts that are easier to terminate. Economic downturns also prevent youngsters from developing their career, as they would have liked (Standing, 2011). Youth unemployment is not only more vulnerable to the effects of a crisis than adult unemployment, but these effects tend to be more persistent (O'Higgins, 2011; O'Higgins, 2012). The combination of high and persistent youth unemployment rate may discourage youth from searching jobs; in some cases, they may decide to remain in the educational system, but, in other cases, they may join the NEET group. The school-to-work transition appears therefore as a key factor in explaining the occurrence of the NEET phenomenon. Early-leavers from educational system find jobs which often-lack long-term security and have low wages and poor-training (Furlong, 2006), increasing their likelihood of being NEET. As noted by Bentley and Gurumurthy (1999), one in five young people who are employed at age 16 will be NEET at 18.

From this literature, three factors emerge as important determinants in understanding the NEET phenomenon. The unemployment rate and its link to the level of economic activity, the level of educational attainment, and the rate of early-leavers from education along with the occurrence of temporary employment or part-time contracts as a key factor in explaining the school-to-work transition (Scherer, 2004; Gebel, 2010). In addition to institutional factors as the educational system and the school-to-work transition, further macro factors are relevant in explain the NETT rate and, specifically, structural factors related to the workforce as the participation rate (Dietrich, 2013). Within the demographic factors of the workforce, the gender composition of NEET has also been explored. Young women may suffer more from youth unemployment and NEET due to family responsibilities in caring their siblings or own children (Eurofund, 2016).

The institutional and structural factors explaining the NEET rates and its size and composition vary greatly across European countries. Based on certain degree of similarities in the NEET population as the number of discouraged workers, previous work experience, gender or educational level, among others, Eurofund (2012) classify the EU countries in four groups with similar NEET population characteristics. These authors conclude that "the NEET problem is most prevalent in southern and eastern European countries, whereas young people seem to be better integrated into education and employment in Scandinavian and central European countries" (Eurofund, 2012, p. 42). This paper, however, neglects the fact that a particular region in a country can be more similar to a region in another country than to some other regions in its own country. In other words, as suggested by Overman and Puga (2002), State membership is not the best way to group regions; skill and sectoral differences are more relevant for understanding, for example, youth unemployment outcomes.

The regional dimension of unemployment was first examined by Blanchard and Katz (1992) whose seminal paper started a debate on the determinants of regional labour performance. Elhorst (2003) surveys this literature and concludes that regional unemployment differentials are wide and persistent, with low and high unemployment regions clustering with regions with similar unemployment rates. Persistence in unemployment has been widely discuss in the literature, since it casts doubts on the existence of a unique (natural) equilibrium rate of unemployment as proposed by Phelps (1967, 1968) and Friedman (1968). High and persistent unemployment suggest rather a situation in which shocks have permanent effects, leading to the so-called unemployment hysteresis (Blanchard and Summers, 1986). The natural rate hypothesis has been also challenged by the structuralist theories of unemployment, which states that unemployment can be endogenous and affected by structural factors in the economy (Layard et al., 1991). The empirical literature on the persistence to shocks to unemployment in European countries is, however, inconclusive (Monfort et al., 2018; Kristic et al., 2019), and not unambiguously determined even for the European countries with the worst records on unemployment, as the PIIGS countries (Cheng et al., 2014).

Regarding unemployment convergence in Europe, Monfort, et al. (2018) conclude that the integration process in Europe has not led to an overall convergence in unemployment, but rather a cluster convergence. Similar results are found by Kristic et al. (2019). These authors analyse unemployment convergence in Europe after the financial crisis and conclude in favour of overall divergence. In the context of regional unemployment in Europe, Beyer and Stemmer (2016) analyse the distribution of unemployment rates and obtained that European regions react very heterogeneously to European and country fluctuations. According to these authors, the observed divergence in European regional unemployment rates after the crisis can be attributed to both country and regional-specific factors.

Ghoshray et al. (2016) analyse both adult unemployment and youth unemployment rates in Europe, and found that whereas adult unemployment is subjected to structural breaks linked to institutional and economic shocks, youth unemployment behaviour is rather linked to economic cycle fluctuations.[2] These authors suggest that lower involvement in the labour market and lower involvement in education activities, that is, growing NEET rates, can explained this result. Bruno et al. (2014) analyse the presence of different patterns in both youth unemployment and NEET rates across groups of regions before and after the Great Recession. These authors classify the regions into five macro- European regions (Continental, Northern, Anglo-Saxon, Southern and New Member States) according to certain common features of labour market institutions and economic setting. The authors conclude that NEET and youth unemployment persistence vary across macro-regions. The impact of the Great Recession on both youth unemployment and the NEET rate is further analysed in Kelly and McGuinness (2015). These authors showed that the school-to-work transition ratios felt dramatically between 2006 and 2011, confirming the close link between youth unemployment and the economic cycle.

The existing literature shows some limitations in the study of NEET rates. First, studying national figures alone is unlikely to reveal the complexity of the NEET phenomenon, which depends on specific regional and territorial aspects. Data at subnational region-level is therefore much needed to help understand the changing patterns of these rates and their long-run determinants. Second, previous literature analysing convergence with panel data either do not consider the existence of clusters, or alternatively exogenously assume the existence and composition of the clusters. Third, this literature does not investigate jointly the convergence of NEET rates at the same time as studying long-run determinants of them, which is important to determine not only the fundamental drivers of the long-run NEET rates, but also the relative importance of each of these drivers.

Our paper is somewhat related to that of Bruno et al. (2014), but differs in many significant aspects. First, we do not impose ad hoc regional clusters. Although the authors provide an economic rationale for the supra-national clustering, the authors assume the existence of these clusters rather than test the existence of clusters. Our paper demonstrates that this can be misleading to the extent that not all regions in a country (or group of countries) should be assigned to the same cluster, as Bruno et al. do. Common characteristics such as geographical contiguity, the population skill level, or the regional sectoral composition can provide a better way of grouping regions into clusters. Second, Bruno et al. (2014) explain NEET rates using a very limited set of explanatory variables, other than the ad hoc grouping, with the analysis focusing exclusively on GDP and its interaction with the financial crisis. Our paper shows, however, that the GINI index, the educational level attained, the rate of early leavers from education, and part-time employment are important determinants of the NEET rates along with the financial crisis. Third, we evaluate the contribution of each determinant to these rates in each cluster to evaluate the risk factors behind them. As such, our paper provides a more comprehensive picture of the NEET phenomenon.

3. The theoretical link between β–convergence and NEET convergence

From a theoretical point of view, Ravallion (2012) shows that under the presence of both β–convergence in average income (or consumption) and a negative effect of income on poverty (also called the "advantage of growth" for poverty reduction), then there is also "poverty convergence". As a result, the speed of convergence in poverty coincides with the speed of convergence observed in income. In the same vein, and from a theoretical point of view, the presence of β–convergence in GDP per capita together with a negative impact of GDP per capita on NEET rates can also generate "NEET convergence". In more detail, if $GDPPC_{i,t}$ is the GDP per capita in region i and at time t, a common empirical specification of β–convergence (Barro & Sala-i-Martin, 1991; Sala-i-Martin, 1996) is:

$$\Delta \ln(GDPPC_{i,t}) = \alpha_i + \beta_i \ln(GDPPC_{i,t-1}) + \gamma_i Z_{i,t} + \varepsilon_{i,t}, \quad (1)$$

where α_i is a region-specific effect, $\beta_i < 0$ is a region-specific convergence parameter, Z_i is a vector of variables and $\varepsilon_{i,t}$ is a zero-mean error term. Next, if the "advantage of growth" for NEET reduction is

$$\ln(NEETrate_{i,t}) = \delta_i + \eta_i \ln(GDPPC_{i,t}) + \nu_{i,t}, \quad (2)$$

where δ_i is a region-specific effect, term $\nu_{i,t}$ a zero-mean error term and $\eta_i < 0$ is the regional elasticity of NEET rates with respect to GDP per capita. Then, using (1) and (2) we obtain

$$\Delta \ln(NEETrate_{i,t}) = \alpha_i^* + \beta_i^* \ln(NEETrate_{i,t-1}) + \gamma_i^* Z_{i,t} + \varepsilon_{i,t}^*, \quad (3)$$

where $\alpha_i^* = \alpha_i\eta_i - \beta_i\delta_i$, $\beta_i^* = \beta_i$, $\gamma_i^* = \eta_i\gamma_i$ and $\varepsilon_{i,t}^* = \varepsilon_{i,t}\eta_i - \beta_i\nu_{i,t-1}$. Equation (3) refers to "NEET convergence". Thus, conditional on a vector of variables, regions starting out with a relatively low level of GDP per capita should enjoy both a higher subsequent growth rate in GDP per capita (equation (1)) and a higher proportionate rate of reduction in their

[2] Acedanski (2016) obtained similar results.

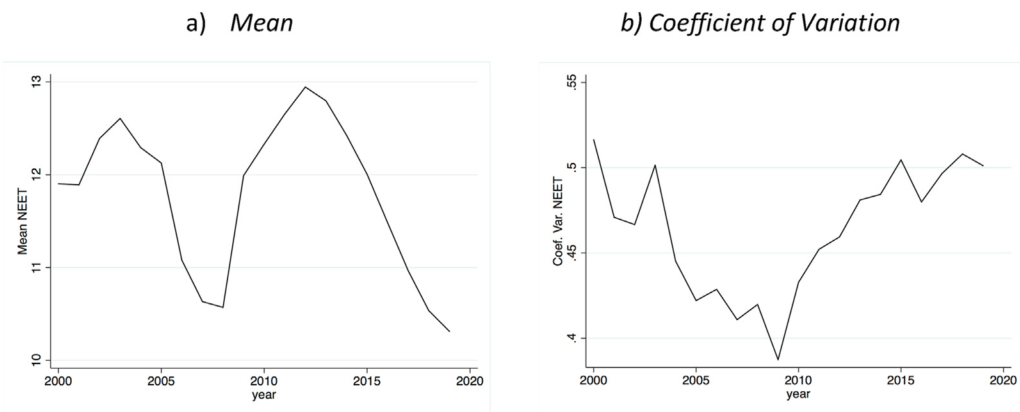

Fig. 1. NEET rate evolution 2000–2019 – EU regions.
Source: Eurostat data.

NEET rates (equation (3)).

Notice however, that there will the possibility of not NEET convergence if the lagged NEET rate has a negative impact on economic growth. More in detail, replacing $Z_{i,t}$ by $NEETrate_{i,t-1}$ in equation (1), then equation (3) becomes equal to:

$$\Delta \ln(NEETrate_{i,t}) = \alpha_i^* + (\beta_i + \eta_i \gamma_i) \ln(NEETrate_{i,t-1}) + \varepsilon_{i,t}^* \tag{4}$$

Now, under the presence of growth convergence $\beta_i < 0$, and the advantage of growth for poverty reduction $\eta_i < 0$, there will the possibility of not NEET convergence if $NEETrate_{i,t-1}$ has a negative impact on economic growth $\gamma_i < 0$ (this happens when $\eta_i \gamma_i \geq -\beta_i$). Although there are different mechanisms behind the link between economic growth, inequality and NEET rates, our goal in this section is to present a simple model that can be helpful for introducing the convergence hypothesis in NEET rates.

4. Evolution of the NEET rates across regions

The NEET rate has been used since 2010 as a tool to study labour market vulnerability among young people in the EU (Eurofund, 2016). On average, this rate has shown different patterns in the EU regions during recent years; it fell from 12.5 percent in 2004 to 10.5 percent in 2007. Then, it increases to 13 percent due to the Great Recession and, finally, decreases to 10.3 percent in 2019 with the economic recovery (see Fig. 1a). The average NEET rate has been decreasing since the beginning of the economic recovery, with the level recorded in 2019 similar to the level in 2000 (just under 12 percent).

Nonetheless, significant differences exist between EU countries in terms of the evolution of their NEET rate, and even among regions in the same country (Bruno et al., 2014). Fig. 1b shows a reduction in the standardized dispersion of these rates across 274 European regions from 2001 to 2009, with a fall of more than 10 percentage points in the coefficient of variation. However, the variability of this rate has been increasing since 2009, reaching a level similar to the one in 2000 (52 percent).

Moreover, NEET rates appear to show different convergence patterns across European regions. Fig. 2 depicts regional NEET rates in 2000 and 2019, suggesting the presence of at least four different clusters despite a general increase observed between 2001 and 2010 followed by a reduction between 2010 and 2019. A first cluster of regions appears to show an increase and then a decrease in NEET rates, starting from levels higher than the average European rate (11.8 percent). This group is composed of regions located in Southern Europe (Spain and Italy), Southeastern Europe (Greece, Bulgaria and Romania), and some regions of the UK. A second group of regions also shows an increase and then a decrease in the NEET rate, but starting from relatively low levels (below 7 percent) and rising to levels around the European average (11.8 percent). These regions are mainly located in UK, Northern Italy, Northern Spain and Central Europe (Czech Republic, Hungary, Poland and Slovakia). A third group, comprised mainly of regions in Portugal, France and the UK, does not show a clear change in NEET rates with respect to the average European rate. Finally, a group of Northern, Western and Central European regions showing some stability in NEET rates, but clearly lying below the average.

5. Methodology: convergence and cluster tests

Panel data models have been widely used to test for regional convergence. In these models, the rejection of the null hypothesis of overall convergence, that is, convergence of all regions in the panel to the same steady state, supports the alternative hypothesis of divergence. However, overall convergence can be rejected not only if all regions in the panel truly diverge, but also under the presence of cluster convergence (Phillips and Sul, 2007). The empirical literature has acknowledged this limitation and panel models have been applied to a limited number of regions to ascertain the existence of regional clusters. However, this ex-ante (or ad-hoc) classification of regions into different groups may introduce selection bias. In this paper, we propose to circumvent this problem through a robust estimation of the regional clusters. Thus, we first use the methodology of Phillips and Sul (2007, 2009) to endogenously identify the regional clusters from a panel including all regions. Once the clusters have been identified, we apply panel methods to analyse the determinants of our variable of interest, the NEET rates for each of the estimated regional clusters.

5.1. Data

We used data from 274 regions of the 28 EU member countries. Data were obtained from EUROSTAT at the NUTS2 level. The NUTS classification (Nomenclature of territorial units for statistics) is used by EUROSTAT to split the economic territory of the EU and the UK into subnational regions that share specific characteristics and facilitate the presentation of statistics. There are three hierarchical NUTS levels, with NUTS 1 the largest and NUTS 3 the smallest; NUTS 1 are the major socio-economic regions, NUTS 2 are basic regions for the application of regional policies and NUTS 3 are small regions for specific diagnoses[3].

Due to data limitations—mainly for the variable of interest, the NEET rate— the analysis was carried out for the period 2000–2019. In Table 1, we have provided the descriptive statistics of the variables used in the

[3] Please, see https://ec.europa.eu/eurostat/web/nuts/background for further information.

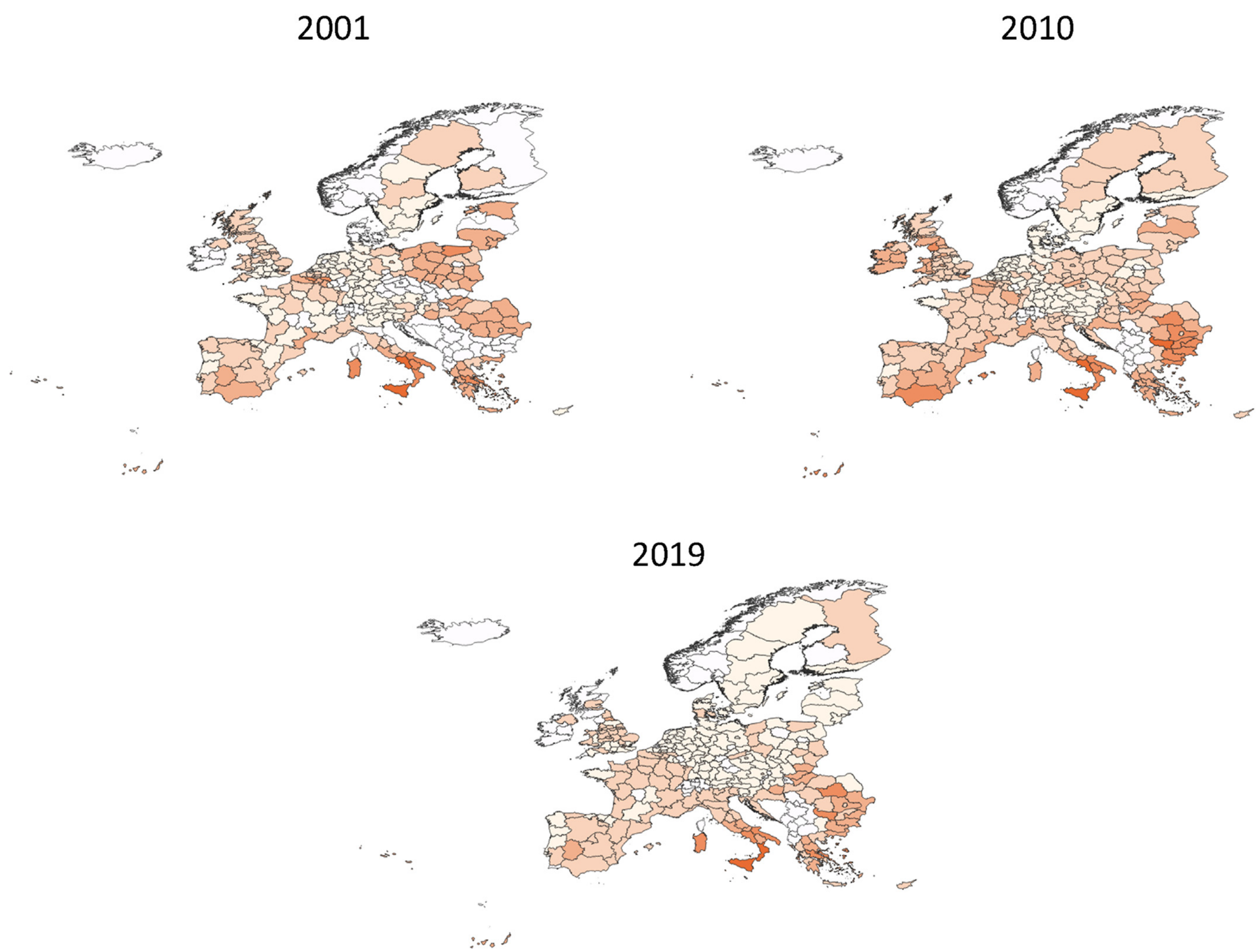

Fig. 2. NEET rates by region (2000 and 2019).
Source: Eurostat data.

Table 1
Descriptive statistics of the variables (2000–2019).

Variables	*Mean*	*Std. D*	*Min*	*Max*	*N*
NEET rate (%)	11.798	5.541	2	35.9	5076
NEET growth rate (growth rate, %)	0.378	17.588	−64.211	110	4779
GDP per capita in PPS (growth rate, %)	2.724	4.164	−16.234	35.354	4887
Population (growth rate, %)	0.277	0.819	−11.046	5.635	5074
Unemployment rate (%)	8.757	5.596	1.2	37	5254
GINI index	30.085	3.393	20.9	40.8	4742
Fertility rate	1.564	0.299	0.86	3.94	4991
Participation rate (%)	10.259	7.295	0.5	36	5113
Educational attainment level 0–2 (%)	27.706	15.387	2.4	87.2	5260
Educational attainment level 3–4(%)	46.787	14.844	6.9	80.3	5260
Educational attainment level 5–8(%)	25.512	9.849	3.7	74.7	5262
Early leavers (%)	13.733	7.818	0.9	58.8	5001
Part-time employment (%)	18.596	10.583	0.575	57.456	5269

Source: Eurostat data.

models. These variables have been chosen based on the discussion on the literature in Section 1. This table shows the mean, the standard deviation, the minimum and maximum value and the number of observations for each dependent and explanatory variable. In addition to this information, we have constructed maps (Fig. 2), showing the evolution of the NEET rate in the European regions. The definitions of these variables and the unit of observation are provided in Appendix 1 (Data).

5.2. *Club convergence*

The time-series approach to convergence analysis can be found in the seminal papers by Carlino and Mills (1993) and Bernard and Durlauf (1995, 1996). These authors developed the concept of stochastic convergence, based on the stationarity properties of the variables under analysis. Thus, two non-stationary variables converge if there is a cointegrating relationship between them. In other words, two non-stationary series converge if they share the same stochastic trend.

This definition of convergence can be empirically tested by means of time-series econometric techniques. However, as pointed out by Phillips and Sul (2009), traditional convergence tests are inadequate when technology is heterogeneous across countries and the speed of convergence is time-varying. To account for temporal and transitional heterogeneity, Phillips and Sul (2007, 2009) introduced cross-sectional and time-series heterogeneity in the parameters of a neoclassical growth model. Appendix 2 shows the technical details of their methodology for testing club convergence.

5.3. Spatio-temporal econometric model

The empirical specification of the NEET convergence model is based in the theoretical model presented in section 2. The methodology explained in this section was applied in two recent papers by Maynou et al. (2015, 2016) to health and economic convergence analyses.

In contrast to more traditional analyses of β–convergence, we do not specify cross-sectional models, but rather estimate spatio-temporal models, i.e., dynamic panel data, from a Bayesian approach. We do this because we want to explicitly consider and model the time and spatial heterogeneity in our data (i.e., levels (regions, countries) and dimensions (spatial and temporal). As we have argued above, the convergence rate may have been different for each region and/or have varied during the period under analysis. Furthermore, with small T, we need a large N to obtain consistent estimates.

In particular, we estimate the following three models:

$$
\begin{aligned}
growthGDPpc_{ijt} &= \alpha_t + \beta_j loggdppc_{ijt-1} + \gamma_1 growthpopulation_{ijt} \\
&+ \gamma_2 unemprate_{ijt} + \gamma_3 Gini_{jt} + \gamma_4 fertilityrate + \gamma_5 participationrate_{ijt} \\
&+ \gamma_6 educlevel02_{ijt} + \gamma_7 educlevel34_{ijt} + \gamma_8 earlyleavers_{ijt} + \gamma_9 parttime_{ijt} \\
&+ \gamma_{10} crisis_t + \gamma_{11} clusters_{ij} + S_i + u_{ijt} \qquad (5)
\end{aligned}
$$

$$
growthNEETrate_{ijt} = \alpha_t + \eta_j growthgdppc_{ijt} + \eta_2 clusters_{ij} + S_i + v_{ijt} \qquad (6)
$$

$$
\begin{aligned}
growthNEETrate_{ijt} &= \alpha_t + \beta_j^* NEETrate_{ijt-1} + \gamma_1^* growthpopulation_{ijt} \\
&+ \gamma_2^* unemprate_{ijt} + \gamma_3^* Gini_{jt} + \gamma_4^* fertilityrate + \gamma_5^* participationrate_{ijt} \\
&+ \gamma_6^* educlevel02_{ijt} + \gamma_7^* educlevel34_{ijt} + \gamma_8^* earlyleavers_{ijt} + \gamma_9^* parttime_{ijt} \\
&+ \gamma_{10}^* crisis_t + \gamma_{11}^* clusters_{ij} + S_i + u_{ijt}^* \qquad (7)
\end{aligned}
$$

The subscript i denotes region (i = 1, …,274); j country (j = 1, …,28); t year (t = 2000,2003, …,2019); α_t, β_j and γ_m (m = 1, …,13) denote unknown parameters; S_i denotes spatial random effects (see below); and u_{ijt} is the normally distributed disturbance term. The dependent and explanatory variables are defined below. The panel that we create with these data is unbalanced. Data was not available for all the period and for all regions. The intercept, α_t, and coefficients of interest, β_j in equation (5), η_j in equation (6) and β_j^* in equation (7), have subscripts to denote country-specific values. In fact, we specify (dynamic) random coefficient panel data models (Hsiao and Pesaran, 2008), allowing the coefficients to be different for the various levels we have considered. When the random effects vary by country, we assume they are identical and independent Gaussian random variables with constant variance, i.e $\upsilon_{jt} \sim N(0, \sigma_\upsilon^2)$. When the random effects vary by year, we assume a random walk of order 1 (i.e., independent increments) for the Gaussian random effects vector (although we also assume constant variance) (R-INLA). See Appendix 3 for the spatio-temporal adjustment and the inference.

Equation (5) replicates equation (1) of the theoretical model. It shows the conditional β-convergence of GDP per capita. Thus, the dependent variable is the GDP per capita growth rate (*growthgdppc*). The growth equation also includes well-known growth drivers (e.g. Gastil, 1990; Barro, 1991; Knack and Keefer, 1997; for a review see, Chirwa and Odhiambo, 2016). More in detail, the population growth rate (*growthpopulation*) and the fertility rate by region (*Fertility rate*) capture the population dynamics. Human capital is proxied by the participation rate in education and training (*Participationrate*) and the percentage of the population with primary and secondary education levels (*Educlevel02* and *educlevel34*, respectively).

Unemployment can also affect economic growth since it implies a continuing waste of labour and of human capital, reducing long-run productivity growth. According to Brauninger and Pannenberg (2002), the long-run level of productivity is reduced if higher unemployment leads to less formal education or to less learning-by-doing. Using a model with endogenous growth, they show that unemployment reduces long-run productivity growth. Then, using panel data from 13 OECD countries from 1960 to 1990, they find evidence that an increase in unemployment scales down the long-run level of productivity. This mechanism may also include early leavers from education and training as well as part time jobs since they tend to reduce formal education and on-the-job-training. According to Isusi and Corral (2004), part-time work is associated with several negative working conditions, such as fewer opportunities for training and career progression and weaker job tenure, generating, therefore, a negative effect on human capital accumulation. Therefore, we include unemployment rate (*Unemprate*), early leavers from education and training as a percentage of the total sample population (*Earlyleavers),* and part-time employment as a percentage of total employment (*Parttime*) in equation (5) as additional drivers of economic growth.

As shown by Quah (1996), to observe convergence two mechanisms need to be in place: i) the growth mechanism, which is captured in our model by the growth drivers, and ii) the convergence mechanism, related to the convergence in income distribution. Following this reasoning, we consider a measure of income distribution, the Gini coefficient (*Gini*), which is defined (according to Eurostat) as the relationship of cumulative shares of the population arranged according to the level of equivalized disposable income to the cumulative share of the total disposable income received by them. Finally, we control for the effects of the Great Recession by including the dummy variable *Crisis* which equals one for the period 2008 to 2012. Further data descriptions can be found in Appendix 1 (Data).

In equations (6) and (7), the dependent variable is the rate of growth of the NEET rate (*growthNEETrate*). Equation (6) replicates equation (2) with endogenous cluster determination. In this equation, only *growthgdppc* appears as explanatory variable allowing us to test the advantage of growth for NEET reduction, which together with convergence of GDP per capita are necessary for NEET convergence. The endogenous determined clusters, that have been obtained using the Phillips and Sul (2007, 2009) methodology, are captured using dummy variables (*Clusters)* for each cluster (1 to n).

Equation (3) from our theoretical model also shows that the determinants of economic growth can affect not only GDP per capita $\beta -$ *convergence* but also NEET $\beta^* -$ *convergence*. Consequently, equation (7) replaces the GDP per capita growth rate by its drivers introduced in equation (5).

6. Results

6.1. Results of estimating club convergence

Convergence in NEET rates has been tested by means of the Phillips and Sul (2007, 2009) method. These authors have proven that the elimination of the cyclical components of the data improves the finite sample power and size of the club convergence test. Therefore, we have eliminated the cyclical components by means of the HP filter (Hodrick and Prescott, 1997). We have also moved the base year to the beginning of the period and discarded some initial observations with the aim of removing the effects created by the initialization. Consequently, the effective sample size was 2005–2019. The test for overall panel convergence was rejected for NEET rates, with a *log t-ratio* of −38.14. The absence of convergence for the panel leads us to consider the possible existence of club convergence.

The results from the cluster analysis for the NEET rates are shown in Appendix 4 (Table A1 and A2). From our results, seven clusters emerge. Given that the cluster analysis procedure tends to find more groups than actually exist, we have tested whether adjacent clusters can be merged into larger groups. According to our results, clusters 1 and 2 can be merged. Hence the final cluster classification contains six groups of regions, which appear in Appendix 4 (Table A3) and Fig. 3.

The country composition of the estimated clusters (Fig. 3) is quite

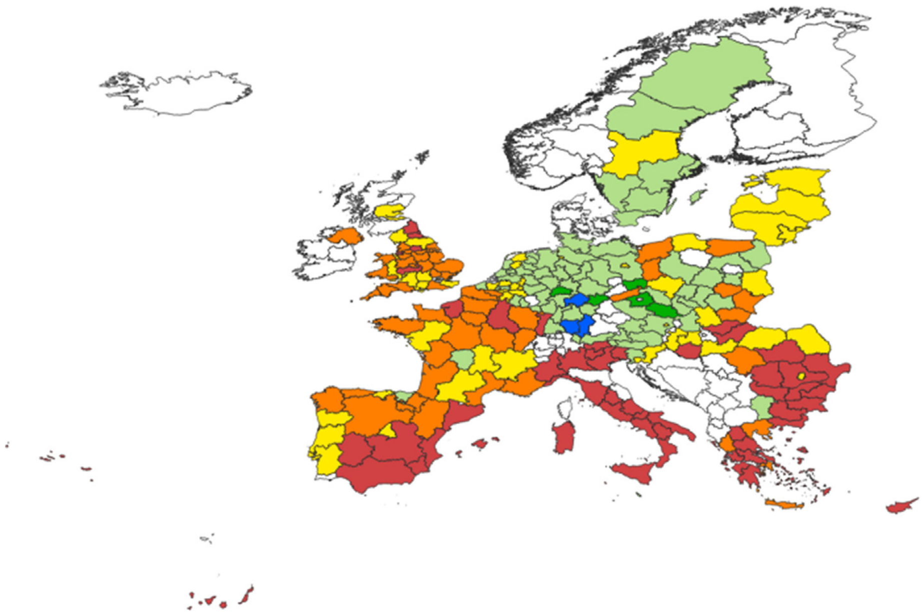

Fig. 3. Clusters.
Source: own construction.

heterogeneous and β_j reflects the graphical patterns shown in section 3 (Fig. 2). More specifically, cluster 1 is mainly composed of regions in Italy (18 regions), Spain (10 regions), Greece (5 regions) and Bulgaria (5 regions), which together represent 64.4 percent of the 59 regions in this cluster. It also contains five regions located the UK. Cluster 2 contains 52 regions, 29.6 percent of which belong to the UK and France. This cluster also contains 14 regions from southern European countries (Spain and Greece), 8 regions form Eastern Europe (most of them in Romania and Poland). Cluster 3 contains 46 regions, 19.6 percent of which are in UK (9 regions), 13.0 percent in Belgium (6 regions) and most of the regions of Portugal (4 regions). The rest of the regions in cluster 3 belong to 7 other countries. Cluster 4 is the biggest with 69 regions, with 62.3 percent concentrated in Germany (21 regions), the Netherlands (8 regions), Austria (7 regions) and Poland (7 regions). The remaining 26 regions belong to 8 different countries. Finally, clusters 5 and 6 only contain 8 regions in total, (6 of them in Germany).

Fig. 4 presents the transition paths for the six final clusters. This graph shows the performance of each cluster relative to the panel average. Thus, a decrease in the transition path of the NEET rate for a given cluster cannot be interpreted as a decrease in the absolute value of this rate, but rather as a decrease in the NEET rate *relative* to the average behaviour of the whole panel, represented in the figure by the value of 1. Therefore, these graphs are a useful way to gauge the degree of divergence among clusters and to determine when, and for how long, this divergence takes place. Divergence among clusters is clear. Clusters 1 and 2 show the worst performance in the panel, while clusters 4, 5 and 6 present a decreasing NEET rate compared to the whole panel. Finally, cluster 3 do not show any such trend; it remains close to the panel average.

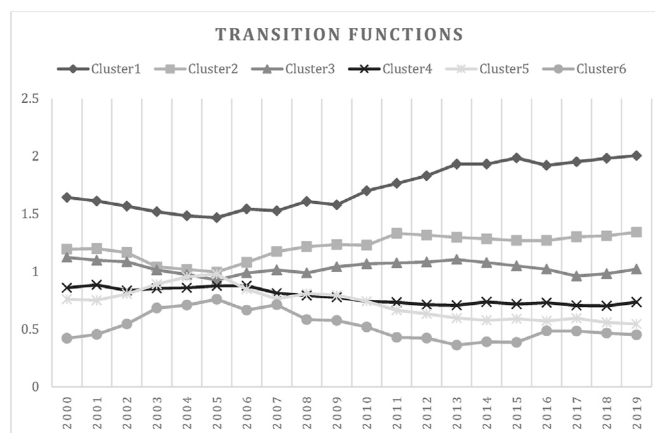

Fig. 4. Transition paths.
Source: own construction.

6.2. Results of estimating convergence models

The results of estimating the models are shown in Table 2. As stated before, the coefficient of interest in this analysis is β^*, which shows whether there is convergence or divergence between regions. Moreover, we also report in Appendix 5 Table A4 the results for a model with an interaction of the lag NEET rate and the GDP per capita growth rate, following Ravallion (2012).

In Table 2, we show the results of the estimations for conditional $\beta-$ *convergence* in economic growth and $\beta^* -$ *convergence* in NEET rates with the clusters (as dummy variables) and a model for each cluster, estimated in the previous analysis, to capture the heterogeneous effect by cluster[4]. These models account for spatio-temporal adjustment and a range of covariates. We present the results only for clusters 1 to 4. Clusters 5 and 6 are not included due to the low number of observations in each cluster.

Model 1 replicates equation (1) of the theoretical model. It shows conditional convergence in GDP per capita, as the β is negative and significant. While, the population growth rate, the unemployment rate and educational attainment level (0–2) have a negative and significant effect on the GDP growth rate, fertility rate has a positive effect. The rest of explanatory variables are not statistically significant.

Model 2 replicates equation (2) of the theoretical model and presents a simple model with only GDP per capita growth rate as the main covariate, showing a negative relationship between NEET growth rate and GDP growth rate. Moreover, this model also incorporates the cluster

[4] Following a referee comment, we have checked the robustness of our results by using the convergence methods proposed by Michail (2020). As shown in Appendix 5 Table A5, the results for the β coefficient are very similar in terms of sign, significance and even magnitude to those reported in Table 2.

Table 2
Results of estimating the conditional β-convergence on GDP and NEET rate.

	1	2	3	4	5	6	7
	GPDpc growth rate with clusters	NEET growth rate with clusters	NEET growth rate with clusters	NEET growth rate: CLUSTER 1	NEET growth rate: CLUSTER 2	NEET growth rate: CLUSTER 3	NEET growth rate: CLUSTER 4
β	*−0.833***[a]		*−3.905***	*−1.916***	*−4.158***	*−5.434***	*−6.200***
	(0.191)		*(0.238)*	*(0.160)*	*(0.283)*	*(0.382)*	*(0.495)*
Fixed effects:							
GDPPC growth rate		*−0.853***					
		(0.077)					
Population growth rate	*−0.659***		*1.037***	*0.683*	*−1.589*	*−0.133*	*2.412***
	(0.065)		*(0.369)*	*(0.507)*	*(1.109)*	*(0.812)*	*(0.819)*
Unemployment rate	*−0.093***		*2.095***	*1.159***	*1.753***	*2.873***	*3.362***
	(0.011)		*(0.081)*	*(0.107)*	*(0.169)*	*(0.233)*	*(0.198)*
GINI index	*−0.003*		*0.124***	*0.081***	*0.118***	*0.046*	*−0.167***
	(0.007)		*(0.031)*	*(0.040)*	*(0.055)*	*(0.053)*	*(0.046)*
Fertility rate	*0.418***		*0.940*	*0.825*	*−0.802*	*−1.143*	*0.078*
	(0.159)		*(0.994)*	*(1.125)*	*(1.383)*	*(1.367)*	*(1.082)*
Participation rate	*0.012*		*−0.322***	*−0.166***	*−0.455***	*−0.104*	*−0.350***
	(0.011)		*(0.058)*	*(0.145)*	*(0.109)*	*(0.116)*	*(0.116)*
Education level 0–2	*−0.016***		*−0.411***	*−0.386***	*−0.252***	*−0.293***	*0.098*
	(0.008)		*(0.063)*	*(0.091)*	*(0.093)*	*(0.104)*	*(0.108)*
Education level 3–4	*0.001*		*0.201***	*0.242***	*0.211***	*0.242***	*0.208***
	(0.006)		*(0.054)*	*(0.097)*	*(0.103)*	*(0.099)*	*(0.081)*
Early leavers	*−0.003*		*1.519***	*1.104***	*1.975***	*1.494***	*1.722***
	(0.010)		*(0.067)*	*(0.102)*	*(0.148)*	*(0.149)*	*(0.178)*
Part-time employment	*0.015*		*−0.001*	*−0.067*	*0.436***	*−0.091*	*0.056*
	(0.011)		*(0.060)*	*(0.117)*	*(0.143)*	*(0.092)*	*(0.091)*
Crisis dummy (– – 2008–2012)	*−1.542*		*2.090*	*5.528***	*2.805***	*3.075***	*3.403***
	(2.433)		*(2.964)*	*(0.941)*	*(1.189)*	*(1.127)*	*(0.969)*
Clusters (base category: regions not clustered[b])							
Cluster 1	*−0.531***	*−0.557*	*3.075***				
	(0.215)	*(0.952)*	*(1.410)*				
Cluster 2	*−0.499***	*−0.646*	*−0.953*				
	(0.202)	*(0.958)*	*(1.317)*				
Cluster 3	*−0.191*	*−0.887*	*−2.178*				
	(0.195)	*(0.973)*	*(1.202)*				
Cluster 4	*−0.144*	*−1.311*	*−3.432***				
	(0.191)	*(0.918)*	*(1.210)*				
Cluster 5	*−0.208*	*−2.318*	*−3.846*				
	(0.354)	*(1.942)*	*(1.978)*				
Cluster 6	*−0.126*	*−0.130*	*−3.322*				
	(0.438)	*(2.302)*	*(2.444)*				
Constant	*13.039*	*3.242*	*7.866*	*1.353*	*5.345*	*12.271*	*7.340*
	(2.390)	*(2.252)*	*(5.541)*	*(6.770)*	*(6.030)*	*(5.805)*	*(5.692)*
Standard deviation of random effects:							
Heterogeneity	*0.128** (0.003)*	*0.004** (0.0001)*	*0.005** (0.0001)*	*0.006** (3.0e-04)*	*4.600e-03** (2.00e-04)*	*4.600e-03** (2.00e-04)*	*0.005** (2.00e-04)*
α_t	*0.086** (0.029)*	*0.082** (0.035)*	*0.058** (0.022)*	*18279.618** (1.827e+04)*	*1.742e+04** (1.786e+04)*	*1.792e+04** (1.818e+04)*	*1.984e+04** (1.905e+04)*
β_j/ η_j	*76.418** (25.950)*	*18451.876** (1.834e+04)*	*0.924** (0.307)*	*12.615** (6.188)*	*4.597** (2.969)*	*1.482** (7.186)*	*0.431** (0.178)*
Spatial effect	*YES*	*YES*	*YES*	*NO*	*NO*	*NO*	*NO*
Years	*2000–2019*	*2000–2019*	*2000–2019*	*2000–2019*	*2000–2019*	*2000–2019*	*2000–2019*
Regions	*274*	*274*	*274*	*59*	*52*	*46*	*69*
Countries	*28*	*28*	*28*	*10*	*9*	*17*	*16*
N	*3846*	*4490*	*3796*	*885*	*814*	*681*	*965*
Deviance Information Criterion (DIC)	*24009.25*	*40546.08*	*39083.88*	*8786.44*	*8008.76*	*7051.24*	*10322.75*
Effective number of parameters	*70.03*	*25.79*	*116.77*	*19.81*	*19.68*	*26.94*	*27.05*
-log(mean(cpo))	*2.458*	*4.242*	*4.089*	*3.992*	*4.121*	*4.122*	*4.085*

Spatial and temporal components are significant.
[a] mean (standard deviation); ** denotes that the 95% credible interval did not contain zero (statistically significant). For the sake of simplicity, we have not reported the random effects for these models but they are available from the authors on request.
[b] It has not been possible to cluster the 40 regions that have few observations for the NEET rate.
Source: own construction

dummy variables (excluded dummy: regions not clustered), but they are not significant. According to this model, an increase of one percent point in the GDP per capita growth rate, reduces the NEET growth rate by 0.85 percentage points. This result goes in line with the theoretical model defined in Section 2, showing the presence of the "advantage of growth" for NEET reduction. The presence of $\beta - convergence$ in economic growth together with the "advantage of growth" for NEET reduction allows us to expect the presence of $\beta^* - convergence$ in NEET rates.

We next test the presence of NEET convergence in models 3 to 7 by removing GDP per capita growth rate in model 2 and adding the range of covariates in model 1 defined as determinants of GDP per capita growth rate. Results show convergence in these rates between EU regions, as the coefficient of interest is negative and statistically significant. For model 3, participation rate in education and training and educational attain-

Table 3
Long-run NEETrates* by cluster and their determinants.

	CLUSTER 1			CLUSTER 2			CLUSTER 3			CLUSTER 4		
	Level	*Coef*	*Contr*	*Level*	*Coef*	*Contr*	*Level*	*Coef*	*Contr*	*Level*	*Coef*	*Contr*
Population growth rate (2000-19)	0.12	0.36	0.04	0.37	−0.38	−0.14	0.27	−0.02	−0.01	0.23	0.39	0.09
Unemployment rate (2019)	11.24	0.60	6.80	7.09	0.42	2.99	4.78	0.53	2.53	3.72	0.54	2.02
GINI index (2019)	33.35	0.04	1.41	30.78	0.03	0.87	29.71	0.01	0.25	27.57	−0.03	−0.74
Fertility rate (2018)	1.46	0.43	0.63	1.62	0.44	0.71	1.58	−0.21	−0.33	1.57	0.01	0.01
Participation rate (2019)	7.58	−0.09	−0.66	12.31	−0.11	−1.35	11.98	−0.02	−0.22	12.62	−0.06	−0.71
Education level 0–2 (2019)	32.36	−0.20	−6.52	21.09	−0.06	−1.28	19.5	−0.05	−1.05	13.94	0.02	0.22
Education level 3–4 (2019)	43.07	0.13	5.44	43.39	0.05	2.20	44.11	0.04	1.96	52.38	0.03	1.76
Early leavers (2019)	15.34	0.58	8.84	10.56	0.47	5.02	9.65	0.27	2.65	8.35	0.28	2.32
Part-time employment (2019)	13.97	−0.03	−0.49	18.49	0.10	1.94	20.29	−0.02	−0.34	25.16	0.01	0.23
Crisis dummy (– – 2008–2012)	0.25	2.89	0.72	0.25	0.67	0.17	0.25	0.57	0.14	0.25	0.55	0.14
Constant	1.35	0.71	0.71	5.35	1.29	1.29	12.27	2.26	2.26	7.34	1.18	1.18
NEET rate (2019)	16.41			10.99			8.37			6.06		
Long-run NEET rate			$\sum$ 16.92			$\sum$ 11.40			$\sum$ 7.84			$\sum$ 6.52

Source: own construction.

ment level (0–2) reduces the NEET growth rate, whereas the population growth rate, unemployment rate, the GINI index, the educational attainment level (3–4) and early leavers increase the NEET growth rate. This model also incorporates cluster dummy variables where cluster 1 is positive and significant and cluster 4 is negative and significant. Summing up, our results indicate that there is (statistically) significant of $\beta^* - convergence$ in NEET rates among the EU-28 regions in the studied period.

In turn, models 4 to 7 report the results of the conditional of $\beta^* - convergence$ for each of the clusters. While these models incorporate the random effects (as in the previous specification), the spatial effect is not included. The main reason for omitting the spatial effect is that in these models the regions are no longer adjacent, and this can yield misleading estimation results. Although convergence is found in all the clusters, their β^* coefficient values differ, showing higher convergence rates for cluster 4 than for clusters 1, 2 and 3. Regarding the covariates, we can also see some differences in the sign and significance. In other words, the NEET rate is affected by different covariates in each cluster. However, unemployment rate (+), early leavers (+), educational attainment level (3–4) (+) and the crisis dummy (+) are all significant in the four clusters.

Comparing model 1 with models 3 to7 in Table 2, it looks like some of the explanatory variables generate direct effects on NEET $\beta^* - convergence$ that not necessarily take place through economic growth. For example, the percentage of the population with secondary education levels, early leavers, the Gini index and participation rate in education and training have a significant negative effect on NEETs in model 3 but not on GDP per capita (model 1). In contrast, unemployment rate reduces economic growth while increases NEET rate in all models. It would be interesting to explore the presence of these direct channels but this is left for future research.

Finally, we calculate the long-run NEET rate $NEETrate_c^*$ in each cluster as well as the relative contribution of each variable to this rate. More specifically, we set $growthNEETrate_{c,t} = 0$ and divide all coefficients in equation (7) by $-\beta^*$ to obtain $NEETrate_c^*$. For example, the long-run contribution of the unemployment rate in a given cluster to the long-run NEET rate is equal to $\frac{\gamma_2}{-\beta^*} \times unemprate_c$. Table 3 presents the estimated long-run NEET rates in a scenario in which the population growth is at the average rate observed between 2000 and 2019. Table 3 also considers the values observed in 2019 for the rest of variables.

The first noteworthy result is that all clusters show NEET rates in 2019 near to their long-run values $NEETrate_c^*$. This implies that if the population growth rate in the clusters remain similar to those observed between 2000 and 2019, and the levels of the rest of variables stay close to the observed values in 2019, then NEET rates are close to reaching their $NEETrate_c^*$. More specifically, clusters 1, 2, 3 and 4 show NEET rates of 16.41, 10.99, 8.37 and 6.06 percent in 2019 while their long-run values are equal to 16.92, 11.40, 7.84, 6.52 percent, respectively.

Table 3 also shows the relative contribution (Contr) of each variable to the $NEETrate_c^*$. This contribution is calculated by multiplying the long-run coefficient (Coef) by the observed level in the regressor (level). For example, the contribution of the unemployment rate to the $NEETrate_c^*$ in Cluster 1 is equal to 11.25*0.60 = 6.8. This implies that the unemployment rate explains 6.8 percentage points of the $NEETrate_c^*$ in cluster 1.

The variable percentage of early leavers from education and training is the most important driver of the $NEETrate_c^*$ in Cluster 1. It generates 52.2 percent of its long-run value (8.84 percentage points). This variable is still important though less relevant in the rest of clusters. It explains 44, 33.8 and 35.6 percent of the $NEETrate_c^*$ in clusters 2, 3 and 4, respectively. A second relevant variable explaining the long-run NEET rates is the unemployment rate. It accounts for 40.2, 26.2, 32.3 and 31 percent of the $NEETrate_c^*$ in clusters 1 to 4, respectively. With respect to the rest of variables, some of them are more important in some clusters than in others. For example, the percentage of individuals with upper secondary (level 3) and post-secondary non-tertiary education (level 4) explains 32.2 percent of the $NEETrate_c^*$ in cluster 1 and 27 percent in cluster 4, but has a lower effect in cluster 2 and 3.

7. Conclusions

The main objective of this paper was to study the convergence in NEET rates (the rate of young people not in employment, education or training) across European regions between 2000 and 2019. To our knowledge, this is the first study that analyses the $\beta^* - convergence$ in NEET rates across EU regions and the drivers of this convergence by combining regional cluster analysis and panel data methods. The results of this study are a relevant contribution to the existing literature on convergence and on the European labour market.

In order to achieve our research goal, we first identified the presence of regional clusters in NEET rates, through convergence club methodology. Secondly, we used a spatio-temporal econometric model to confirm the presence of $\beta^* - convergence$ in NEET rates, identify their drivers in each cluster and calculate their long-run NEET rates ($NEETrate^*$).

The convergence club methodology allowed us to identify four major clusters in NEET rates in the European regions. These clusters reflect the graphical representation of the NEET rate shown in Fig. 2. The first two clusters mainly contain regions located in Southern and Eastern Europe as well as in UK and France. Both clusters show an increase with respect to the average NEET rate, but at a different speed. The third cluster contains regions located mainly in UK, Belgium and Portugal, and it remains close to the panel average. The fourth cluster contains regions located mostly in Central and North Europe and shows a decreasing NEET rate compared with the average trend. Our results on the NEET rates support previous findings on both regional labour market performance and NEET dynamics in the EU, that is, the existence of a core-periphery pattern with Southern and Eastern regions showing higher NEET rates.

The econometric results showed that there was conditional $\beta^* - convergence$ in the NEET rates across the European regions from 2000 to 2019. Moreover, this convergence held when analysed by cluster. Regarding the long-run NEET rates ($NEETrate^*$), the percentage of early leavers from education and training and the unemployment rate were the main drivers of the $NEETrate^*$ in all clusters. These two variables explained between 92.4, 70.2, 66.1 and 66.6 percent of the long-run NEET rate of clusters 1, 2, 3 and 4. Following Ravallion (2012), we also find the presence of "advantage of growth" for NEET reduction, which together with the presence of $\beta - convergence$ in economic growth explain, at some level, the observed $\beta^* - convergence$ in NEET rates.

In terms of policy, our results suggest that measures aimed at reducing the NEET problem and promoting youth inclusion should distinguish between the particular patterns observed across the regional clusters and take into account the specific characteristics revealed in the club convergence analysis and in the long-run NEET rates determinants. Member States need to be more active in designing and implementing policy measures aimed at increasing the employability of young people and their participation in employment. More effort needs to be taken to prevent young people from leaving school early and to encourage them back into education. An efficient school-to-work transition is a key factor in reducing the NEET problem. These are all parts of the Youth Guarantee which encourages the reintegration of young people into the labour market or education, and provides good quality apprenticeships and traineeships to improve the school-to-work transition.

To summarize, this study showed $\beta^* - convergence$ in the NEET rates across the European regions from 2000 to 2019. We have provided evidence that the NEET rates were different across the four key clusters identified. The unemployment rate and the percentage of early leavers from education and training were the main determinants of the NEET rate in all clusters.

Finally, although we have thoroughly studied convergence of NEET rates and the relative contributions of the main drivers to the long-run NEET rates, our analysis does not explore the nature of the direct effects of the explanatory variables on the NEET $\beta^* - convergence$. This is an area which we believe would benefit from further research.

Conflicts of interest/Competing interests

There are no conflicts of interest for any of the authors. All authors freely disclose any actual or potential conflict of interest including any financial, personal or other relationships with other people or organizations that could inappropriately influence, or be perceived to influence, their work.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.econmod.2022.105808.

References

Acedanski, J., 2016. Youth unemployment and welfare gains from eliminating business cycle - the case of Poland. Econ. Modell. 57, 248–262. https://doi.org/10.1016/j.econmod.2016.05.012.

Barro, R., 1991. Economic growth in a cross section of countries. Q. J. Econ. 106, 407–443. https://doi.org/10.2307/2937943.

Barro, R., Sala-i-Martin, X., 1991. Economic Growth. The MIT Press, Boston.

Bell, D.N.F., Blanchflower, D.G., 2010. Youth Unemployment: Déjà Vu? IZA Discussion Paper No. 4705. Bonn.

Bell, D.N.F., Blanchflower, D.G., 2011. Young people and the great recession. Oxf. Rev. Econ. Pol. 27, 241–267. https://doi.org/10.1093/oxrep/grr011.

Bentley, T., Gurumurthy, R., 1999. Destination Unknown: Engaging with the Problems of Marginalised Youth. Demos, London.

Bernard, A.B., Durlauf, S.N., 1995. Convergence in international output. J. Appl. Econom. 10, 97–108. https://doi.org/10.1002/jae.3950100202.

Bernard, A.B., Durlauf, S.N., 1996. Interpreting tests of convergence hypothesis. J. Econom. 71, 161–173. https://doi.org/10.1016/0304-4076(94)01699-2.

Blanchard, O.J., Katz, L.F., 1992. Regional evolutions. Brookings Pap. Econ. Activ. 23, 1–75.

Blanchard, O.J., Summers, L.H., 1986. Hysteresis and the European unemployment problem. In: Fischer, S. (Ed.), NBER Macroeconomic Annual. MIT Press, Cambridge.

Bouvet, F., 2010. EMU and the dynamics of regional per capita income inequality in Europe. J. Econ. Inequal. 8, 323–344. http://hdl.handle.net/10.1007/s10888-010-9129-0.

Brauninger, M., Pannenberg, M., 2002. Unemployment and productivity growth: an empirical analysis within an augmented Solow model. Econ. Modell. 19 (1), 105–120. https://doi.org/10.1016/S0264-9993(00)00065-1.

Bruno, G., Marelli, E., Signorelli, M., 2014. The rise of NEET and youth unemployment in EU regions after the crisis. Comp. Econ. Stud. 56, 592–615. https://doi.org/10.1057/ces.2014.27.

Carlino, G., Mills, L., 1993. Are US incomes converging? A time series analysis. J. Monetary Econ. 32, 335–346. https://doi.org/10.1016/0304-3932(93)90009-5.

Cheng, S., Wu, T., Lee, K., Chang, T., 2014. Flexible fourier unit root test of unemployment for PIIGS countries. Econ. Modell. 36, 142–148. https://doi.org/10.1016/j.econmod.2013.09.021.

Chirwa, T., Odhiambo, N., 2016. Macroeconomic determinants of economic growth: a review of international literature. S. East Eur. J. Econ. Bus. 11, 33–47. https://doi.org/10.1515/jeb-2016-0009.

Choudhry, M.T., Marelli, E., Signorelli, M., 2012. Youth unemployment rate and impact of financial crisis. Int. J. Manpow. 33, 76–95. https://doi.org/10.1108/01437721211212538.

Cuestas, J.C., Monfort, M., Ordóñez, J., 2021. The education pillar of the Europe 2020 strategy: a convergence analysis. Empirica 48, 1113–1129. https://doi.org/10.1007/s10663-021-09504-x.

Dietrich, H., 2013. Youth unemployment in the period 2001–2010 and the European crisis – looking at the empirical evidence. Transfer: Eur. Rev. Labour Res. 19, 305–324. https://doi.org/10.1177/1024258913495147.

Elhorst, J.P., 2003. The mystery of regional unemployment differentials: theoretical and empirical explanations. J. Econ. Surv. 17, 709–748. https://doi.org/10.1046/j.1467-6419.2003.00211.x.

Eurofund NEETs – Young People Not in Employment, Education or Training: Characteristics, Costs and Policy Responses in Europe, Publications Office of the European Union, Luxembourg.

Eurofund, 2016. Exploring the Diversity of NEETs. Publications Office of the European Union, Luxembourg.

Furlong, A., 2006. Not a very NEET solution: representing problematic labor market transitions among early school-leavers. Work. Employ. Soc. 20, 553–569. https://doi.org/10.1177/0950017006067001.

Friedman, M., 1968. The role of monetary policy. Am. Econ. Rev. 58, 1–17. https://www.jstor.org/stable/i331921.

Gastil, R.D., 1990. The comparative survey of freedom: experience and suggestions. Stud. Comp. Econ. Dev. 25, 25–50. https://doi.org/10.1007/BF02716904.

Ghoshray, A., Ordóñez, J., Sala, H., 2016. Euro, crisis and unemployment: youth patterns, youth policies? Econ. Modell. 58, 442–453. https://doi.org/10.1016/j.econmod.2016.05.017.

Hodrick, Robert J., Prescott, Edward C., 1997. Postwar U.S. Business cycles: an empirical investigation. J. Money Credit Bank. 29, 1–16. https://doi.org/10.2307/2953682.

Hsiao, C., Pesaran, M.H., 2008. Random coefficient panel data models. In: Mátyás, L., Sevestre, P. (Eds.), The Econometrics of Panel Data, Advances Studies in Theoretical and Applied Econometrics, vol. 46. Springer, Berlin, Heidelberg, pp. 185–213.

Jimeno, J.F., Rodríguez-Palenzuela, D., 2002. Youth unemployment in the OECD: demographic shifts, labour market institutions and macroeconomic shocks. ECB Work. Pap. 155.

Kelly, E., McGuinness, S., 2015. Impact of the Great Recession on unemployed and NEET individuals' labour market transition in Ireland. Econ. Syst. 39, 59–71. https://doi.org/10.1016/j.ecosys.2014.06.004.

Knack, S., Keefer, P., 1997. Does social capital have an economic payoff? A cross-country investigation. Q. J. Econ. 112 (4), 1251–1288. https://www.jstor.org/stable/2951271.

Kristic, I., Dumancic, L.R., Arcabic, V., 2019. Persistence and stochastic convergence of euro are unemployment rates. Econ. Modell. 76, 192–198. https://doi.org/10.1016/j.econmod.2018.07.032.

Lafuente, J.A., Marco, A., Monfort, M., Ordóñez, J., 2020. Social exclusión and convergence in the EU: an assessment of the Europe 2020 strategy. Sustainability 12, 1–22. https://doi.org/10.3390/su12051843.

Layard, R., Nickell, S., Jackman, R., 1991. Unemployment. Macroeconomic Performance and the Labor Market. Oxford University Press, Oxford.
Maynou, L., Saez, M., Bacaria, J., Kyriacou, A., 2016. The impact of cohesion funds on convergence of the eurozone (1990-2010). Reg. Stud. 50, 1127–1139. https://doi.org/10.1080/00343404.2014.965137.
Maynou, L., Saez, M., Bacaria, J., Lopez-Casasnovas, G., 2015. Health inequalities in the European union: an empirical analysis of the dynamics of regional differences. Eur. J. Health Econ. 16, 543–559. https://doi.org/10.1007/s10198-014-0609-1.
Michail, N.A., 2020. Convergence of consumption patterns in the European Union. Empir. Econ. 58 (3), 979–994. https://doi.org/10.1007/s00181-018-1578-5.
Monfort, M., Ordóñez, J., Sala, H., 2018. Inequality and unemployment patterns in Europe. Does integration lead to (real) convergence? Open Econ. Rev. 1–22. https://doi.org/10.1007/s11079-018-9488-x.
O'Higgins, N., 2011. The impact of the economic and financial crisis and the policy response on youth employment in the European Union. In: Presented at the EACES International Workshop, pp. 10–11. Perugia.
O'Higgins, N., 2012. This time it's different? Youth labor markets during the 'great recession. Comp. Econ. Stud. 54, 395–412. https://doi.org/10.1057/ces.2012.15.
Overman, H., Puga, D., 2002. Unemployment clusters across Europe's regions and countries. Econ. Pol. 17, 115–148. https://doi.org/10.1111/1468-0327.00085.
Phelps, E.S., 1967. Phillips curves, expectations of inflation and optimal unemployment over time. Econometrica 34, 257–281 https://doi.org/2552025.
Phelps, E.S., 1968. Money wage dynamics and labor market equilibrium. J. Polit. Econ. 76, 678–711. https://www.jstor.org/stable/1830370.
Phillips, P., Sul, D., 2007. Transition modeling and econometric convergence tests. Econometrica 75, 1771–1855. https://doi.org/10.1111/j.1468-0262.2007.00811.x.
Phillips, P., Sul, D., 2009. Economic transition and growth. J. Appl. Econom. 24, 1153–1185. https://doi.org/10.1002/jae.1080.
Quah, D., 1996. Twin peaks: growth and convergence in models of distributional dynamics. Econ. J. 106, 1045–1055 https://doi.org/2235377.
Ravallion, M., 2012. Why don't we see poverty convergence? Am. Econ. Rev. 102, 504–523. https://www.jstor.org/stable/41408782.
Ruesga-Benito, S.M., González-Laxe, F., Picatoste, X., 2018. Sustainable development, poverty, and risk of exclusion for young people in the European union: the case of NEETs. Sustainability 10, 1–15. https://doi.org/10.3390/su10124708.
Sala-i-Martin, X., 1996. Regional cohesion: evidence and theories of regional growth and convergence. Eur. Econ. Rev. 40, 1325–1352. https://doi.org/10.1016/0014-2921(95)00029-1.
Scarpetta, S., Sonnet, A., Manfredi, T., 2010. `Rising youth unemployment during the crisis: how toprevent negative long-term consequences on a generation?. In: OECD Social, vol. 6. Employment and Migration Working Papers, Paris.
Standing, G., 2001. The Precariat: the New Dangerous Class. Bloomsbury Academic, London, UK.
Verick, S., 2011. The impact of the global financial crisis on labor markets in OECD countries: why youth and other vulnerable groups have been hit hard. In: Islam, I., Verick, S. (Eds.), From the Great Recession to Labor Market Recovery: Issues, Evidence and Policy Options. Palgrave Macmillan, New York, pp. 119–145.