Social Indicators Research (2022) 162:739–761
https://doi.org/10.1007/s11205-021-02813-5

ORIGINAL RESEARCH

NEETs and Youth Unemployment: A Longitudinal Comparison Across European Countries

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Accepted: 19 September 2021 / Published online: 17 January 2022

Abstract
Young people's place in the labor market has been a topic of interest to the European Union and national governments for many years. This study analyzes young people who are Not in Employment nor in Education or Training (NEET) and Youth Unemployment (YU) in the European Union member states, through data collected over a period of sixteen years, considering the influence of some macroeconomic factors through an hidden Markov model. This approach is based on maximum likelihood estimation of the model parameters, and provides a dynamic classification of the countries into clusters representing different levels of the phenomena. We discover three clusters of countries, and we show that whereas Italy was the worst performing country in terms of both NEETs and YU, the Czech Republic was the best performing country in reducing NEETs, and Poland and Slovakia were the best performing in reducing YU.

Keywords Expectation-maximization algorithm · Discrete latent variable · Hidden Markov model · Model-based clustering · Panel data · NEET · Youth unemployment

JEL Classification C18 · J80 · J20 · J64

1 Introduction

Young people are one of the groups most sensitive to the fluctuations of labor market. It is in the social interest of the entire European community to create conditions enabling them to enter the labor market and start a professional career. Observing the labor markets of various European countries, some differences between young people's professional activities are apparent. Their situation is evaluated by measuring both youth unemployment (YU) and numbers of individuals who are "not in employment, education, or training" (NEETs), where NEETs comprise those who are unemployed and those who are outside the labor force (see Sect. 3 for precise definitions of NEETs

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and YU). Bal-Domańska (2020) showed that in Europe, young people have the highest levels of unemployment and the biggest differences in employment rates between countries. For example, in Italy, in 2019, 22.2% of 15–29 years old were NEETs, whereas in the Netherlands the figure was only 5.7%.

Another important problem is the persistence of unemployment among those aged 15–24. The unemployment rate refers to individuals who are without work, available for work, and actively seeking work, as a percentage of the labor force, based on the definition provided by the international labor office, where the labor force comprises the total number of people employed and unemployed. The YU rate (for individuals aged 15 to 24) differs widely among EU countries, for example, in 2019 it ranged from 5.8% in Germany to 35.2% in Greece.

National authorities have actively attempted to create better conditions for young people as an incentive to enter employment. Labor market institutions differ widely across countries and are changing over time. In general, they have become more "flexible" during the last twenty years (Parisi et al. 2015). Moreover, since 2002 the European Union (EU) has promoted youth policy cooperation based on the principles of active participation and equal access to opportunities (European Council 2002). Regulation of this kind will continue in the coming years as part of the EU Youth Strategy 2019–2027 (European Commission 2012; European Council 2018; Mascherini 2018). Member states are required to transpose these directives and implement them as part of national policies.

The economic literature has shown that young people's activity in the labor market is influenced by numerous factors, including: (*i*) economic determinants, such as the economic structure, and its growth dynamics (Blinder 1997), as well as productivity, the balance of trade in goods and services, inflation, general unemployment, labor costs, and the jobs offered; (*ii*) legal regulations and social policy tools; (*iii*) the educational and vocational training systems; (*iv*) technological change, for example, research and development expenditure, the human resources employed in science and technology, and the application of information and communication technologies (ICT); (*v*) cultural and social conditions; (*vi*) the globalization processes; (*vii*) demographic changes (e.g., population aging, migration, fertility rates, and youth cohort sizes).

NEETs are young people who are disengaged from both education and the labor market (Mascherini and Ledermaier 2016). This cohort of people overlaps with the unemployed, and many NEETs are ready to take up employment. In 2019, the NEET rate (aged 15–29) for the EU was 12.5%, moreover, among persons intending to work (seeking employment or not), it was 7.5%, and for persons who do not want to work was 4.5%. In this respect, the measure is similar to the YU index, and both are closely linked to economic performance and business cycle. However, NEETs also include young people who are long-term unemployed, fleetingly unemployed, looking after children or relatives at home, temporarily sick or long-term disabled, putting their efforts into developing artistic or musical talents, or simply taking a short break from work or education. More time and support are required to get people from this group back into employment (Furlong 2006).

It is worth highlighting that there is a gender imbalance in the NEET group. In 2019 NEETs accounted for 14.4% of women aged 15–29, and 10.7% of men in the same age range. According to Eurostat "young female NEETs were more likely to be inactive, while young male NEETs were more likely to be unemployed" (Eurostat 2020). Such a large difference is not observed in younger age groups, e.g., the NEET rate for those aged 15–24 was 10.4% for women and 9.9% for men. The difference may be due to the greater involvement of women within the family. Summarizing, the scale of YU largely results from the condition of the economy, and NEET rates may also be influenced by socio-demographic factors related to the family model or migration. Despite the differences between these indicators, both are important in the overall debate on situation of youth in the European labor market (Eurofound 2012).

We contribute to the existing literature by monitoring the dynamics of NEETs and YU through an hidden Markov (HM) model (Bartolucci et al. 2014) tailored for analyzing longitudinal data (Frees 2004; Hsiao 2014). We assume that the observed continuous response variable depends on a latent variable following a first-order Markov chain and having a discrete distribution. We assess the influence of some important macroeconomic factors on the transition between states representing latent clusters of countries. The HM model allows us to probabilistically infer unobserved heterogeneous subpopulations that share similar dynamics thus extending the finite mixture model of Gaussian distributions (Titterington et al. 1985; McLachlan and Peel 2000) to the case of longitudinal observations. As proposed by Bartolucci et al. (2013) the HM model with covariates on the latent model is made of two sub-models: the measurement model on which the clustering is based and the latent model used to explain the clustering structure. Maximum likelihood estimation of the model parameters is carried out through the expectation-maximization (EM) algorithm (Dempster et al. 1977; Welch 2003). With respect to the other model-based clustering procedures (Bouveyron et al. 2019), we model the complex data structure in a flexible way since the distribution of the underlying latent variable is left unspecified with an arbitrary number of support points.

The NEET and YU rates of the 28 European countries from 2004 to 2019 are investigated by examining the differences between the countries' economies, including the United Kingdom which was a member state in the considered period, and using exogenous macroeconomic variables that measure the countries' economic and labor market statuses. Our analysis has the following features: (*i*) countries' patterns of change in the response variables are identified to check whether they differ significantly; (*ii*) we examine to what extent these patterns are due to the countries' economic and labor market conditions; (*iii*) European countries are dynamically classified on the basis of NEETs and YU, separately, using a model-based dynamic clustering approach.

The remainder of this paper is organized as follows. Section 2 reviews the literature on the influence of economic conditions and regulations on NEETs and YU. Section 3 describes the available data and the conceptual framework. Section 4 introduces the proposed model, and Sect. 5 reports the results of the estimated model for NEETs and YU. Section 6 provides some final remarks.

2 A Focus on the Literature on NEETs and YU

Economists and politicians have always been interested in the differences between countries' economic and political institutions. As part of the very large literature on this topic, studies have attempted to understand the associations between growth dynamics and unemployment; see, among others, International Monetary Fund (2010) and Nagel (2015). Nevertheless, further exploration of the subject, including general patterns and deviations from them, can contribute to a better understanding of unemployment, in particular youth unemployment, and allow governments to take better decisions and actions.

It is worth mentioning two approaches to examining types of economies that focus on institutional complementarities and how they reinforce the differences between liberal and coordinated market economies. Hall and Soskice (2001) divided economies into two groups according to how they are “coordinated" by markets or other institutions. They showed that countries with liberal market economies (e.g., Great Britain, Ireland) tend to rely on markets to coordinate both financial and industrial systems. In other words, firms coordinate their activities primarily via hierarchies and competitive market arrangements. In contrast, countries with coordinated market economies (e.g., Germany, the Netherlands, Belgium, Sweden, Denmark, Finland, Austria) have institutions in financial and industrial spheres that reflect higher levels of non-market adjustment. In this model, firms depend more heavily on non-market relationships to coordinate their efforts with other actors.

Another approach classifies markets according to whether they use active or passive labor market policy instruments. According to their scale and method of financing active instruments, the European markets can be divided into four types: Scandinavian (Nordic), Continental (cooperative), Mediterranean (Latin), and Liberal (Anglo-Saxon). The Scandinavian countries, where an active policy is a central issue, spend the highest amount on active labor market instruments (relative to Gross Domestic Product (GDP)), whereas the smallest amount is observed under the liberal model, in which the free market mechanism is a priority (Gallie and Paugam 2000; Greve 2001; Nagel and Smandek 2010; Frączek 2015).

Labor policy instruments used by countries’ authorities include: minimum wage regulations, employment protection laws, reductions in employers’ social security contributions for low-paid/low-skilled workers (and sometimes young workers), and labor market flexibility (facilitating temporary and part-time work, OECD 2010). These instruments have varied importance for particular groups of the unemployed. Parisi et al. (2015) found that employment protection legislation was not particularly relevant in explaining the total unemployment rates. This legislation appeared more important for younger than older employees. In fact, employment protection legislation has been found to impact the distribution and duration of unemployment by affecting worker turnover more than the unemployment level itself (OECD 2006a). More flexible labor markets help young people to access labor positions, and analyses based on cross-sectional data have found a positive impact of part-time contracts on employment of young people (Bal-Domańska and Sobczak 2020).

One of the basic macroeconomic indicator, determining the condition of the economy and the labor market, is the level of economic development, which guarantees appropriate levels of remuneration for workers. In the case of economic advancement, both the level of development and the growth rate are of key importance. Studying the euro area, Salvador and Leiner-Killinger (2008) found that economic conditions, represented by economic growth, are negatively correlated with the YU rate. Ebaidalla (2016) used a simplified panel data model to analyze YU in 32 countries of the Organization of Islamic Cooperation (OIC) from 1993 to 2012, focusing on the impacts of economic, demographic, and institutional factors. The empirical results show that YU is influenced by the economic environment, measured by GDP growth, inflation, and domestic investment. A study conducted by Bayrak and Tatli (2018) covering 31 OECD countries, using data referred to the period 2000–2015, indicated that low growth rates of GDP, inflation, and savings (measured as percentages of GDP) negatively affect YU, whereas labor productivity has a positive impact. These results suggest that development of the economy supports job creation and employment for young people.

Young people in the labor market are more sensitive to business cycle conditions and economic crises than older people or the workforce overall (Hutengs and Stadtmann 2013). Research carried out by Bruno et al. (2017) examining OECD countries over the period

1981–2009 showed that the impact of financial crises (related to production, income, expenditure, etc.) on YU rates is always lagged. However, over and above the effects of the business cycle, some structural demand-side barriers persist regarding high labor costs, partly due to relatively high minimum wages, and unbalanced employment protection legislation between temporary and permanent employment (OECD 2010).

Strong associations between the overall condition of the labor market and both the total unemployment rate and total long-term unemployment for young people are also confirmed in a recent study by Bal-Domańska (2020). Moreover, in the case of NEETs, the reduction of YU is influenced by other country-related factors. In particular, we mention participation levels in education and training and the tendency to continue education (affecting the percentage of early leavers), as well as other economic factors such as the level of involvement in the knowledge and research-based economy and the proportion of total labor costs (wages plus taxes minus subsidies) relative to non-wage costs incurred by organizations in industry, construction, and services.

Knowledge is a key resource in stimulating economic transformations, and ICT is a key element in creating jobs for young people because it can offer new skills, creativity, and a fresh approach to a company's operation. Such knowledge can subsequently be manifested in innovation, which is a crucial determinant of long-term economic growth. Nevertheless, the development of a knowledge-based economy and innovation involves certain requirements to create critical levels of basic production factors, human capital, and knowledge. When preparing young people to enter the labor market, particular attention should be paid to the development of skills primarily required and valued by employers in a given market, and to fields of study, thus strengthening educational capital[1] (Howard et al. 1996; Bal-Domańska 2018; Bal-Domańska and Sobczak 2020). Education level is perceived as a precondition both for entering the labor market and for the development of a knowledge-based economy offering high productivity, attractive work, and higher quality of living. The demand for new skills as well as soft skills (Heckman and Kautz 2012) can change the regular generational occupational replacement model; because the labor market is dynamic, occupations keep changing and young people are frequently more capable to fulfill the latest needs. Moreover, in some occupations, employees in certain jobs are not replaced when they retire, and instead, the jobs opened for youth are new ones (Lemaître 2013).

There is also another scenario according to which young people who lack work experience are considered to be unskilled workers requiring extensive training and time to achieve the required level of skills. This scenario reduces a young person's chances to enter the labor market quickly and effectively, and the problem is particularly relevant for NEETs. Among such individuals are those with good contacts and credibility, who could be 'turned around' to labor activity relatively quickly, and others who need more protracted attention, intervention, and patience (Williamson 2010).

Analyses conducted by Bal-Domańska (2018) at the regional level, based on spatial data for 267 NUTS-2 EU regions in 2016, demonstrate the importance of educational capital for young people in EU labor markets. The regions featuring a high percentage of scientists and engineers in the active population are more favorable places for young people to take up professional activity. Willingness to continue learning is also of greater importance for improving the employment rate among young people than older workers. In addition, regional markets with well-developed formal and non-formal adult education and training

[1] Educational capital is a part of human capital that includes formal education and professional qualifications.

facilities have lower problems of professional and educational inactivity among young people. According to results obtained for two Czech regions (the Ústecky region and the Jihoéský region) by Novák et al. (2016), unemployed persons typically have no previous job experience, have completed only primary education, and are not willing to travel to work.

3 Data and Conceptual Framework

We assess the situation of young people in European labor markets using data on both NEETs and YU collected by Eurostat[2] through the labor force survey[3] covering a period of sixteen years from 2004 to 2019 that includes the 2008 global financial crisis. This crisis significantly impacted unemployment among young people in all of the EU's domestic markets (Bruno et al. 2017). In Table 1 we report a description of NEET and YU. NEETs include both active jobseekers and inactive non-workers aged 15 to 29, and YU is defined as the rate of unemployment among individuals aged between 15 and 24. These categories cover both teenagers (aged 15–19) and young adults (aged 20–29). The most desirable solution for teenagers in these categories is to support them in returning to school, whereas for young adults it is more important to help them to acquire work experience or new skills through training (OECD 2006b).

We consider the covariates described in Table 2 since they may explain variations in labor market outcomes for young people in various ways and to different extents. We focus on changes in the responses, and how these are related to the general macroeconomic situation within EU countries. We assume that the observed response variables may be affected by measurement errors because they derive from data aggregations concerning several individual measures. Accordingly, the latent variable is of interest, and we assume that this is a discrete variable following a first-order Markov process to capture time-varying heterogeneity. We estimate two univariate HM models, one for NEETs and the other for YU, and we allow for the effects of the covariates on the latent model. This model has been effectively employed for the analyses of categorical panel data, especially for its interpretability (Bartolucci et al. 2014; Pennoni and Genge 2020). In the present study we aim to classify countries into a certain number of clusters (latent states) estimated from the model. This number is chosen according to a model selection criterion and the clusters are interpreted as different degrees of exposure of the countries to the analyzed phenomenon. Specific parameters measure the effects of the macroeconomic factors listed in Table 2 on the initial probabilities of the underlying latent process, other parameters measure their effects on the transition probabilities from occasion $t-1$ to occasion t to depict the cluster evolution over time, as explained in the following section. The covariates employed for the NEETs and YU models are the same with the exception of labor cost index, which is employed only in the YU model.

[2] Retrieved from: https://ec.europa.eu/eurostat.

[3] For more information see the webpage of the European Union labor force survey: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=EU_labour_force_survey. Data retrieved in April 2021.

Table 1 Description of NEET and YU elaborated according to the Eurostat definition (data labels are reported in parentheses)

Label	Description
NEET	*Young people Neither in Employment nor in Education and Training (edat_lfse_22)*. The share over the population of a given age group 15 to 29 not employed and not involved in further education or training (further analyzed by sex). The numerator refers to persons who meet the following two conditions: (*i*) they are not employed (i.e., unemployed or inactive according to the ILO definition); and (*ii*) they have not received any education or training (either formal or non-formal) during the four weeks preceding the survey. The denominator is the total population in the corresponding age and sex group. The value is expressed as a percentage.
YU	*Youth Unemployment rate (fst_r_lfu3rt)*. The share of the labor force aged 15 to 24 that is unemployed. The labor force (active population) is the total number of people employed and unemployed. The source for regional labor market information down to NUTS 2 level is the EU labor force survey (EU-LFS). This survey follows the definitions and recommendations of the ILO and defines unemployed persons as those not employed during the reference week who had actively sought work during the past four weeks and were ready to begin working immediately or within two weeks from the survey. The value is expressed as a percentage.

It is known that GDP influences unemployment and an improvement in GDP is associated with an increase in demand for workers (Blinder 1997). Both part-time and temporary contracts support employment growth by offering favorable conditions for employers (in particular, by providing trial periods) and to employees with no experience or qualifications. Part-time contracts can enhance employment by offering attractive working conditions for employees who can only work for part of the day and for employers who have limited demand for work. The employment decisions made by employers are also influenced by the size of labor costs relative to other operating costs. High labor costs may discourage employers from increasing employment in favor of investing in alternative solutions. As a result, high labor costs may be associated with higher productivity. It has been shown that demand for human resources in science and technology is an important factor in improving employment prospects for young people by making new jobs targeted at creative people, and promoting new skills. Such jobs are created in various sectors, favoring the employment of diverse social groups with different qualifications (Perugini and Signorelli 2010). A culture of improving qualifications and lifelong learning is one of the elements responsible for making people active in the labor market and adapting employees' skills to the labor market's constantly changing needs.

3.1 Data Description

The 28 countries that were members of the EU during the considered period are shown in Table 3. The observed values of the response variables by years are summarized in Table 4. The data show that after the global financial crisis, which started in 2008, the labor market got worse for young people. Both NEETs and YU reached their highest levels in 2011–2013, then started to decrease. We observe that there was substantial variability between years and countries, especially for YU.

Table 2 Description of macroeconomic variables according to the Eurostat definition (data labels are reported in parentheses)

Label	Description
dgdp	*Gross domestic product at market prices chain linked volumes (index: 2005=100, nama_10_gdp).* Economic growth is associated with periods of prosperity in which economic activity develops and expands; it helps create new jobs and promote employment.
part	*Part-time employment as a percentage of total employment (among those aged 15–64, lfsi_pt_a).* Developing flexible forms of employment supports the professional activity of young people. Contracts ensure higher flexibility on the labor demand side to respond to fluctuations in output, reducing risk associated with information asymmetry for non-observable factors.
temp	*Temporary contracts as percentage of total employment (among those aged 15–64, lfsi_pt_a).* Temporary and part-time jobs offer individuals the opportunity to fill their experience gaps. Part-time contracts provide employment for people who cannot work full-time, e.g., due to childcare or family members' care.
hrst	*Persons employed in science and technology as a percentage of the active population (among those aged 15–74, hrst_st_ncat).* A proxy for labor demand for highly skilled workers independent of their formal education level.
pedu	*Participation rate in education or training during the four weeks preceding the survey (among those aged 25–64, trng_lfse_04).* This characterizes the tendency of companies and institutions, as well as employees, towards acquiring skills that are lacked and upgrading qualifications.
el	*Early leavers from education and training (edat_lfse_14).* This refers to persons (recorded in the EU-LFS) from the total population aged 18–24 who have completed the lowest secondary education cycle and have not participated in further education or training. Early school leaving has a negative impact on young people's employment outcomes because individuals' relatively low qualifications give them limited opportunity to take up well-paid jobs and so they must seek employment in less technologically advanced sectors. An increase in the number of early school leavers may favor the formation of a group of people facing various barriers to entering the labor market.
lci	*Labor cost index, expressed relative to non-wage costs, for organizations in industry, constructions, and services (except public administration, defense, and compulsory social security, lc_lci_lev).* Labor cost is defined as core expenditure borne by employers for the purpose of employing staff (compensation of employees plus taxes minus subsidies). The index represents the cost pressure arising from the production factor "labor". A high proportion of labor costs (wages) in relation to other costs may discourage employers from increasing employment, including for young people lacking professional experience (the values for the years 2005–2007, 2009–2011, and 2013–2015 are proxies).

Figure 1 shows observed rates of NEETs and YU for three countries: Italy, Poland, and Denmark, which differ substantially in both measures, along with the EU average values.

We notice that the NEET rate of Italy is always above that of the other countries, and the peak (around 26%) was reached in 2014. In Poland, a rapid decrease in this rate was observed from 2004 to 2008, and after a slight increase from 2009 to 2013, a new reduction was registered from 2014 to 2018. In Denmark, NEETs and YU rates were always below 15%, although both measures increased slightly over the observed period.

For YU, Italy experienced a long period of increase from 2008 to 2014, when it peaked at around 40%, followed by a slight decrease in subsequent years. Poland experienced a rapid decrease after 2013, and in 2019 matched the low values observed in Denmark.

Summary statistics for the covariates are shown in Table 5. The relatively few missing values for these covariates have been imputed using observed values at the previous time occasion. We notice that average dgdp increased over time, and there was high variability among countries. The average share of persons employed in science and technology (hrst)

Table 3 Alphabetical list of the member states of the European Union (until 2019) and their country code

Country	Label	Country	Label
Austria	AT	Italy	IT
Belgium	BE	Latvia	LV
Bulgaria	BG	Lithuania	LT
Croatia	HR	Luxembourg	LU
Cyprus	CY	Malta	MT
Czech Republic	CZ	Netherlands	NL
Denmark	DK	Poland	PL
Estonia	EE	Portugal	PT
Finland	FI	Romania	RO
France	FR	Slovakia	SK
Germany	DE	Slovenia	SI
Greece	EL	Spain	ES
Hungary	HU	Sweden	SE
Ireland	IE	United Kingdom	UK

Table 4 Average yearly rate and standard deviation (Sd) of NEETs and YU across EU countries. Source: Eurostat

Year	NEET		YU	
	Average	Sd	Average	Sd
2004	14.354	5.321	19.418	8.123
2005	14.054	4.777	18.764	6.764
2006	12.750	4.111	17.218	6.092
2007	12.164	3.659	15.104	5.039
2008	12.050	3.419	15.443	4.775
2009	14.093	4.304	21.171	6.920
2010	14.718	4.980	23.329	8.632
2011	14.821	5.333	24.025	9.527
2012	15.404	5.488	25.829	11.403
2013	15.582	5.947	26.364	12.859
2014	15.039	5.549	24.532	11.966
2015	14.389	5.104	22.239	11.376
2016	13.668	4.905	20.132	10.097
2017	12.711	4.559	17.854	9.154
2018	12.007	4.164	15.704	8.327
2019	11.575	3.848	14.746	7.476

increased by approximately two percentage points. The average share of participation in education and training (pedu) also increased over time. During the same period, the countries reduced the incidence of early school leavers (el) and the average proportion declined from 15% to 9%. We observe a slight decline in average labor cost (lci). There was no clear trend for the flexible forms of employment such as part time (part) and temporary contracts (temp), although we notice that these variables, along with dgdp, appeared to change in response to the global financial crisis.

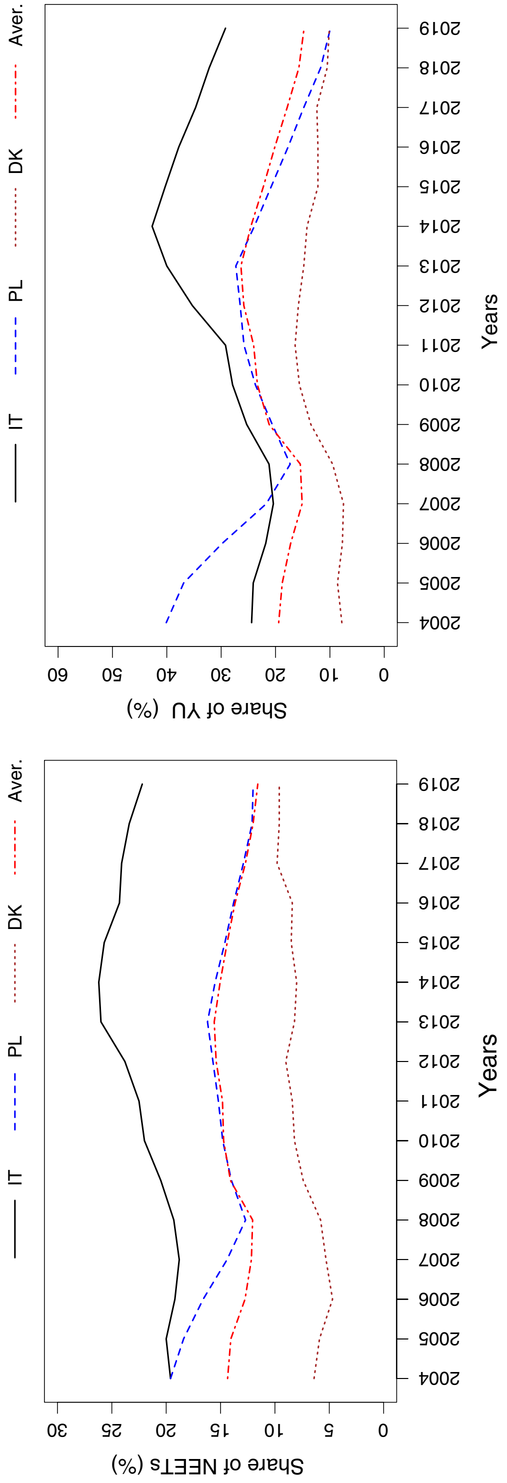

Fig. 1 NEETs (left panel) and YU (right panel) share for Italy, Poland, and Denmark with the average value of the EU countries (Aver.) by year

Table 5 Average values of the covariates and standard deviation (Sd) across EU countries by year

Year	Values	dgdp	part	temp	hrst	pedu	el	lci
2004	Average	96.196	12.954	9.246	25.575	9.014	15.143	22.607
	Sd	(2.359)	(9.181)	(5.312)	(5.826)	(7.321)	(9.511)	(6.850)
2005	Average	96.196	13.154	9.464	26.064	9.068	14.414	22.607
	Sd	(2.359)	(9.350)	(5.622)	(5.596)	(7.236)	(8.327)	(6.850)
2006	Average	105.043	13.289	9.514	26.589	9.279	13.968	22.607
	Sd	(2.476)	(9.496)	(5.981)	(5.522)	(7.447)	(8.089)	(6.850)
2007	Average	110.371	13.318	9.589	27.107	9.154	13.632	21.704
	Sd	(5.325)	(9.676)	(6.072)	(5.460)	(6.941)	(7.790)	(6.391)
2008	Average	111.757	13.429	9.257	27.704	9.486	13.450	21.704
	Sd	(6.807)	(9.871)	(5.884)	(5.586)	(7.166)	(7.438)	(6.391)
2009	Average	105.654	14.179	9.075	28.029	9.639	12.721	21.704
	Sd	(6.848)	(9.917)	(5.428)	(6.502)	(7.391)	(6.924)	(6.391)
2010	Average	107.336	14.646	9.521	28.125	9.825	12.204	21.704
	Sd	(7.654)	(9.992)	(5.357)	(6.664)	(7.775)	(6.417)	(6.391)
2011	Average	109.321	14.857	9.725	29.350	10.161	11.518	21.589
	Sd	(8.994)	(9.990)	(5.303)	(6.800)	(7.581)	(5.703)	(6.431)
2012	Average	109.132	15.096	9.536	29.857	10.232	11.100	21.589
	Sd	(10.533)	(10.093)	(5.180)	(7.324)	(7.611)	(5.171)	(6.431)
2013	Average	109.743	15.325	9.732	30.186	10.682	10.418	21.589
	Sd	(11.745)	(10.184)	(5.257)	(7.621)	(7.823)	(4.957)	(6.431)
2014	Average	112.411	15.375	10.125	30.650	10.607	9.904	21.550
	Sd	(13.192)	(10.141)	(5.576)	(7.789)	(8.011)	(4.877)	(6.302)
2015	Average	116.793	15.364	10.439	30.954	10.818	9.846	21.455
	Sd	(15.931)	(10.187)	(5.752)	(7.015)	(8.051)	(4.503)	(6.229)
2016	Average	120.161	15.357	10.500	31.575	10.875	9.479	21.368
	Sd	(17.192)	(10.284)	(5.921)	(6.955)	(7.770)	(4.388)	(6.200)
2017	Average	124.654	15.161	10.429	32.243	11.321	9.411	21.304
	Sd	(19.191)	(10.284)	(6.000)	(6.920)	(7.792)	(4.034)	(6.163)
2018	Average	128.989	14.807	10.229	32.971	11.568	9.193	21.293
	Sd	(21.659)	(10.310)	(5.859)	(7.142)	(7.746)	(4.002)	(6.280)
2019	Average	132.893	14.696	9.861	33.675	11.821	8.993	20.468
	Sd	(23.990)	(10.416)	(5.469)	(7.245)	(8.319)	(3.782)	(6.786)

4 Hidden Markov Model

Let Y_{it} be the continuous response variable measured at time t, $t = 1, \dots, T$, for country i, $i = 1, \dots, n$, and let $\boldsymbol{U}_i = (U_{i1}, \dots, U_{iT})'$ be the vector of time-varying discrete latent variables influencing the distribution of the responses. This latent process is defined for each country i as a first-order Markov chain with a finite number of states denoted by k. Under the local independence assumption the responses collected into the vector $\boldsymbol{Y}_i = (Y_{i1}, \dots, Y_{iT})'$ are conditionally independent given the hidden process. A Gaussian distribution is assumed as follows:

$$\boldsymbol{Y}_i | U_{it} = u \sim N(\boldsymbol{\mu}_u, \boldsymbol{\Sigma}), \qquad u = 1, \dots, k,$$

where u denotes a realization of U_{it}, the vector $\boldsymbol{\mu}_u$ denotes the component-specific means, and $\boldsymbol{\Sigma}$ denotes the variance-covariance matrix which is constant across states under the assumption of homoscedasticity. This assumption may be suitably relaxed according with the specific applicative context.

The covariates collected into the vector $\boldsymbol{x}_{it}$ at the t-th time occasion are assumed to affect the distribution of the latent process. Another possible model formulation accounts for a direct effect of the covariates on the response variable (Bartolucci et al. 2013, Chapter 5). Let $\pi_{iu|\boldsymbol{x}} = p(U_{i1} = u|\boldsymbol{x}_{i1})$ denote the class weight for component u, $u = 1, \dots, k$, and $\pi_{i,u|\bar{u},\boldsymbol{x}} = p(U_{it} = u|U_{i,t-1} = \bar{u}, \boldsymbol{x}_{it})$, $t = 2, \dots, T$, $u, \bar{u} = 1, \dots, k$, denote the transition probabilities of the Markov chain between latent states for country i. When these probabilities are time homogenous, the same evolution for all time occasions is conceived, and a more parsimonious model results; however, this assumption can be relaxed formulating a model with heterogeneity or partial time homogeneity across time occasions. We assume a parameterization based on the following multinomial logits

$$\log \frac{\pi_{iu|\boldsymbol{x}}}{\pi_{i1|\boldsymbol{x}}} = \beta_{0u} + \boldsymbol{x}'_{i1}\boldsymbol{\beta}_{1u}, \quad u = 2, \dots, k, \tag{1}$$

$$\log \frac{\pi_{i,u|\bar{u},\boldsymbol{x}}}{\pi_{i,\bar{u}|\bar{u},\boldsymbol{x}}} = \gamma_{0\bar{u}u} + \boldsymbol{x}'_{it}\boldsymbol{\gamma}_{1\bar{u}u}, \quad u = 1, \dots, k,\ \bar{u} = 1, \dots, k+1,\ \bar{u} \neq u, \tag{2}$$

where $\boldsymbol{\beta}'_u$ and $\boldsymbol{\gamma}'_{\bar{u}u}$ are parameter vectors to be estimated.

The manifest distribution of the observed responses $\boldsymbol{y}_i$ for sample units $i = 1, \dots, n$ is defined as

$$f(\boldsymbol{y}_i) = \sum_{u=1}^{k} \left(\prod_{t=1}^{T} f(\boldsymbol{y}_{it}|u_{it}) \right) \left(\pi_{iu|\boldsymbol{x}} \prod_{t=2}^{T} \pi_{i,u|\bar{u},\boldsymbol{x}} \right),$$

where $f(\boldsymbol{y}_{it}|u_{it})$ refers to the conditional distribution of $\boldsymbol{Y}_i$ given $U_{it} = u$. The observed log-likelihood is:

$$\ell(\boldsymbol{\theta}) = \sum_{i=1}^{n} \log f(\boldsymbol{y}_i),$$

where $\boldsymbol{\theta}$ is the vector of all model parameters. The EM algorithm (Dempster et al. 1977; Welch 2003) is employed to obtain maximum likelihood estimates of the model parameters. It maximizes $\ell(\boldsymbol{\theta})$ by alternating two steps until convergence. At the *E-step* we compute the conditional expected value of the *complete data log-likelihood* $\ell^*(\boldsymbol{\theta})$, given the observed data and the current value of the parameters. At the *M-step* we obtain the estimate of $\boldsymbol{\theta}$ by maximizing the expected value of $\ell^*(\boldsymbol{\theta})$ calculated at the *E-step*. These two steps are iterated until convergence which is checked on the basis of the relative log-likelihood. This algorithm requires that the parameters are initialized using suitable starting rules (Bartolucci et al. 2013, Chapter 3). The number of unobserved components is selected according to the minimum value of the Bayesian Information Criterion (BIC, Schwarz 1978) having expression

$$BIC_k = -2\hat{\ell}_k + \log(n)\#par_k,$$

Table 6 Results of the HM models for NEETs and YU for increasing number of hidden states (k), showing maximum log-likelihood ($\hat{\ell}_k$), corresponding number of parameters ($\#par_k$), and realized values of the BIC index (BIC_k)

k	$\hat{\ell}_k$	$\#par_k$	BIC_k
NEETs			
1	−1,343.602	2	2,693.869
2	−1,141.111	24	2,362.195
3	−1,017.790	60	2,235.513
4	−958.309	110	2,283.161
5	−899.924	174	2,379.652
YU			
1	−1,649.265	2	3,305.195
2	−1,479.582	27	3,049.134
3	−1,346.322	68	2,919.234
4	−1,307.804	125	3,032.133
5	−1,288.177	198	3,236.131

where $\hat{\ell}_k$ denotes the maximum of the log-likelihood of the model with k states and $\#par_k$ denotes the number of free parameters. Once the parameter estimates are computed, standard errors may be obtained on the basis of the observed or expected information matrix. Otherwise, a parametric (or non-parametric) bootstrap procedure (Zucchini and MacDonald 2009; Bartolucci et al. 2013, see Chapter 3 and Chapter 6, respectively) may be employed as an alternative method.

Let $p(\hat{U}_{it}|\boldsymbol{Y}_i = \boldsymbol{y}_i)$ be the estimated posterior probabilities obtained through the Bayes rule, *path prediction* is performed with the maximum-a-posteriori rule. In this way, using local decoding (Juang and Rabiner 1991) we predict the sequence of latent states for a given country for each time occasion as follows:

$$\tilde{u}_{it} = \max_{\hat{U}_t} p(\hat{U}_{it}|\boldsymbol{Y}_i = \boldsymbol{y}_i). \tag{3}$$

Suitable functions to estimate a general class of HM models including the proposed model are available within the package LMest (Bartolucci et al. 2017) of the open source R software (R Core Team 2021). The data and the implemented code are available from authors upon request.

5 Results

In the following we show the results of the models estimated for both NEETs and YU. The model for NEETs includes the following covariates: dgdp, part, temp, hrst, pedu, and el (see Table 2); the model for YU also includes lci. The results of the fitting procedure with an increasing number of latent states ranging from 1 to 5 are reported in Table 6.

For both models, the BIC_k index suggests that three latent states are preferable. The estimated expected averages under the HM model with three states are reported

Table 7 Estimated expected averages under the HM models with $k = 3$ states for NEETs and YU

	$u = 1$	$u = 2$	$u = 3$
NEETs	8.441	13.501	20.357
YU	12.644	21.883	37.968

Table 8 Estimated averaged initial and transition probabilities under the HM models with $k = 3$ states for NEETs and YU

	$u = 1$	$u = 2$	$u = 3$
NEETs			
$\hat{\pi}_{u,x}$	0.298	0.382	0.320
$\hat{\pi}_{u\|1,x}$	0.499	0.437	0.064
$\hat{\pi}_{u\|2,x}$	0.117	0.794	0.089
$\hat{\pi}_{u\|3,x}$	0.073	0.349	0.578
YU			
$\hat{\pi}_{u,x}$	0.399	0.490	0.111
$\hat{\pi}_{u\|1,x}$	0.833	0.086	0.081
$\hat{\pi}_{u\|2,x}$	0.204	0.687	0.109
$\hat{\pi}_{u\|3,x}$	0.067	0.523	0.410

in Table 7. The estimated common variance is 4.177 and 18.902 for NEETs and YU, respectively.

We notice that the three states define clusters of countries whose average shares of NEETs and YU are very different, and they are ordered according to increasing values. The first group contains the best performing countries, the second the intermediate countries, and the third the worst performing countries.

Table 8 reports the estimated parameters of the latent model for NEETs and YU. For NEETs, we notice that the first group of countries, about 30% in 2004, shows low values of this rate (8.44 on average according to Table 7). We estimate that from 2005 to 2019, 44% of countries move from the first (best) to the second (intermediate) cluster, thus showing worsening performance. Countries in the second group, about 38% in 2004, show the highest persistence probability (0.79), and are thus expected to remain in the intermediate group throughout the study period. Countries in the third group, about 32% in 2004, are defined as worst performing countries and show a relatively high estimated probability (around 0.35) of moving into the second group, thus improving their performance during the observed period.

In the results for YU reported in Table 8, we notice that the first group of countries, about 40% of countries in 2004, characterized by the lowest average value of YU, shows the highest persistence probability (0.83) from 2005 to 2019. The intermediate group of countries, 49% in 2004, shows the highest probability (0.20) of moving into the first group, thus reducing YU. The group of worst performing countries, about 11% in 2004, characterized by very high levels of YU shows a comparatively high probability (around 0.52) of moving into the intermediate group during the period. We also observe that about 7% of worst performing countries move into the first group, thus showing a significant improvement in reducing YU.

Table 9 Estimates of logit regression parameters of the initial probabilities for for the second and the third state with respect to the first state under the HM models with $k = 3$ for NEETs and YU (significance levels are denoted as †10%, *5%, **1%)

Effect	NEETs		YU	
	$u = 2$	$u = 3$	$u = 2$	$u = 3$
Intercept	62.066**	−46.67**	−35.828**	0.383**
dgdp	−0.395	0.857	0.055	0.642
part	0.392	−0.692	−0.551	−1.108
temp	−0.078	−0.148	−0.214	0.088
hrst	−0.525	0.263	0.023	−2.175
pedu	−1.756	−4.268**	0.553	−0.505
el	0.122	−0.107	0.311	−2.560
lci	–	–	1.234†	0.831

Table 10 Estimates of the logit regression parameters of the transition probabilities under the HM models with $k = 3$ states for NEETs and YU (significance levels are denoted as †10%, *5%, **1%)

Effect $\bar{u}, u$	1–2	1–3	2–1	2–3	3–1	3–2
NEETs						
Intercept	31.554	25.793	−27.816	15.005	−28.32†	−7.297
dgdp	−0.090	−0.377	0.039	−0.097	0.037	0.041
part	−0.293	−1.525	−0.188	0.005	−0.219	−0.116
temp	−0.072	1.289	−0.045	−0.046	−0.015	0.027
hrst	−0.679	0.199	0.677	−0.190	0.142	0.047
pedu	−0.181	−2.240†	−0.011	−0.170	1.396	0.338
el	0.396	1.363	0.170	−0.070	−0.988	−0.101
YU						
Intercept	12.534	63.777**	−13.345†	39.615*	−50.314**	−15.700
dgdp	−0.012	−0.590*	0.045*	−0.345*	0.074	0.143
part	0.007	−0.772	−0.208*	0.142	−2.117	−0.230
temp	0.131	−2.541*	−0.311*	0.235*	−0.310	−0.114
hrst	−0.440**	0.747	0.522*	−0.151	1.520	0.318
pedu	0.041	−1.407	−0.156	−0.163	−0.569	0.726
el	−0.149	−0.187	−0.072	−0.112	1.563	−0.070
lci	−0.124	0.188	−0.099	−0.212	−0.265	−0.461

Concerning the three selected countries illustrated in Figure 1 we report that in 2004 Denmark started with the most favorable situation for young people (for both NEETs and YU) and is in the first group for both models, Poland started with the worst situation and is in the third group for both models, and Italy is in the group of worst performing countries (third) for NEETs and in the intermediate group (second) for YU. We also notice that for both measures Denmark has the highest persistent probability in the group of best performing countries (first), Poland has the highest transition probability from the worst performing (third) to the intermediate (second) group of countries, and Italy has the highest persistence probability in the group of worst performing countries (third).

Table 9 shows the estimated regression parameters for the initial probabilities. These represent the effects of the macroeconomic factors estimated as in Eq. (1). The statistical significance of the coefficients of the model for NEETs is established using standard errors obtained from a parametric bootstrap according to 900 replications. The estimated standard errors of the coefficients of the model for YU are obtained using the inverse of the expected information matrix.

The log-odds for rate of participation in education and training (pedu) is negative and statistically significant for the third logit for NEETs, indicating that in the initial period, countries with high values of pedu tend to belong to the first group rather than the third. The log-odds for labor cost index (lci) is positive and statistically significant for YU for the second logit, indicating that countries with high values of lci tend to belong to the second group of intermediate countries rather than the first.

The first panel of Table 10 reports the coefficients on the transition probabilities for NEETs estimated as in Eq. (2). We observe that the only statistically significant coefficient is the participation rate in education and training for the transition from the first to the third state. This indicates that the probability of transitioning from the best group (first) to the worst performing group (third) decreases for a point increase in pedu (the odds ratio is equal to exp(-2.24) = 0.11), all other macroeconomic variables held fixed. We therefore note the importance of educational attainment, which may constitute a key feature for active policies to reduce NEETs.

The second panel of Table 10 reports the estimated coefficients for YU. We notice that an increase of a point percentage of people employed in science and technology (hrst) reduces the transition probability from the first (best) to the second (intermediate) group, all the other variables held fixed (the odds is exp(-0.44) = 0.64), and increases the transition probability from the second to the first group (the odds is exp(0.52) = 1.68). Therefore, these results suggest that the best performing countries should continue to develop employment in the science and technology sector to retain their leading position, and intermediate countries should increase investment in this field to reduce YU. Gross domestic product (dgdp) and temporary contracts (temp) reduce the probability of transition from the first to the third group, and are thus important factors for countries that wish to ensure low YU. High dgdp also increases the probability of transition from the second to the first group. On the other hand, part-time (part) and temporary contracts (temp) do not increase the probability of transition from the second to the first group. According to Table 8 20% of members of the second group transition into the first and we show that hrst has a positive effect on this transition probability. We observe that none of the macroeconomic variables can explain the estimated transition from the third to the second group, and we conclude that unmeasured factors appear likely to contribute to this transition.

Using *local decoding* we predict the patterns of each country over time through the most likely sequence of latent states on the basis of the estimated maximum posterior probabilities, as in Eq. (3). Figure 2 shows the percentages of the countries allocated in the three clusters each year. From the patterns in Figure 2, we observe that a reduction in NEETs is predicted to be more difficult than a reduction in YU, and the NEET phenomenon is more resistant to changes in the countries' economies. In particular, during the financial crisis period, the number of countries predicted in the best group for NEETs (shown in green) is constant, and only a small proportion of countries improved their position during the last three years.

For YU the proportion of countries improving their position is much higher than for NEETs, and thus YU shows a clearer negative immediate reaction and subsequent recovery following the global financial crisis. In the current economic situation, many European

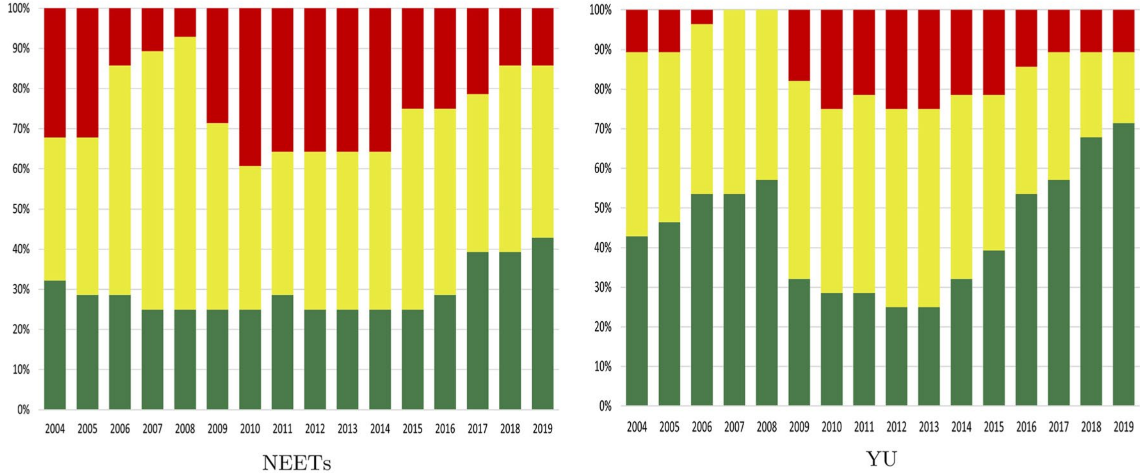

Fig. 2 Countries predicted in each cluster for each year under the HM models with $k = 3$ states for NEETs (left panel) and YU (right panel); green, yellow, and red denote the first (best), the second (intermediate), and the third (worst) cluster, respectively

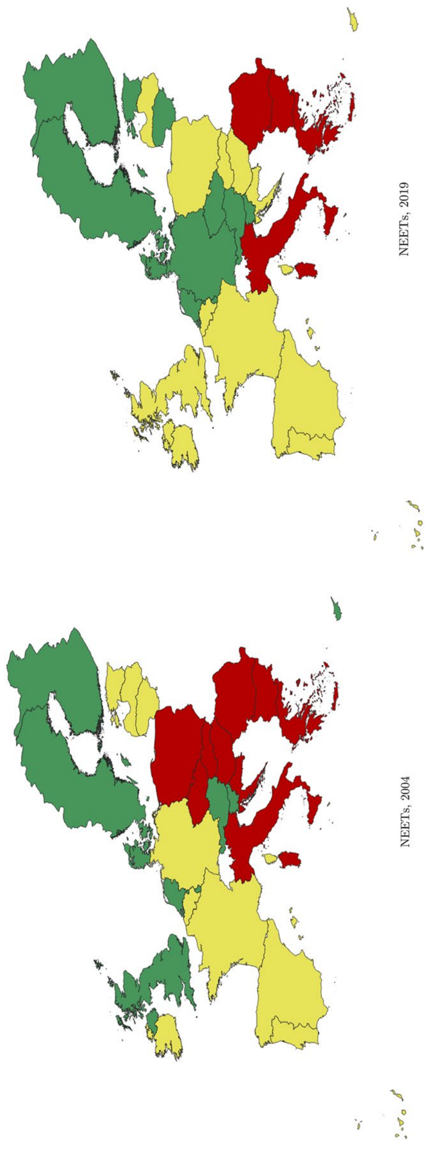

Fig. 3 Maps of the European countries showing the predicted states for NEETs: left panel in 2004 and right panel in 2019, under the HM models with $k = 3$ states; green, yellow, and red denote the first (best), the second (intermediate), and the third (worst) cluster, respectively

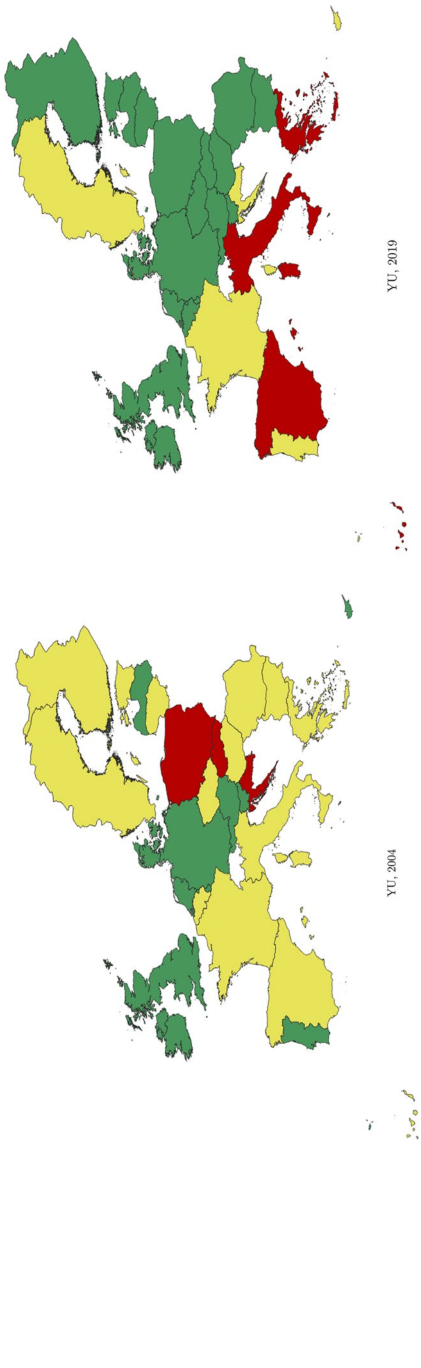

Fig. 4 Maps of the European countries showing the predicted states for YU: left panel in 2004 and right panel in 2019, under the HM models with $k = 3$ states; green, yellow, and red denote the first (best), the second (intermediate), and the third (worst) cluster, respectively

countries are predicted to transit to the best group, thus achieving a consistent reduction in YU, and only a few countries are predicted to stay in the worst group (shown in red). Compared to NEETs, fewer countries are predicted in the intermediate group for YU (shown in yellow), especially in the last few years.

Concerning the groupings for NEETs, we estimate that ten countries retained the same position for the duration of the study period, six of which belong to the first group. These six countries can be considered a benchmark for EU policies aimed at decreasing the proportion of NEETs of the other EU countries. Generally, the best performing countries are those with coordinated market economies (Hall and Soskice 2001). At the same time, these countries follow the Scandinavian model, and are generally the countries that spend the most on active labor market instruments. The only country that improved its position from the worst to the best group is the Czech Republic. Germany, Estonia, Lithuania, and Malta improved their grouping from the intermediate to the best group.

Focusing on groupings for YU, we estimate that eight countries retained the same position for the duration of the study period, six of which belong to the first group. The countries that improved their position from the worst or intermediate group up to the best are Bulgaria, the Czech Republic, Estonia, Lithuania, Hungary, Poland, Romania, Slovakia, and Finland. These are mainly countries from Central and Eastern Europe (CEE), except for Estonia and Finland. The results suggest that after joining the EU, CEE countries took the opportunity to introduce structural changes that improved their economic and labor market conditions.

Figures 3 and 4 use geographical maps to show the grouping of each country at the beginning of the period of observation in 2004 and at the end in 2019, according to the *local decoding* as in Eq. (4). Figure 3 shows groupings for NEETs in 2004 (right) and 2019 (left). We notice that in 2004 Bulgaria, the Czech Republic, Greece, Italy, Hungary, Poland, Romania, and Slovakia are in the third group (red) of worst performing countries, and at the end of 2019, only Bulgaria, Italy, Greece, and Romania, remain in this group, showing that the efforts of these countries to tackle the NEET phenomenon were not effective.

Figure 4 shows groupings for YU. There are three countries allocated to the worst performing group in 2004 and three in 2019, but they are not the same countries. In 2004, these are Croatia, Poland, and Slovakia, and in 2019 they are Greece, Spain, and Italy. We also observe that many CEE countries were able to reduce YU substantially.

6 Conclusion

Longitudinal rates of NEETs and YU across EU countries over a recent sixteen year period from 2004 to 2019 are analyzed through an hidden Markov model. The model is estimated separately for the two response variables, assessing the effects of the countries' macroeconomic factors in the distribution of the latent process. This approach allows us to characterize differences among countries and to evaluate changes whilst comparing the countries' dynamics. We choose a model with three clusters through the Bayesian information criterion. They represent different degrees of exposure of the countries for both response variables, and are ordered according to increasing values of the estimated averages of NEETs and YU rates. The first cluster refers to the best performing countries, the second to the intermediate countries, and the third to the worst performing countries. We estimate the effects of macroeconomic factors on the initial and transition probabilities using a suitable parameterization. The estimated initial probabilities provide the weight of each cluster at the beginning of the period in 2004, and the estimated averaged transition matrix provides an exhaustive description of the transitions across clusters from 2005 to 2019.

We find that only the participation rate in education and training shows a statistically significant influence on the initial probabilities for NEETs, and other factors appear to be irrelevant. Thus, differences across countries are mainly related to unobserved factors accounted for by the latent variable. Labor cost index expressed relative to non-wage costs is instead statistically significant for YU indicating that at the beginning of the period countries with high labor costs are allocated in the intermediate cluster with respect to the best one. A limited number of macroeconomic factors are found to influence changes between clusters. For NEETs, we find a positive effect of the participation rate in education and training, favoring a country in the best performing group staying in that group. For YU, we find multiple factors that are influential for specific transitions. Positive effects are observed for the scale of human resources employed in science and technology, gross domestic product at market prices, and mixed effects are observed for flexible forms of employment.

Using *local decoding* we predict the countries' allocations over time. We notice that changes in groupings are connected to the economy's evolution and especially to the 2008 global financial crisis. After the crisis most countries show an improvement, which is especially visible for YU. Comparing the transition patterns for NEETs and YU, we observe some similarities in the effects of the crisis for the worst performing group of countries. However, the transition patterns of the best performing countries differ substantially between NEETs and YU. These countries seem to be resilient to economic changes for NEETs, even during the global financial crisis, and tend to persist in the same cluster. In contrast, for YU they are substantially influenced by the crisis.

Finally, we observe that countries with coordinated markets that spend a sizeable part of gross domestic product on active labor market policies are the best performing for NEETs over the entire period. An exception is Slovenia, which despite a relatively low share of active labor market expenses, has developed a youth friendly labor market. The Central and Eastern European countries have improved their performance in youth employment to the greatest extent. Countries in Southern Europe mainly belong to the worst group for both NEETs and YU. Some countries recorded substantial positive changes in YU, and some improved their performance in both measures, for example, the Czech Republic transitioned from the vulnerable group to the best group for NEETs. On the other hand, the UK's grouping for NEETs worsened, as did Portugal's grouping for YU, and Cyprus's groupings for both NEETs and YU.

We notice that a limitation of this study can be due to the data used for the analyses which are aggregated at the country level. This allowed us to understand the influence of countries' characteristics (e.g., national labor market regulations, the condition of the economy) on youth employment and activity in the labor market. However, the country level data present aggregate information for very large territorial units. More in-depth conclusions could be reached using regional data (e.g., NUTS-2 level), and these would allow us to operationalize regional diversity to better understand the role of economic factors.

Acknowledgements Bal-Domańska acknowledges the financial support from the grant of the Ministry of Science and Higher Education in Poland under the programme Regional Initiative of Excellence 2019–2022 project number 015/RID/2018/19.

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