



Household Overcrowding and Related Aspects in the EU

Beata Stehlikova,¹ Maria Zubkova,² Janka Zajacova³

¹ Pan-European University, Faculty of Economics and Business, Bratislava, Slovak Republic

² Slovak University of Technology, Faculty of Civil Engineering, Bratislava, Slovak Republic

³ Slovak University of Technology, Faculty of Civil Engineering, Bratislava, Slovak Republic

Corresponding Author: Maria Zubkova

ABSTRACT: In this paper, we aim to verify the link between household overcrowding and other socio-economic factors in EU countries. The partial goals are to identify and quantify the dependencies of overcrowding rate and selected socio-economic facts. Partial objectives include the identification of clusters of EU countries that are similar in terms of factors analysed. Using a random forest algorithm, we determine the significance of analysed factors on overcrowding. We use cluster analysis to create groups of countries with similar values of analysed indicators. The most significant factor was GDP per capita. The coefficients of determination of the prediction model are sufficiently high (0.94). The optimal number of clusters is three. The first cluster includes Belgium, Germany, Austria, Finland, France, Denmark, the Netherlands, and Sweden, which are characterised by socially oriented housing policies. In the third cluster are Ireland and Luxembourg, and the second cluster has the remaining EU countries. The paper's results suggest that housing overcrowding should not only be addressed by direct housing policy instruments, but that tackling selected socio-economic aspects - such as education, long-term unemployment, and income inequality – also contributes both to housing issues as well as overall living standards in EU countries.

KEYWORDS: housing; inequality; long term unemployment; education; GDP

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I. INTRODUCTION

The right to housing is enshrined in the Universal Declaration of Human Rights and the International Covenant on Economic, Social and Cultural Rights (General Comment Nos. 4 and 7) as part of the right to a decent standard of living. Research has identified housing as one of the key socio-economic indicators to assess quality of life. Housing is more than just shelter. People's overall happiness or quality of life correlates with housing satisfaction and conditions, and such satisfaction can also be seen as an indicator of individual happiness and well-being (Toscano and Amestoy, 2008).

As key concepts in policy and social development strategies (Kozera, A., Kozera, C., and Hadyński, 2021), living standards and social inequality have long been the subject of economic analysis and research. There are several dimensions to well-being but a good place to start is the measurement of material well-being or living standards. (Stiglitz, Sen, and Fitoussi; 2009). The availability of sufficient space in a dwelling is a key issue in assessing housing quality, since it influences how and where people prepare and consume food, how they socialise, how they manage household waste and recycling, and how they store things.

II. THEORETICAL BACKGROUND

The overcrowding rate is defined as the percentage of the population living in an overcrowded household. Crowding indices are tools used to measure the level of household crowding, whereby the standard measure is persons-per-room in a dwelling unit. Others consider the total number of persons in a unit, regardless of unit size; the ratio of persons to floor space in square feet; and the person-to-size ratio adjusted for household composition, structure type, location, or lot size (Blake, Kellerson, and Simic, 2007). These measures are known as (Khajehzadeh and Vale; 2016) the American Crowding Index (ACI) or People Per Room (PPR), Equalised Crowding Index (ECI), Canadian National Occupancy Standard (CNOS), British Bedroom Standard (BBS), Occupancy Rating Standard, and the People per Floor Area Index (Goodyear et al. 2011).

2.1 Determinants of Overcrowding

A major lowering of housing affordability across the EU is evident due to the high growth of rents and house prices in previous years. According to Eurostat from 2010 until the fourth quarter of 2022, rents increased by 19% and house prices by 47%, while housing prices have more than doubled in Estonia, Hungary, Luxembourg, Lithuania, Latvia, the Czech Republic, and Austria. For rents, prices increased in 26 EU countries and decreased in one, with the highest rises in Estonia (+216%) and Lithuania (+160%). According to Eurostat, property prices fell in the first quarter of 2023 for the first time since 2015. Scope for further falls is limited mainly due to the high cost of new builds. An additional recent factor is the higher interest rates that push mortgage rates higher.

Some sources state the main causes of overcrowding are housing unaffordability and poverty, which are also systemic barriers to the right to housing. Hick, Pomati, and Stephens (2022) show that wealth is strongly associated with overcrowding, suggesting that further improvements in GDP per capita would likely further reduce overcrowding rates in poorer EU Member States.

There is a potential link between unemployment and housing overcrowding, as both are related to poverty and inequality: the unemployed may find it difficult to secure adequate housing and may have to co-share living space or live in substandard conditions. Parkinson et al. (2019) found that at the national level, and focusing only on capital cities, there is a significant association between overcrowding and unemployment rates. Unemployment and overcrowding are more common among certain ethnic groups, which may face discrimination and barriers in accessing education, employment, health care and housing services.

Johnson et al. (2015) found that men, older people (45 years plus), those with low educational attainment, and the unemployed (or those outside the labour market) were at higher risk of homelessness. Locations with more social housing and higher unemployment were also found to be strongly associated with higher overcrowding. Yet overcrowded households are also increasingly being found in locations with lower unemployment rates, suggesting that people may be living in overcrowded dwellings to access work or education. Overcrowding's underlying risk factors appear to be different from those of other homeless groups, who are more likely to come from lower educational backgrounds and live in places with cheaper housing and higher unemployment. While indigenous groups are over-represented in the homeless population, this is not the case for migrants and students. The results of Johnson et al. (2015) show a link between concentrations of poverty, local labour markets and overcrowding or homelessness, with the housing market being the main structural driver.

2.2 Consequences of Overcrowding

Overcrowding can determine social and health outcomes, resident safety, and lead to property damage. The relationship between health and housing has long been recognized (D'Alessandro and Appolloni, 2020). Countries with lower GDP per capita are likely to be associated with more deprived populations, meaning poorer health conditions and limited access to health services. A country's better economic situation and higher health spending positively contribute to lower mortality rates.

Housing affordability - related to the financial pressure caused by payments for housing and housing-related services - is one of the main causes of household overcrowding. Affordability issues can also contribute to overcrowding, as households seek to share accommodation costs. An indirect impact is reduced resources for healthy food and health care (Ranmal, Tinson, and Marshall, 2021), and households are often left with minimal, if any, resources for relaxation, sport or even holidays, which further harm their physical and mental health. Better housing is one of the keys to our health. Countries with lower GDP per capita are likely to have more deprived populations, which means poorer health conditions and limited access to health services, whilst higher GDP and higher spending on health positively contribute to lower general mortality rates. Given that public health problems can result from inadequate housing conditions, as well as the consequent mental health problems related to economic stress, countries with higher rates of housing shortages should promote policies aimed at improving housing conditions (Ayala et al., 2022).

Many studies report a direct link between overcrowding and some certain infectious diseases – such as the spread of airborne infectious diseases. During the COVID-19 pandemic, housing played a significant role in the progression of the pandemic and responses to it (Power, Rogers, and Kadi, 2020). According to Rolfe et al. (2020) housing is an important social determinant of health. Rosenberg et al. (2020) report that one of the most important dimensions of inequality that affects pandemics is housing. Poor housing conditions, and overcrowded dwellings were associated with higher prevalence of COVID- 19, note Tinson and Clair (2020).Households overcrowding negatively affects not only physical but also mental health over time (Ruiz-Tagle, and Urria, 2022).

Checa-Olivas, de la Hoz-Rosales, and Cano-Guervos (2021) find that the Human development index (HDI) decreases as the rate of overpopulation in a country increase. This result confirms the authors' hypothesis,

which argues that when people live in overpopulated conditions their ability to achieve their life goals is low or lower.

Harker (2007) found that living in crowded houses also increases the risk of children contracting viral or bacterial infections, thereby leading to a higher risk of life-threatening diseases. Investigating the effects of overcrowding on children's health, Bratt (2002) showed that it leads to a higher incidence of respiratory and stomach illnesses.

Goux and Maurin (2005) provide estimates of the causal effect between overcrowded housing and educational performance, with children in large families (families with three or more children) performing much worse than children in small families. Contreras, Delgado, and Riveros (2019) suggest that overcrowding is a negative and statistically significant factor that even exceeds the effect of certain levels of maternal education on children's educational performance. While Barnes, Butt, and Tomaszewski (2011) examined the extent to which the length of time living in poor housing affects children's poor school performance. Their results suggest that children experiencing persistent bad housing (for three or more years), often had worse outcomes than those children who merely experienced housing problems on a temporary basis (for one or two years). Overcrowding can contribute to increased risk of family conflict, household breakdown and homelessness, and increased fire and/or safety risks and property damage (Herath and Bentley 2018, Gurran et al. 2019).

This paper aims to test the link between household overcrowding and other socio-economic factors in EU countries.

III. MATERIAL AND METHODS

We will use the Eurostat definition of household overcrowding. The overcrowding rate is defined as the percentage of the population living in overcrowded households.

A person is considered as living in an overcrowded household if the household does not have at its disposal a minimum number of rooms equal to:

- one room for the household;
- one room per couple in the household;
- one room for each single person aged 18 or more;
- one room per pair of single people of the same gender between 12 and 17 years of age;
- one room for each single person between 12 and 17 years of age and not included in the previous category;
- one room per pair of children under 12 years of age.

Overcrowding data derives from EU SILC 2021 (Statistics on Income and Living Conditions). EU-SILC is the primary European survey on households' living standards and contains a number of relevant housing-related variables. Based on the literature, we also included other variables from the Eurostat database whose association with the overcrowding rate will be explored in the analysis (Table 1).

Table 1: Indicators and data sources

Indicator	Acronym	Source and Dataset name
Overcrowding rate	OcRate	Eurostat [ILC_LVHO05A]
Tertiary education (levels 5-8) percentage of population from 15 to 64 years	EduTerc	Eurostat [EDAT_LFSE_03]
Upper secondary and post-secondary non-tertiary education (levels 3 and 4) percentage of population from 15 to 64 years	EduSec	Eurostat [EDAT_LFSE_03]
S80/S20 - measure of the inequality of income distribution (age class: less than 65 years)*	IneqU65	Eurostat [ILC_PNS4]
Long-term unemployment rates persons aged 15 to 74. Unemployment rates represent unemployed persons as a percentage of the labour force.	LTUnemp	Eurostat [UNE_LTU_A]
GDP per capita	GDPperCapita	Eurostat [NAMA_10_GDP__custom_6257150] / [TPS00001]

Comment:/ It is calculated as the ratio of total income received by the 20 % of the population with the highest income (the top quintile) to that received by the 20 % of the population with the lowest income (the bottom quintile). All incomes are compiled as equivalised disposable incomes.*

In the first step, we calculated descriptive characteristics for the analysed variables. We plotted the evolution of overcrowding rate values between 2013 and 2021 in EU countries using box plots. After visual comparison of histograms and kernel densities in 2013 and 2021, we chose Hartigan's dip-test for unimodality

(Hartigan, J.A. and Hartigan, P.M., 1985). A bimodal distribution would affect our choice of methods, interpretation results, and conclusions. Finally, we examined the spatial distribution of overcrowding in 2021.

In the second step, we used Pearson's correlation coefficient (Hair Jr, Page, and Brunsveld, 2019) to measure of the strength of a linear association between two variables: the larger the absolute value of the coefficient, the stronger the relationship between the variables.

In the third step, we used random forest regression to identify influential variables. Random forest is a supervised learning algorithm that uses an ensemble learning method for regression (Liu, Wang, and Zhang, 2012). Random forest combines the results of multiple predictions. Increase in Node Purity (IncNodePurity) is the total reduction of impurity nodes from the distribution per variable, averaged over all trees. IncNodePurity was used as a measure of variable importance. There are some evaluation metrics that can help determine the model's quality (Watson and Teelucksingh, 2002). MAE is defined as the average of absolute difference between forecasted values and true values. The coefficient of determination (R-squared) tells how well the predictor variables can explain the variance of the dependent variable. It represents the proportion of the variance in the dependent variable which is explained by the model.

In the last step, we identified groups of similar countries in terms of evaluated indicators and OcRate using hierarchical cluster analysis. Cluster analysis is an algorithm that groups similar objects into groups called clusters (Anderberg, 2014). We verified the clusterability of the data set using the Hopkins statistic (Frank and Todeschini, 1994). We determined the number of clusters using the NbClust package, which provides 30 indices for determining the number of clusters. We used a dendrogram to visually represent the results of hierarchical clustering.

We used the R computing environment (R Core Team, 2021).

IV. RESULTS AND DISCUSSION

In the previous section, we highlighted the interrelationship between household overcrowding and living standards in EU countries, expressed in terms of GDP per capita, educational attainment, and unemployment.

The basic features of the indicators: overcrowding rate, tertiary education, upper secondary and post-secondary non-tertiary education, inequality of income distribution, long-term unemployment rates (for persons aged 15 to 74) are described in Table 2.

Table 2: Descriptive statistics of analysed indicators

Indicator (Acronym)	Average	Standard deviation	Median	Minimum	Maximum	Skewness
OcRate	17.43	12.71	14.30	2.30	41.30	0.59
EduTerc	32.19	7.68	34.20	16.40	45.20	-0.26
EduSec	46.27	10.38	46.40	25.60	64.50	0.02
IneqU65	4.90	1.29	4.59	3.20	7.83	0.76
LTUnemp	2.49	1.85	2.00	0.80	9.20	2.7
GDPperCapita	33832.86	23031.41	25443.15	10392.99	112016.32	1.73

The median share of the population in overcrowded households did not change significantly across EU countries between 2013 and 2021 (Figure 1). The quartile range for 2018 to 2020 has decreased slightly compared to 2017 (Figure 1), while the median in 2021 increased slightly compared to 2020. The maximum share decreased slightly during the assessment period, and the maximum share of the population in overcrowded households decreased more significantly in 2021. We did not observe extreme outliers in any year.

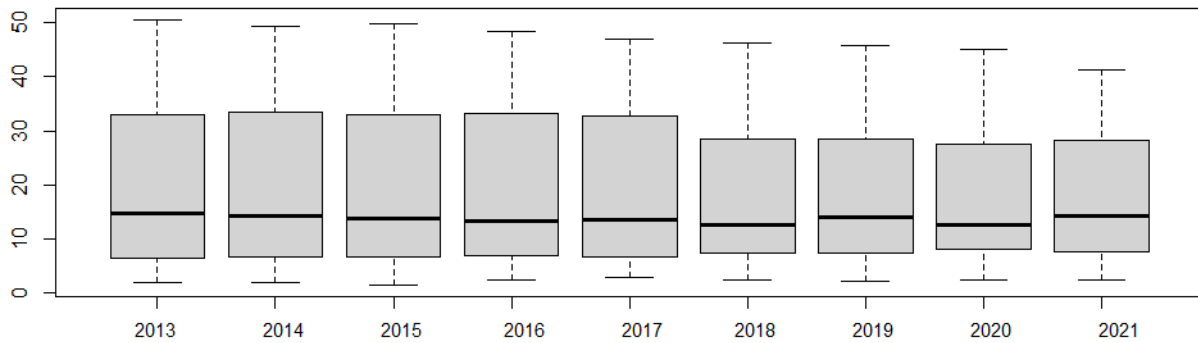


Figure 1: Box plots for the proportion of the population in overcrowded households (2013-2021)

In terms of the data histograms, we observed a reduction in overcrowding rate above 40 percent (which corresponds to the decrease maximum of values). At first glance (**Figure 2**), the probability distribution in 2021 appears bimodal. But the opposite is true. The value of Hartigans' dip test statistic for unimodality D is 0.053419 and the corresponding p -value is 0.8159, i.e., we cannot reject the null hypothesis of unimodality.

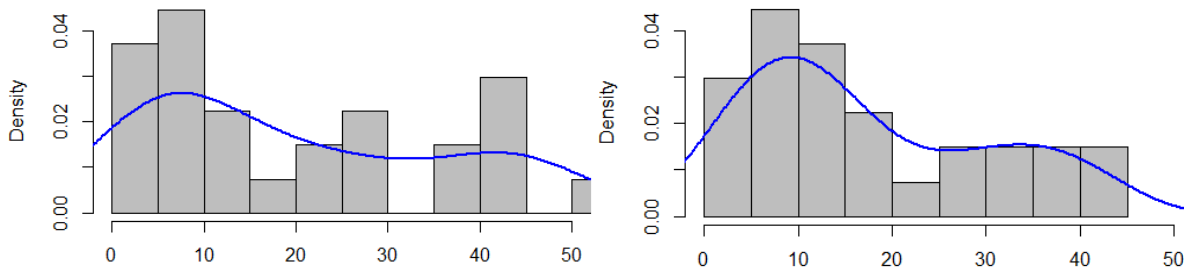


Figure 2: Histogram and kernel density function for the share of overcrowded households in the EU (2013 and 2021)

Overcrowding rate is highest in eastern and southern EU countries (**Figure 3**), namely Latvia (41.3), Romania (41.0) and Bulgaria (37.9). Overall, a high proportion of the population in overcrowded households is typical of the former socialist countries. The lowest proportion of residents in overcrowded dwellings is in Malta (2.9), the Netherlands (3.4), and Ireland (3.4).



Figure 3: Cartogram for the share of population in overcrowded households in the EU (2021)

The dot plot combined with the histogram and correlation matrix is shown in **Figure 4**. That higher household crowding reflects relatively low values of GDP per capita raises the need to focus on economic

growth, which - in addition to reducing overcrowding - will also promote housing affordability and improve quality of life. GDP per capita does not show a statistically significant linear relationship with the long-term unemployment rate and inequality of income distribution S80/S20. The overcrowding rate is statistically significantly related to all indicators, except long-term unemployment rate.

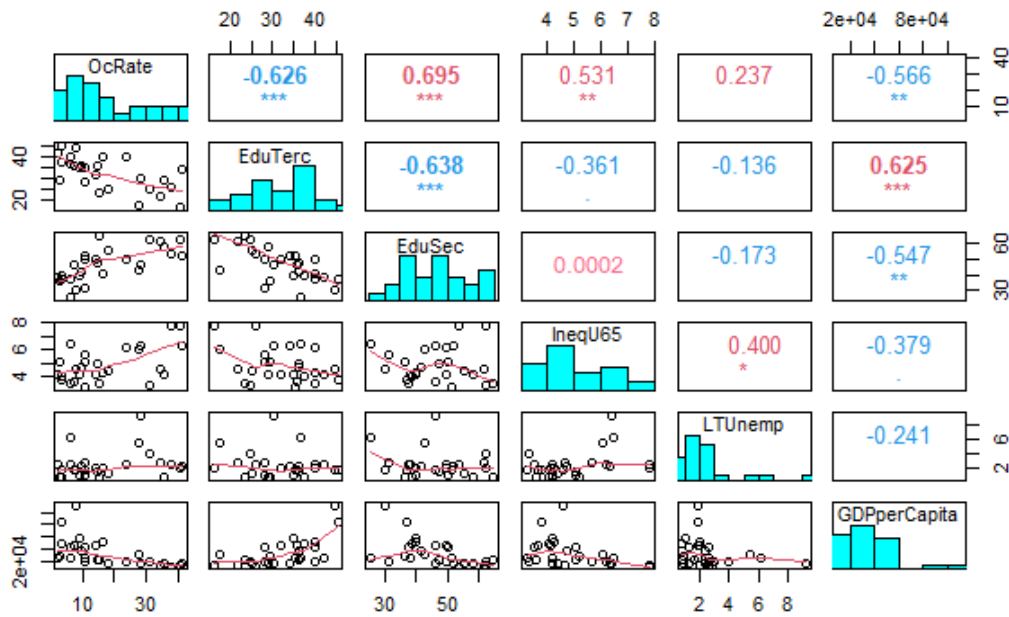


Figure 4: Dot plot combined with the histogram and correlation matrix (2021)

Variable importance is a measure of by how much removing a variable decreases accuracy, and vice versa. Using Random forest algorithm, the feature importance can be measured as the average impurity decrease computed from all decision trees in the forest. The indicator GDPperCapita, has the highest IncNodePurity value (Figure 5), followed by EduSec, EduTerc, IneqU65, LTUnemp. This order is the order of importance of the variables.

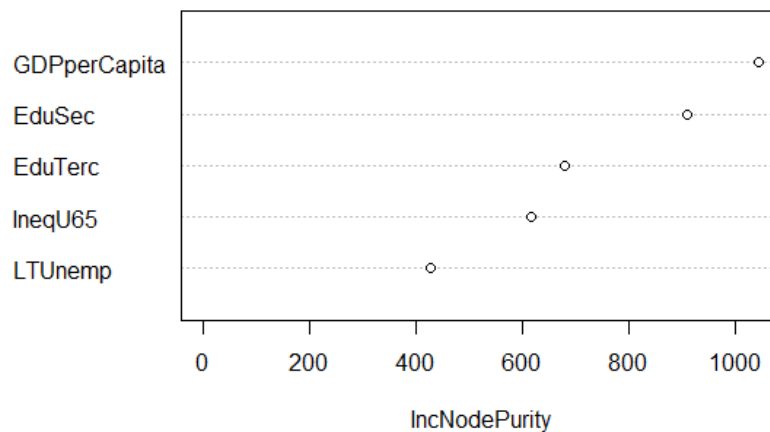


Figure 5: Random forest variables importance - Inc Note Purity

The mean absolute error (MAE) allows us to measure the accuracy of a given model is 3.2310, i.e., an acceptable value. The coefficient of determination for the Random forest regression is high at 0.936955. The predictor variables included in the random forest explain the variation in the dependent variable OcRate very well (Figure 6).

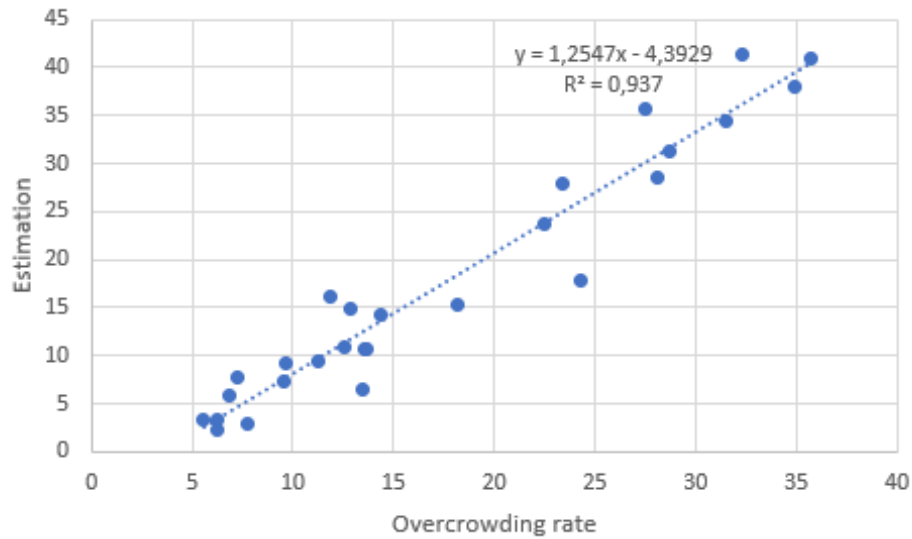


Figure 6: Overcrowding rate (OcRate) estimation using Random forest regression- predicted values versus the actual values

The data tends to cluster. The value of the Hopkins statistic is a very high 0.9998678. We next proceeded to form clusters based on similar values of the scaled factors. According to the majority rule, the best number of clusters is 3 (Figure 7).

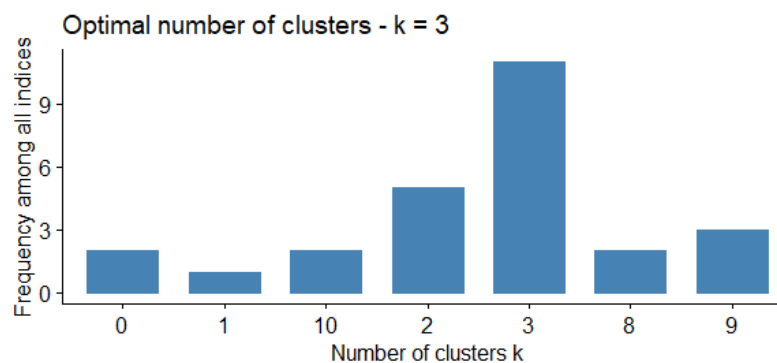


Figure 7: The optimal number of clusters

The result of clustering is shown in **Figure 8**. The first cluster included countries Belgium, Germany, Austria, Finland, France, Denmark, the Netherlands, and Sweden, all of which are characterised by a high standard of living and high GDP per capita. Housing policies are socially oriented, which positively influences the overcrowding rate.

In the third cluster are Ireland and Luxembourg, with signs of inhomogeneity. The overcrowding rate is low, but for different reasons than in the first cluster. However, the EU SILC data does not include homeless people who are excluded from the sample according to current EU SILC methodology. An increase in social housing stock is needed to sustain the housing sector and reduce future house prices and rents in Ireland, this is where current policy has failed and led to a worsening housing crisis throughout Ireland: such as low-income families, the homeless, and undergraduates sleeping in cars and travelling long distances (Hearne). As approximately 70 per cent of workers in Luxembourg commute across the border, the indicator OcRate does not reflect reality.

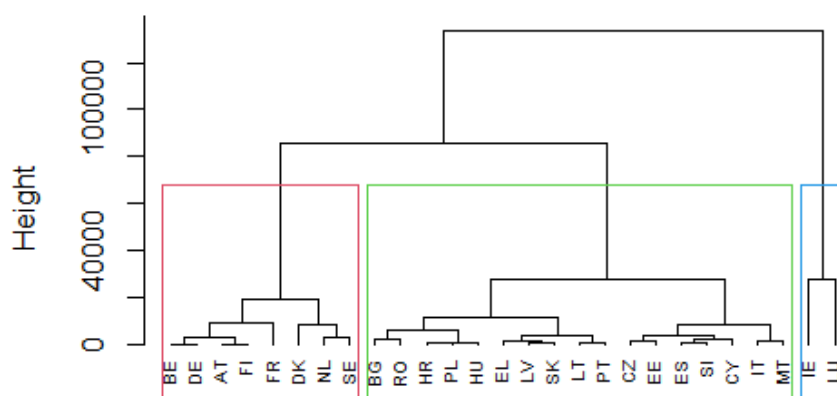


Figure 8: Dendrogram

The remaining EU countries are in the second cluster. The second cluster includes more countries than the first and third clusters. These are post-communist countries, as well as Portugal, Italy, Greece, Spain, Cyprus, and Malta, i.e., mainly tourism-reliant countries for about half the year. So, both the post-communist countries and 'tourism' countries are in a worse starting position than first and third cluster countries, with consequent higher income inequality, overcrowding, and educational disparities. For each cluster, the average value is computed for each of the variables (Table 3).

Table 3: Average values of variables for clusters

Indicator (Acronym)	1st cluster	2nd cluster	3rd cluster
OcRate	9.55	22.52941	5.55
EduTerc	35.43	29.17647	44.85
EduSec	43.01	49.27059	33.75
IneqU65	4.19	5.310588	4.19
LTUnemp	1.71	2.935294	1.8
GDPperCapita	46 404	20 352	98 130

The economic and social level of society and regions is increasingly influenced by intellectual wealth (Kuzmishin, Kuzmishinova, 2010). The share of population with tertiary education is highest in the third cluster, where Ireland and Luxembourg have the most residents aged 25-34 with tertiary education (45.2; 44.5 per cent). The average in the first cluster is 35.43 per cent, and only 29.18 per cent in the second cluster. The EU target for 2030 is that 45 per cent of the EU population in this age group should have tertiary education. It can be hypothesized that increasing educational attainment is associated with a decline in long-term unemployment and GDP growth, which may contribute to a reduction in the overcrowding rate.

The importance of skills increases steadily over time. In high-income countries, a large proportion of youth continues to university. Educational inequality can thus be a driver of labour market inequality, as well as low social mobility. According to Camel et al. (2005), income inequality leads to a wider disparity in educational attainment. Residents of second cluster countries have a significantly higher average share of secondary education, and a higher value of income inequality.

According to Tasci and Ozdemir (2006), long-term unemployment is one of the most worrying factors for both labour market and general economic performance. According to Andronie and Andronie (2014), studies have shown some differences between graduates and non-graduates in terms of unemployment, and the consequences of long-term unemployment are too great to for lifelong learning to be neglected. Such learning can prevent a disparity between workers' competences and those required by the labour market. According to Alhawarin and Kreishan (2010), jobseekers with no prior work experience are at risk of longer unemployment, which corresponds with the results obtained. Countries in the second cluster have a smaller share of the population with tertiary education, and also have a higher share of long-term unemployed.

V. CONCLUSIONS

That countries with higher housing shortage rates should support policies aimed at improving housing conditions is a conclusion reached not only by us, but also by Ayala et al. (2022) and Zajacova, Zubkova, Stehlikova (2023).

The toughest challenge will be to reduce income inequality, which affects educational opportunity and access to higher education. Higher income inequality is typical of second cluster countries (post-communist countries, as well as Portugal, Italy, Greece, Spain, Cyprus, and Malta).

Our objective was to test the association between household overcrowding and other socio-economic factors in EU countries. Household overcrowding should not only be tackled by direct housing policy instruments, instruments closely related to addressing these socio-economic aspects can also make an important contribution to increasing their effectiveness. Raising educational levels should be a priority for all governments, since improving education and increasing access has a direct impact on reducing long-term unemployment and income inequality. The related synergistic effect of these interventions will positively impact the housing situation.

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