CLUSTERS AS ENGINES OF SUSTAINABLE EMPLOYMENT GROWTH IN ROMANIA[1]

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Abstract
The imperative for sustainable growth has elevated clusters as pivotal tools for economic and social inclusion, fostering job creation, equitable income distribution, and regional competitiveness. A cluster comprises interrelated companies and institutions in close geographical proximity, establishing expertise and a robust network of suppliers and skills. Clusters enhance productivity and catalyze development by concentrating enterprises and labor within a unified framework, surpassing isolated firms in regional impact. This study aims to examine whether clusters act as accelerators of employment growth over time and space. Using Simple Linear Regression (SLR) to analyze data from the Romanian Association of Clusters (CLUSTERO) and the National Institute of Statistics (Tempo INS) for 2013, 2015, 2019, and 2022, we investigate the research question: Do firms within clusters, as defined by European Policy criteria, contribute to accelerating employment creation? Specifically, we assess whether the ratio of employment in clustered firms relative to total employment shows a positive trend over time. Findings reveal that clusters contribute significantly to employment growth, validating their function as a strategic asset in enhancing workforce specialization, economic development, and regional resilience. Policy recommendations underscore the need for inclusive growth strategies that incorporate sustainability to maximize cluster impact on social and economic objectives.

Keywords: Clusters, Employment creation, Economic growth, Sustainability, Social inclusion
JEL Classification: L52, R11, O18, Q56, J23

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Introduction

Clusters, defined as groups of geographically proximate companies, related economic actors, and institutions with specialized expertise, have been recognized as catalysts for both economic and social development. The formation of clusters leads to the multiplication and specialization of enterprises and the workforce, potentially accelerating employment creation (Porter 1990). This paper explores the theoretical and empirical evidence supporting the role of clusters in enhancing employment opportunities (Delgado, Porter, and Stern 2014).

1.1. Theoretical Background

The development of clusters over time and space provides empirical evidence supporting the theoretical assumption that clusters are effective in boosting employment and driving economic growth. Clusters foster increased efficiency and productivity through enterprise multiplication and specialization, highlighting the benefits of a concentrated network of companies and institutions in stimulating economic activity (Marshall 1890). The implications of cluster development extend beyond job creation to broader economic growth and social progress, supporting balanced regional development by reducing regional disparities and promoting inclusive growth strategies (European Commission 2021).

Support from entities such as the Romanian Ministry of Research and Innovation underscores the significance of advanced research, including GIS modelling, in understanding labour market trends and fostering innovation within clusters (Romanian Ministry of Research and Innovation 2023). Additionally, the **European Industrial Policy and Competitiveness approach** emphasizes the high importance of clusters. Beyond their geographical conceptualization, clusters are certified based on quality criteria:

- **By Activity Domain**: Membership in any of the industrial ecosystems.
- **International Networking and Connectivity**: Registration with the European Cluster Collaboration Platform (ECCP) or national association CLUSTERO.
- **Management and Administration**: Recognition by the Romanian Ministry of Economy, Entrepreneurship, and Tourism.

1.2. Goals of the Paper

This paper aims to investigate whether firms that are members of clusters, as defined by European policy criteria, contribute to accelerating employment creation. Specifically, it examines if there is a positive relationship over time between the ratio of employment in cluster-member firms and total employment in all firms.

To achieve this goal, the paper will:

Analyse the impact of cluster membership on employment growth within firms.

- Evaluate the sustainability of cluster development while achieving rapid economic growth.
- Propose strategies for policymakers to balance economic growth with long-term sustainability and social equity.

1.2.1. Research Question

Do firms that are members of clusters, defined by European policy criteria, contribute to accelerating employment creation? In relative terms, does the ratio between employment in cluster-member firms and total firm employment show a positive trend over time?

Literature Review

2.1 Theoretical Framework

Marshall's early 20th-century theories proposed that firms co-locate to reduce costs related to the transportation of goods, people, and ideas. This concept of agglomeration has since led to the emergence of high-tech clusters in cities like San Francisco and Boston, as well as industrial clusters, such as the automotive industry in Detroit (Marshall 1890). Cluster agglomeration plays a crucial role in job creation, driving both economic development and innovation. Forces such as reduced costs, increased productivity, and regulatory pressures that encourage innovation further underscore the benefits of clusters (Porter 1990; Porter and van der Linde 1995).

In the context of sustainability, clusters support regional resilience by concentrating resources, expertise, and infrastructure, which collectively promote efficiency and reduce environmental impact. According to Porter and van der Linde (1995), environmental regulations can also spur innovation within clusters, as firms seek competitive advantages by optimizing resources and minimizing waste. Consequently, clusters foster a more sustainable economic ecosystem where companies not only reduce costs but also contribute to broader environmental goals. The concentration of industries within clusters further amplifies knowledge sharing and collaboration on sustainable practices, reinforcing the alignment of economic growth with environmental and social objectives.

2.2 Previous Studies

Studies have further developed Marshall's theories by quantifying the factors contributing to cluster formation. O'Clery et al. (2019) used network-based methods to assess the roles of customer-supplier relationships, labour sharing, and idea exchange in cluster formation, finding that these factors significantly influence cluster dynamics. Gomez-Lievano and Fragkias (2024) expanded this research with insights from urban complexity theory and urban scaling, illustrating how city size and economic complexity impact cluster resilience. Additional research highlights that large cities tend to be more resilient to automation impacts on employment, largely due to their specialized labor markets (Frank et al. 2017). Ladias and Ruxho (2024) further emphasized the role of regional economic indicators in identifying economic disparities and shaping policies for balanced regional development. Their research underscores the importance of tailored strategies for mitigating economic disparities across regions, which is crucial for fostering cluster formation and supporting sustainable economic growth.

Clusters have been recognized as catalysts for economic growth, regional resilience, and employment creation, particularly in developing economies. Studies highlight the role of clusters in fostering specialization and collaboration, which enhance productivity and innovation. For instance, Lincaru et al. (2020) demonstrate the utility of GIS and multivariate clustering in analyzing employment patterns within tourism sectors at the local level, emphasizing the spatial dynamics of cluster-based employment growth. Furthermore, Stroe and Lincaru (2022) underscore the socioeconomic impact of clusters in mitigating rural poverty and breaking cycles of economic decline, showcasing their potential to address regional disparities. In exploring labor market challenges, Stroe and Cojanu (2018) provide insights into in-work poverty dynamics, highlighting how cluster strategies could amplify social inclusion efforts by integrating vulnerable workforce segments. Additionally, Stroe (2022) analyzes the effectiveness of guaranteed minimum income programs as tools for enhancing resilience and employment among disadvantaged groups, aligning these findings with the broader objectives of cluster policies to foster equitable growth.

The study of regional inequalities has garnered significant attention within both academic and policy-making circles. Ladias et al. (2009) present a comprehensive methodology for depicting and analyzing regional disparities in Greece, emphasizing the spatial dimensions of economic imbalances. This work aligns with broader efforts to understand and address disparities through sustainable development strategies. Further exploring the intersection of sustainability and regional development, Amoiradis et al. (2012) highlight Greece's potential as a sustainable tourism destination, offering insights into balancing economic growth with environmental preservation. Ladias's contributions extend to environmental attitudes, where Goula et al. (2016) investigate the influence of urban and rural origins on eco-conscious behaviors, underscoring the role of regional and cultural factors. Collectively, these studies provide a foundational framework for addressing regional inequalities through integrated, sustainability-driven approaches.

The role of government policies in promoting green industries has been extensively studied, with particular emphasis on their spatial distribution and economic impact. Park and Lee (2017) analyze

the development of green industries in South Korea, **applying a panel regression model** to identify spatial patterns and assess the effectiveness of policy interventions from 2006 to 2012. Their findings underscore the importance of strategic regional policies in fostering sustainable industrial growth, which is crucial for addressing disparities and achieving long-term economic and environmental goals.

2.3 Research Gaps

Although existing research supports the economic benefits of clusters, several gaps remain. One is the challenge of precisely measuring agglomeration economies due to factors such as self-selection, where more productive individuals are drawn to larger cities, creating an effect independent of clustering itself (Gomez-Lievano and Fragkias 2024). Additionally, while research acknowledges the potential for clusters to drive employment, there is limited empirical evidence on how cluster membership impacts job creation relative to non-cluster firms over time.

2.4 Concepts and Definitions

Clusters, according to the European Commission **(Appendix 1**), are defined as "geographically proximate groups of interconnected companies, specialized suppliers, service providers, firms in related industries, and associated institutions (e.g., universities, standards agencies, trade associations) in particular fields that both compete and cooperate." This concept emphasizes that clusters encourage collaboration, innovation, and productivity by pooling resources, specialized labour, and knowledge-sharing networks (European Commission 2021). These elements contribute to enhanced economic growth and competitiveness, particularly when supported by EU initiatives like Smart Specialization Strategies (S3) and the Europe 2020 Strategy.

Methodology

3.1 Research Design

This study adopts a quantitative research design to investigate how company membership in clusters contributes to accelerated job creation. The primary goal is to test whether the ratio between employment in cluster-member firms and total firm employment has a positive relationship with time, suggesting a faster increase in employment within clusters compared to the national average (Lincaru et al. 2024). This research is based on regionally collected data (NUTS 2) and applies statistical methods to highlight trends over time.

3.2 Data Collection

We use data for the statistics of firms in clusters by the definition of Clusters in European Policy provided by CUSTERO – Romania and statistics for all the firms provided by National Statistics Institute.

Clusters are described in complex manner, beyond the geographical proximity of the companies in the same domain are respond also to the criteria interconnection and association, according to the Definition of Clusters in European Policy.

Data was collected from national sources, including the Romanian Cluster Association (CLUSTERO) and the National Institute of Statistics (INS). CLUSTERO provides data on the number of firms and employees in Romanian clusters (Table 1), while INS offers national statistics on total firms and employees. (Table 2) The dataset spans the years 2013, 2015,2019 and 2022 and includes variables such as the number of firms and employees in clusters compared to regional totals. Specifically, the analysis uses the INS indicator *TEMPO_INT102D_20_8_2024*, which includes data on active local unit personnel by national economic activities, CAEN Rev.2 section levels, company size classes, macro-regions, development regions, and counties (National Institute of Statistics 2024).

The Table 1 shows the evolution of employed persons in active enterprises from registered clusters across various regions in Romania from 2013 to 2022, highlighting a significant national increase in employment, with a 2022/2013 ratio of approximately 3.45 (from 71,169 in 2013 to 245,856 in 2022). Notable regional variations include substantial growth in Bucharest-Ilfov, which recorded the highest increase with a ratio of 4.42, followed closely by North-West with a ratio of 4.21. In contrast, the Center region shows a modest increase (ratio of 1.06), while regions like South and South-West present significant declines or incomplete values, reflecting disparate economic growth and employment patterns across the regions.

Table 1. Employed persons in active enterprises from registered Clusters (persons)

	Oc_CL 2013	Oc_CL 2015	Oc_CL 2019	Oc_CL 2022
Total	**71169**	**103925**	**189193**	**245856**
Bucuresti Ilfov	12200	17321	32903	53894
Centru	18301	27218	45242	19338
Nord Est	4067	7423	12339	6208
Nord Vest	12200	17321	32903	51388
Sud	2033	2474	8226	1800
Sud Est	10167	14846	28790	4928
Sud Vest	4067	4949	8226	?
Vest	8134	12372	20564	8780

Source: Sursa: Asociația Clusterelor din România –CLUSTERO

The Table 2 shows the change in employment in active enterprises across various regions in Romania from 2013 to 2022, with a national growth ratio of approximately 1.07 (from 3.98 million persons in 2013 to 4.26 million persons in 2022). Significant regional differences are evident, with Bucharest-Ilfov leading in growth with a ratio of 1.19, indicating a substantial increase in employment over this period. The North-East and North-West regions also show notable growth ratios of 1.10 and 1.10, respectively. In contrast, regions like the Center and South-East display more modest increases, with ratios close to 1.03 and 0.95, respectively, reflecting a slower employment growth rate in these areas. These variations highlight the uneven economic dynamics and employment opportunities across Romania's regions.

Table 2. Employed persons in active enterprises all firms (persons)

	Oc_ 2013	Oc_ 2015	Oc_ 2019	Oc_ 2022
Total	**3979678**	**4054082**	**4284738**	**4255995**
Bucuresti Ilfov	971631	1009465	1111698	1153753
Centru	520933	519189	555592	535600
Nord Est	385784	386098	419354	425474
Nord Vest	528051	556808	591359	580561
Sud	445488	450868	466989	458461
Sud Est	422828	420389	414179	403579
Sud Vest	292078	286418	299879	295257
Vest	412885	424847	425688	403310

Source: Tempo INS TEMPO_INT102D

3.2.1. Cluster Initiatives in Romania

As per the latest records by the Ministry of Economy, Directorate of Industrial Policies and Competitiveness, Romania has 78 cluster initiatives. Of these, 53 clusters are members of the Romanian Cluster Association (CLUSTERO), including two from the Republic of Moldova. CLUSTERO serves as a community for best practices and represents clusters nationally, across Europe, and internationally (CLUSTERO 2024).

a) European Certification of Romanian Clusters

The **European Secretariat for Cluster Analysis** (ESCA) conducted a rigorous certification process, categorizing the clusters as follows:

- Seven clusters with the Gold Label (the highest performance level in Eastern Europe),
- Twelve clusters with the Silver Label,
- Forty-one clusters with the Bronze Label.

b) Regional and Thematic Cluster Consortia

Romanian clusters are organized into regional and thematic consortia to enhance collaboration. These include:

- **Consortium of Clusters from Northern Transylvania** (North West Region),
- **Consortium of Clusters from Transylvania** (Central Region),
- **Consortium of Clusters from the North East Region**,
- **"Lower Danube" Cluster Consortium** (South East Region),
- **Wallachia Hub** (South Muntenia Region),
- **Consortium of Clusters from the Bucharest-Ilfov Region**.

Additionally, thematic consortia focus on specific industries:

- **"Noatex"** for the textile industry,
- **Wood and Furniture Industry Consortium**,
- **Agro-Food Sector Consortium**,
- **Medical Field Consortium "MEDRO"**,
- **ICT Field Consortium**,
- **Ecological Agriculture Consortium "Inter-Bio"** (CLUSTERO 2024).

c) Distribution and Industrial Ecosystem Coverage

Romanian clusters span 12 of the 14 European industrial ecosystems, excluding Commerce and Social Economy. The highest concentrations are in the Agri-Food and Digital sectors, with 12 clusters each, followed by Renewable Energy and Construction, with nine clusters each.

d) **Regional Distribution**:

- The **Bucharest-Ilfov** region hosts the most clusters (20),
- The **Center Region** follows with 14 clusters,
- The **South East Region** has 11 clusters.

A total of 62 Romanian clusters are registered on the **European Cluster Collaboration Platform (ECCP)**, demonstrating their integration into broader European cluster networks (ECCP 2023).

3.3 Analysis Methods

The primary analysis method is **Simple Linear Regression (SLR),** applied to determine whether a significant relationship exists between the dependent variable *Oc_cl/Oc* and the independent variable *t* (year: 2013, 2015, 2019, 2022) at regional level NUTS 2 (8 regions). The analysis involves 8 steps.

3.3.1. Dependent Variable (Oc_cl/Oc)

The dependent variable in this analysis, *Oc_cl/Oc*, represents the employment ratio of cluster-member firms relative to total employment in firms within a given region. This ratio is calculated by dividing the number of employees in firms belonging to clusters (*Oc_cl*) by the total number of employees in all firms within the region (*Oc*). Mathematically, it is expressed as:

$$Oc\_cl/Oc = \frac{Oc\_cl}{Oc} \; |Ri_{tj} \qquad (1)$$

Oc_cl - the number of employees in cluster-member firms.(Table 1)
Oc - the total number of employees in all firms within a region. (Table 2)
Oc_cl/Oc, represents the employment ratio of cluster-member firms relative to total employment in firms within a given region
Ri – region NUTS 2 level from 1 to i (8 regions)
tj – time for Surveys (from j=1 to 4)
This formula calculates the ratio of employment in cluster-member firms to total employment, providing a measure of the clusters' contribution to regional labour force employment.
The significance of this variable lies in its ability to illustrate the concentration and growth of employment within clusters as compared to the overall labour market. A higher *Oc_cl/Oc* ratio suggests that clusters contribute a substantial share to regional employment, indicating the role of clusters as potential accelerators of job creation. By tracking changes in this ratio over time, we can assess whether clusters are indeed fostering employment growth at a faster pace than the general economy.
Results are interpreted by evaluating regression coefficients, the R-squared value, and statistical significance (Montgomery, Peck, and Vining 2012).

3.3.2. Methodological Steps for Simple Linear Regression (SLR)

We run the (SLR) to understand if there is any relationship between two continuous variables: the time as independent variable (predictor) and **Oc_cl/Oc** as dependent variable (outcome). For this purpose we execute the following steps:

Step 1. Formulate the Hypotheses:

- **Null Hypothesis (H_0)**: There is no relationship between the independent variable "t" and the dependent variable "**Oc_cl/Oc"**
- **Alternative Hypothesis (H_1)**: There is a significant relationship between the independent variable "t" and the dependent variable "**Oc_cl/Oc"**

Step 2. Collect the Data ***from Clustero and Tempo INS (see 3.2)***

Step 3. Pre-process the Data:

- **Calculate the ratio** for the Employment in firms' members in Clusters to Employment in all firms by region (NUTS 2) in years 2013, 2015, 2019 and 2022 (see Table 3)
- **exclusion** as Outlier of the value of Oc_CL_2022

Step 4. Step-by-Step Check for Linear Regression Assumptions

Step 4.1. Linearity. To check if there is a linear relationship between the independent variable (t) and the dependent variable (Oc_cl/Oc):

- **Visual Inspection**: Create a scatter plot of Oc_cl/Oc against t.
- **Correlation Coefficient**: Calculate Pearson's correlation coefficient to see the strength and direction of the linear relationship.

Step 4.2. Independence of Residuals. To ensure the residuals are independent: **Durbin-Watson Test**: This test detects the presence of autocorrelation in the residuals from a regression analysis. A value close to 2 suggests that there is no autocorrelation, while a value closer to 0 or 4 indicates positive or negative autocorrelation, respectively. (Durbin and Watson 1950).

Step 4.3. Homoscedasticity. Homoscedasticity means that the residuals should have constant variance across all levels of the independent variable.

- **Visual Inspection**: Create a scatter plot of residuals against the predicted values. The spread of residuals should be roughly constant across all levels of the predicted values.
- **Breusch-Pagan Test**: This is a formal statistical test for homoscedasticity. A non-significant result (p-value > 0.05) indicates that the assumption is met. (Breusch and Pagan 1979).

Step 4.4. Normality of Residuals The residuals should be normally distributed if it happens:

- **the Histogram** follow a normal distribution
- **Q-Q Plot**: A quantile-quantile (Q-Q) plot can be used to check if the residuals are normally distributed. Points should lie approximately on the diagonal line if the residuals are normally distributed.
- **Shapiro-Wilk Test**: This statistical test formally checks the normality of residuals. A non-significant result (p-value > 0.05) suggests normality.

Step 5. Perform the Simple Linear Regression:

- Use SPSS statistical software to perform the regression.
- Fit the regression model using the formula:

$$\mathbf{Oc\_cl/Oc}|Ri,t=\beta_0+\beta_1 t+\epsilon \quad (2)$$

Where:

Oc_cl/Oc $|Ri,t$: *the dependent variable, representing the employment ratio of cluster-member firms relative to total employment within a specific region Ri over time t.*

β0: the intercept, representing the baseline employment ratio across all regions and times.

β1: the slope (regression coefficient) for time ttt, indicating how the employment ratio changes over time.

t: the independent variable representing time (survey periods).

ϵ (epsilon): the error term, accounting for residual variation in the employment ratio not explained by region or time.

Step 7. Report the Findings:

Report the regression results, including the coefficients, R^2 value, and significance levels, and interpret the findings in the context of the research question. For instance, a positive and significant regression coefficient would indicate a growing trend in the employment ratio within clusters over time, relative to total employment. It's essential to discuss any model limitations, such as high

variability across regions, that may affect the interpretation of results (Montgomery, Peck, and Vining 2012).

Include visualizations, such as scatter plots with the regression line, to illustrate the relationship between the variables and help readers visualize trends in the data. Visual aids provide an intuitive grasp of the model fit and can highlight any deviations from the assumed linear relationship, making the findings more accessible and meaningful (Fox and Weisberg 2019).

Step 8. Draw Conclusions and Recommendations:

Based on the results, draw conclusions regarding the relationship between the variables and suggest potential implications or recommendations for further research. (Durbin and Watson 1950; Breusch and Pagan 1979).

Results/Analysis

4.1 Descriptive Analysis

The Table 3 illustrates the ratio of employed persons in firms from registered clusters to the total employed persons at the NUTS 2 level across Romanian regions from 2013 to 2022. At the national level, this ratio increased substantially from 1.79 in 2013 to 5.78 in 2022, indicating a significant rise in cluster employment's share within the overall workforce. Bucharest-Ilfov saw a notable increase in this ratio, reaching 4.67 in 2022, reflecting the region's dynamic cluster growth. The North-West region displayed the highest ratio by 2022, reaching 8.85, while regions like the South and South-East showed low ratios (0.39 and 1.22, respectively), highlighting less integration into cluster-based employment. These disparities underscore the varying regional roles of cluster employment within Romania's broader labor market dynamics.

Table 3. Ratio of employed persons from firms in registered clusters to total employed persons at NUTS 2 level

	Oc_cl/Oc 2013	Oc_cl/Oc 2015	Oc_cl/Oc 2019	Oc_cl/Oc 2022
Total	1,79	2,56	4,42	5,78
București Ilfov	1,26	1,72	2,96	4,67
Centru	3,51	5,24	8,14	3,61
Nord Est	1,05	1,92	2,94	1,46
Nord Vest	2,31	3,11	5,56	8,85
Sud	0,46	0,55	1,76	0,39
Sud Est	2,40	3,53	6,95	1,22
Sud Vest	1,39	1,73	2,74	
Vest	1,97	2,91	4,83	2,18

Source: calculated by authors

The increasing ratios of employed persons in registered clusters relative to total employment suggest a growing significance of cluster-based firms within Romania's economy, particularly in regions like North-West and Bucharest-Ilfov. This trend indicates a regional concentration of economic activity and employment opportunities within clusters, reflecting advancements in specialization, collaboration, and productivity. However, the much lower ratios in regions like South and South-East suggest an uneven distribution of cluster development, pointing to regional disparities in economic modernization and the benefits associated with cluster-based employment. Overall, this trend highlights a shift towards clustered economic structures, which may drive innovation and competitiveness, but also underscores the need for balanced regional development to ensure inclusive economic growth across all regions.

4.2 Key Findings

Step 4.1. Linearity.

- **Visual Inspection**: See in Figure 1 the scatter plot of Oc_cl/Oc against t. Points form a roughly straight line, this suggests a linear relationship by each NUTS 2 region.

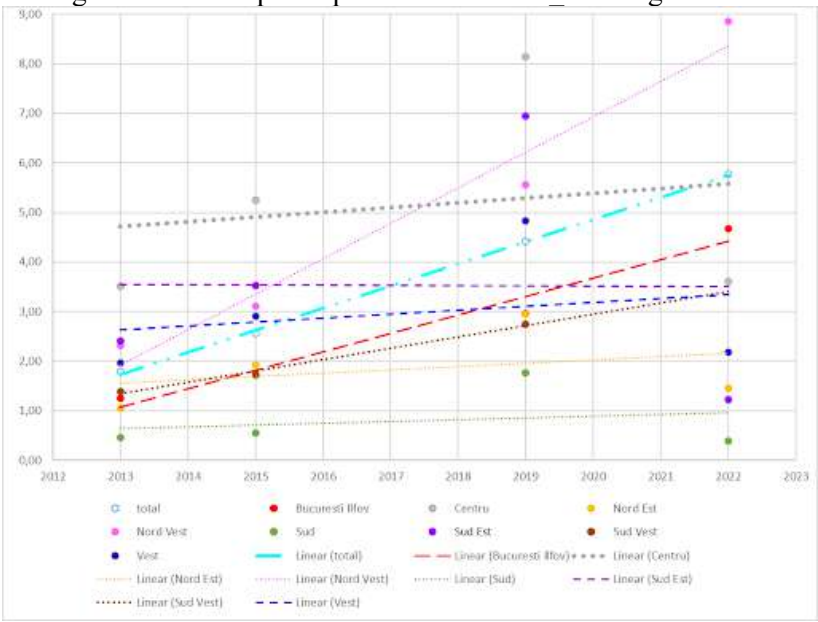
The scatter plot in Figure 1 illustrates the employment ratio **Oc_cl/Oc** for cluster-member firms relative to total employment in active firms across various regions in Romania over the years 2013,

2015, 2019, and 2022. Each region is represented with a different color and marker, with trend lines indicating the general direction of the employment ratio over time. We remark:

- **North-West** (pink dashed line) shows the steepest increase, suggesting a significant rise in the employment ratio for cluster-member firms in this region, indicating stronger cluster growth relative to total employment.
- **Bucharest-Ilfov** (dashed red line) and **Total** (light blue dashed line) also display upward trends, though at a more moderate rate than North-West. This suggests that cluster employment is growing steadily in these areas.
- **South-East** (purple dotted line) shows a declining trend, indicating a decrease in the employment ratio for cluster-member firms in this region over time.
- **South** (green dotted line) shows a relatively stable trend with minimal increases, indicating a slower rate of cluster employment growth compared to other regions.
- **South-West** (brown dotted line) and **Vest** (dark blue solid line) display less clear or fluctuating patterns, which may indicate variable cluster employment dynamics or regional differences in the impact of cluster development.

Overall, the plot demonstrates regional variability in the role of clusters in employment, with certain regions showing strong, consistent growth in cluster employment relative to the total workforce, while others exhibit less pronounced trends. The trends suggest that clusters contribute increasingly to employment in certain regions, underscoring the potential for regional policies to leverage cluster-based development as a strategy for economic growth.

Figure 1. Scatter plot representation of Oc_cl/Oc against t



Source: Graphic created by authors

- **Correlation Coefficient**:

Table 4 displays the Pearson correlation coefficients between the variables OcCl_OC and t.

Table 4. Pearson Correlations between the variables OcCl_OC and t.

		OcCl_OC	t
Pearson Correlation	OcCl_OC	1.000	.395
	t	.395	1.000
Sig. (1-tailed)	OcCl_OC		.009
	t	.009	
N	OcCl_OC	35	35
	t	35	35

Source: calculated by authors

The results interpretation is:

1. Pearson Correlation

- **OcCl_OC with OcCl_OC**:
  - The Pearson correlation of OcCl_OC with itself is 1.000, as any variable is perfectly correlated with itself.
- **OcCl_OC with t**:
  - The Pearson correlation coefficient between OcCl_OC and t is **0.395**.
  - This indicates a **moderate positive correlation**, meaning that as t increases, OcCl_OC tends to increase as well. However, the correlation is not very strong.
- **t with t**:
  - The Pearson correlation of t with itself is also 1.000.

2. Significance (Sig. 1-tailed)

- **OcCl_OC with t**:
  - The p-value (Sig.) for the correlation between OcCl_OC and t is **0.009** (one-tailed test).
  - Since this p-value is less than 0.05, the correlation is **statistically significant**. This means there is a statistically significant positive relationship between OcCl_OC and t, and the likelihood that this correlation is due to chance is very low.

3. N (Sample Size)

- The sample size (N) for both OcCl_OC and t is **35**.

Step 4.2. Independence of Residuals. **Durbin-Watson**: The value is **1.506**.

- This statistic tests for autocorrelation in the residuals from a statistical regression analysis. The value ranges from 0 to 4, where:
  - A value of 2 means no autocorrelation.
  - A value less than 2 indicates positive autocorrelation.
  - A value greater than 2 indicates negative autocorrelation.

A value of 1.506 suggests that there is some positive autocorrelation, but it's not too strong. Autocorrelation is generally a concern in time series data or when observations are not independent. (Montgomery, Peck, and Vining 2012, 206) Then, The Durbin-Watson statistic suggests some positive autocorrelation in the residuals, but it's not excessive.

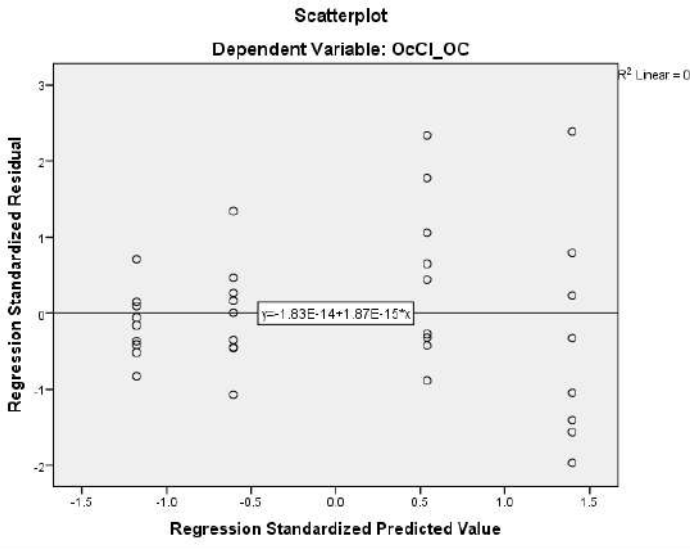
Step 4.3. Homoscedasticity.

In the Figure 2 which represents the Residuals vs. Predicted Values Scatterplot for Assessing Homoscedasticity in OcCl_OC Regression Model the scatterplot:

- The points appear fairly evenly distributed around the horizontal line, without any obvious pattern of increasing or decreasing spread.
- This suggests that the assumption of homoscedasticity is likely met, as there is no strong indication of a systematic change in the variance of residuals across different predicted values.

If further verification is needed, statistical tests such as the Breusch-Pagan test can also be used to formally test for homoscedasticity.

Figure 2. Residuals vs. Predicted Values Scatterplot for Assessing Homoscedasticity in OcCl_OC Regression Model



Source: Graphic created by authors

Breusch-Pagan Test: **While** p-value < 0.05 then the assumption of homoscedasticity is violated.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	245.007	1	245.007	9.523	.004[b]
	Residual	848.989	33	25.727		
	Total	1093.996	34			

a. Dependent Variable: Sqres

b. Predictors: (Constant), t

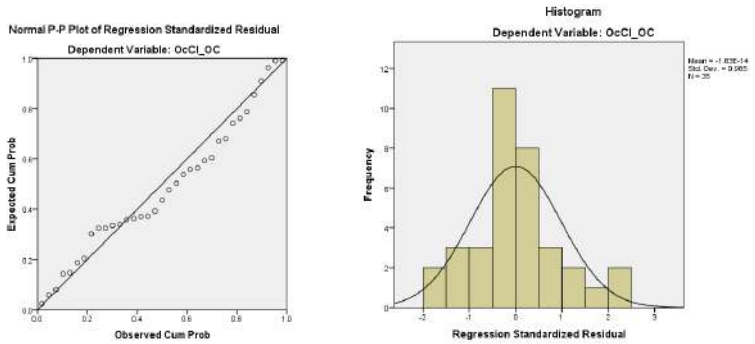
If the assumption of homoscedasticity is violated, it means that the residuals (the differences between the observed and predicted values) do not have constant variance across all levels of the independent variable. Instead, the residuals might display a pattern where the variance changes (e.g., increases or decreases) with the level of the predictor variable.

Violating the homoscedasticity assumption primarily affects the reliability and validity of our regression model's standard errors, confidence intervals, and hypothesis tests. **It does not bias the estimates of the coefficients themselves but makes them less efficient.** Taking steps to address this violation can lead to more accurate and reliable results.

Step 4.4. Normality of Residuals

The normality of residuals in the *OcCl_OC* regression model was assessed using a histogram and a Normal P-P Plot. (Figure 3) The histogram displays the distribution of standardized residuals and shows a roughly symmetric, bell-shaped pattern centered around zero, with a slight positive skew. This suggests that the residuals are approximately normally distributed, though with minor deviations. The P-P Plot further supports this observation, as most data points align closely with the 45-degree line, indicating that the residuals largely follow a normal distribution. Together, these plots confirm that the assumption of normality in the residuals is reasonably met, enhancing the reliability of the regression analysis results.

Figure 3. Normality Assessment of Regression Residuals for OcCl_OC: Histogram and P-P Plot



Source: Graphic created by authors

*Step 5. Perform the Simple Linear Regression**: and** Step 7. Report the Findings*

A simple linear regression was conducted to examine the relationship between time (t) and the employment ratio in cluster-member firms (*OcCl_OC*). The model explained 15.6% of the variance in *OcCl_OC* (R^2=0.156). (Table 5)

Table 5. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	0.395[a]	0.156	0.131	1.95186	0.156	6.111	1	33	0.019	1.506

a. Predictors: (Constant), t

b. Dependent Variable: OcCl_OC

The coefficient for time was 0.237 (p = 0.019), indicating a significant positive relationship. Each additional year is associated with an increase of 0.237 in the employment ratio. (Table 6a)

Table 6. Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
(a)	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
(Constant)	-474,356	193,140		-2,456	0,019	-867,302	-81,410
t	0,237	0,096	0,395	2,472	0,019	0,042	0,432

Diagnostic tests indicated that residuals were approximately normally distributed, and no severe multicollinearity was observed (VIF = 1.00). (Table 6b)

Table 7. Regression Coefficients

	Correlations			Collinearity Statistics	
(b)	Zero-order	Partial	Part	Tolerance	VIF
(Constant)					
t	0,395	0,395	0,395	1,000	1,000

a. Dependent Variable: OcCl_OC

These findings suggest that clusters are increasingly contributing to employment growth over time.

The model diagnostics provide insights into the performance and reliability of the regression analysis.

a) **Descriptive statistics** of the dependent variable *OcCl_OC* (Appendix 2, Table 8) show a mean of 3.086 and a standard deviation of 2.093 across 35 observations, indicating variability in the employment ratio among cluster-member firms and emphasizes the heterogeneity within the dataset.
b) **Collinearity diagnostics**, presented in Appendix 2, Table 9, reveal a high condition index of 1170.811. This value exceeds the commonly accepted threshold of 30, which suggests potential multicollinearity issues within the model. The high condition index is paired with variance proportions of 1.00 for both the constant and the predictor variable *t*, concentrated in the second dimension. Although there is only one predictor in this model, this condition index may be attributed to the scaling of the data or inherent characteristics of the dataset. Multicollinearity, when present, can lead to instability in coefficient estimates and should be considered when interpreting the model results.
c) **Residual statistics**, as shown in Appendix 2, Table 10, provide further insight into model fit and residual behaviour. The residuals are centred around zero with a mean of 0 and a standard deviation of 1.92294, suggesting that the model's predictions are generally unbiased. The range of standardized residuals, from -1.968 to 2.386, indicates that no extreme outliers are present, which supports the model's reliability. However, the spread in residuals reflects some differences between observed and predicted values, highlighting potential areas for improvement in model accuracy. Together, these diagnostics confirm that while the model meets basic assumptions for linear regression, attention should be given to the multicollinearity warning indicated by the condition index.

Step 8. Formulate Insights and Recommendations:

The analysis reveals a statistically significant positive relationship between time (t) and the employment ratio (*OcCl_OC*) in cluster-member firms. This suggests that, over time, cluster employment is contributing increasingly to overall regional employment, indicating clusters' growing role in economic development.

Diagnostics indicate that while the model fits reasonably well, a high condition index signals potential multicollinearity concerns. Although multicollinearity does not invalidate the model, it may affect the precision of coefficient estimates, which should be considered in interpretation.

The residuals exhibit minimal signs of bias and no extreme outliers, confirming the model's reliability. However, some spread in residuals suggests that the model could benefit from additional predictors to improve accuracy.

Recommendations:

- **Policy Recommendations**: Given the positive association between time and cluster employment, regional policymakers should consider expanding support for cluster initiatives, particularly in regions where growth in cluster employment is pronounced. Such support might include funding, training, and infrastructure improvements aimed at fostering clusters in key sectors.
- **Model Improvement**: To address potential multicollinearity, future models could incorporate standardized variables or employ regularization techniques if multiple predictors are included. This would reduce multicollinearity's impact on coefficient stability, ensuring more precise estimates.
- **Further Research**: Additional predictors related to economic factors, regional investments, and sector-specific variables should be explored in future studies to improve the explanatory power of the model. This would provide a more nuanced understanding of the factors driving cluster employment growth across different regions.

Discussion

5.1 Interpretation of Results

The regression analysis demonstrates a statistically significant positive relationship between time (t) and the employment ratio in cluster-member firms (*OcCl_OC*). This finding suggests that over the observed period, employment within clusters has steadily increased relative to the total regional employment. Such a trend indicates that clusters are likely becoming more influential in the Romanian regional economic landscapes, contributing a growing share to local job markets.

The positive coefficient for time (B = 0.237, p = 0.019) suggests that for each additional unit of time (likely a year), the employment ratio *OcCl_OC* increases by 0.237 units on average. This statistically significant relationship underscores the progressive strengthening of cluster employment, likely driven by the maturation and expansion of cluster initiatives over time. The model's explanatory power, with an R^2 of 0.156, implies that while time accounts for some variation in cluster employment,

other factors not included in the model also play a substantial role in explaining employment dynamics within clusters.
Diagnostic assessments, however, highlight some areas for caution. The high condition index in the collinearity diagnostics suggests potential multicollinearity concerns, which could affect the stability of coefficient estimates. This issue may not invalidate the model but indicates that additional predictors or adjustments (such as standardizing variables) might improve precision. Residuals analysis shows minimal bias and no extreme outliers, confirming the general reliability of the model's predictions despite a slight spread in residuals.
Overall, these results reinforce the notion that clusters play an increasingly significant role in employment growth over time.

5.2 Comparison with Literature

The findings of this study align with existing literature on the positive economic impact of cluster development in regional labour markets. Studies have shown that industrial clusters enhance employment by fostering networks, innovation, and economic resilience (Porter 1998; Delgado, Porter, and Stern 2014). Like the findings of this model, which reveal a positive relationship between time and cluster employment (OcCl_OC), prior research supports the notion that clusters can catalyse regional growth by concentrating resources and talent within specific industries (Audretsch and Feldman 2004).

However, the model's indication of multicollinearity, as suggested by the high condition index, prompts further discussion. Although multicollinearity is not uncommon in regional economic models due to overlapping economic factors, it can complicate the estimation of precise impacts (Wooldridge 2012). Some studies address this by introducing standardized or composite variables, an approach that could refine the stability of the model here, especially if additional predictors are introduced in future analyses.
The study's finding of a moderate but significant increase in cluster employment over time suggests that clusters are steadily strengthening their role within regional economies. This supports Delgado, Porter, and Stern's (2016) findings that cluster presence correlates with stronger employment and wage growth. The literature further suggests that policies fostering cluster formation, such as incentives for industry-specific training and infrastructure investment, can magnify these effects, highlighting an area where future regional policies could benefit from targeting clusters more strategically (Ketels 2013).
In this study, we leveraged a unique dataset provided by CLUSTERO, the Romanian Cluster Association, which offers valuable insights into the employment dynamics within clusters across Romania. While this dataset allows for an in-depth examination of cluster development over time, highlighting specific regional trends and industry concentrations, it also presents certain limitations due to its scope and granularity. Our research contributes original insights by analyzing this data through a comprehensive framework, offering a nuanced understanding of clusters not only as spatially proximate entities but as complex, interdependent ecosystems that drive regional economic growth. This approach underscores the significance of clusters as strategic assets for economic policy and regional development.
In sum, this study's results contribute to the growing body of evidence on cluster-driven regional development. While the positive relationship between time and cluster employment aligns with broader economic theories, addressing multicollinearity and expanding the model with additional predictors could enhance accuracy and insight in future research.

Conclusions

6.1 Summary of Findings

Clusters have been widely recognized as key drivers of sustainable regional economic development, offering a framework for collaboration and innovation across industries. Derlukiewicz et al. (2023) explore how EU policies support clusters as instruments for achieving sustainable development, emphasizing their role in fostering economic and social resilience while addressing environmental challenges. Complementing this perspective, Chen et al. (2023) examine the dynamics of an automotive cluster, highlighting how firm-level contributions within clusters drive regional growth and sustainability. Adding to these insights, Daniel et al. (2023) discuss strategies for selecting

and supporting clusters that maximize economic growth, emphasizing the importance of alignment between cluster capabilities and regional development goals. These studies collectively underscore the critical role of clusters in promoting inclusive and sustainable economic strategies.

This study provides a comprehensive analysis of employment trends within clusters in Romania, using a unique dataset from CLUSTERO. Our findings indicate a statistically significant positive relationship between time and the employment ratio in cluster-member firms, demonstrating that clusters play an increasingly prominent role in regional labor markets. The positive coefficient for time suggests steady growth in cluster employment over the observed period, emphasizing the value of clusters as economic drivers. Despite some indications of multicollinearity, diagnostics confirmed that the model reliably reflects employment trends without extreme outliers, supporting the robustness of the results.

6.2 Implications

The findings of this study carry important implications for regional economic policy and cluster development strategies. Based on the regression model's positive slope, we conclude that employment in cluster-member firms (*Oc_cl*) is growing at a faster rate than total employment (*Oc*) over the data period of 2013-2022. This trend reinforces the role of clusters as catalysts for economic growth, contributing significantly to employment dynamics within their regions. Targeted policies that bolster cluster ecosystems could therefore amplify these effects, particularly through strategic investments in infrastructure, training, and sector-specific support.

Furthermore, this study aligns with current efforts under the INTERREG DANUBE Project, "Plan-C-Moving Plastics and Machine Industry towards Circularity," where CLUSTERO is a project partner. Coordinated by Biz-Up Austria, the Plan-C project aims to transform the plastics value chain towards a circular economy by achieving three main objectives: designing plastics for circularity, creating circular life cycle phases in the machine industry, and developing a strategic transformation roadmap for the plastics value chain. The model developed in this study could be applied successfully to these industrial sectors, specifically the plastics industry, providing a benchmark for employment assessment in cluster-member firms. This approach also offers a best-practice framework that can be adapted by other national industries and Plan-C project partner regions to evaluate employment contributions within clusters, supporting broader efforts in the shift towards circular economies.

This expanded perspective on clusters—viewing them as complex, interconnected ecosystems—reinforces the European Commission's definition, which emphasizes clusters' role in driving innovation, economic resilience, and regional competitiveness. Recognizing clusters as multifaceted structures highlights their potential as strategic assets in policy frameworks aimed at sustainable and resilient economic growth.

6.3 Limitations and Future Research

The findings of this study carry important implications for regional economic policy and cluster development strategies. As clusters contribute to employment growth and economic resilience, targeted policies that foster cluster ecosystems can amplify these benefits. Policymakers might consider strategies that provide infrastructure, funding, and specialized training to reinforce cluster growth in high-impact sectors. This study also broadens the conceptualization of clusters, viewing them not merely as geographically concentrated entities but as complex ecosystems of interconnected organizations that collectively enhance regional competitiveness. This perspective aligns with the European Commission's multidimensional definition of clusters, which emphasizes their role in driving innovation and economic integration.

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Appendices

Appendice 1. Definition of Clusters in European Policy

[A1].1. European Cluster Definition:

The European Commission defines clusters as:

"**Geographically proximate groups of interconnected companies, specialized suppliers, service providers, firms in related industries, and associated institutions (e.g., universities, standard agencies, and trade associations) in particular fields that compete but also cooperate**."

Clusters are viewed as important for fostering economic growth because they:

- **Encourage collaboration and knowledge-sharing:** Clusters bring together diverse actors who can collaborate and innovate, leading to the exchange of ideas and technological advancements.
- **Improve productivity:** By clustering geographically, companies can benefit from a shared pool of specialized labor, suppliers, and services, leading to reduced costs and increased efficiency.
- **Promote innovation and competitiveness:** Clusters stimulate competition while promoting collaboration, resulting in a dynamic environment conducive to innovation.

[A1].2. Key Documents Defining and Supporting Clusters in European Policy:

- **European Cluster Memorandum (2007):** This document emphasized the importance of clusters for regional development and innovation. It provided guidelines on fostering clusters within Europe.
- **European Cluster Observatory Reports:** The European Cluster Observatory, an initiative launched by the European Commission, provides detailed reports and analyses on cluster dynamics across Europe, including statistical data and case studies of successful clusters.
- **Smart Specialization Strategies (S3):** Under the European Union's cohesion policy, regions are encouraged to develop Smart Specialization Strategies (S3) to identify niche areas of competitive strength, foster clusters, and drive innovation.
- **Europe 2020 Strategy:** The European Union's Europe 2020 strategy, particularly its flagship initiative "An Industrial Policy for the Globalisation Era," emphasizes the role of clusters in fostering innovation, sustainability, and competitiveness in Europe.

[A1].Significance of Clusters in European Industrial Policy

Clusters are integral to the EU's industrial policy because they:

- **Enhance regional innovation capacity:** Clusters are considered innovation hotbeds due to the close interaction between businesses, research institutions, and universities.
- **Support SMEs and entrepreneurship:** Clusters provide a supportive environment for small and medium-sized enterprises (SMEs), which are essential for job creation and economic dynamism.
- **Facilitate internationalization:** Clusters can help firms, especially SMEs, access international markets by pooling resources and leveraging shared branding and marketing efforts.

Clusters are a cornerstone of the EU’s strategy to boost competitiveness, economic growth, and innovation by fostering collaboration and knowledge exchange among companies and institutions within a geographical area.

Appendice 2. **Diagnostics Tables**

Table 8. Descriptive Statistics

	Mean	Std. Deviation	N
OcCl_OC	3,0857	2,09343	35

Table 9. Collinearity Diagnostics[a]

Model		Eigenvalue	Condition Index	Variance Proportions (Constant)	t
1	1	2,000	1,000	,00	,00
	2	1,459E-06	1170,811	1,00	1,00

a. Dependent Variable: OcCl_OC

Table 10. Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2,1119	4,2421	3,0857	,82748	35
Residual	-3,84214	4,65786	,00000	1,92294	35
Std. Predicted Value	-1,177	1,398	,000	1,000	35
Std. Residual	-1,968	2,386	,000	,985	35

a. Dependent Variable: OcCl_OC