

Foutakis, Dimitris

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Article

Identification and Visualization of Clusters Using Network Theory Methods: The Case of the Greek Production System

Dimitris Foutakis

Department of Surveying and Geoinformatics Engineering (Serres), International Hellenic University, 62124 Serres, Greece; dfoutakis@ihu.gr or dfoutakis@gmail.com

Abstract: The interest in clusters in the economy and regional space, which has persisted for nearly three decades, has reignited the understanding of the economy as a system of interdependencies between industries. Although the concept of clusters can be traced back to contributions dating from the early 20th century, they have become a central focus of regional development policies in recent decades, as they have been linked to enhancements of innovation, the knowledge economy, and ultimately, territorial competitiveness. Arguably, the most effective and comprehensive way to present the systemic nature of the economy is through input–output tables. The main feature of these tables, on which this work is based, is that they describe the relationships and flows between industries (or products) during the production process. These fundamental relationships among the industries in the production system are depicted in the inter-industry (and intra-industry) transaction matrix of an economy’s input–output tables. To analyze these relationships, we use network theory, in the context of which the transaction matrix can be seen as the adjacency matrix of a directed, weighted graph (or network) with loops. In this study, clusters are identified for the case of Greece, using two different approaches based on the modularity of the network, utilizing the 2010 input–output tables for this country. As a result, five clusters of industries that structure the country’s production system across 62 industries are identified, which are also presented through graphical visualizations.



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Keywords: clusters; input–output tables; graph/network theory; production system; Greece

1. Introduction

The aim of this article is to present a method for identifying and visualizing clusters, using the production system of Greece as a case study. Although the concept of clusters appeared in economic theory as “industrial districts” (Marshall, 1964, Chapter 10) as early as the late 19th century (1890), it re-emerged in work by Porter (1998) and others at the end of the 20th century with a rather ambiguous content.¹ However, the geographical level of reference remains unclear: it could refer to a neighborhood in a metropolitan area, a region (however defined), a country, or even groups of countries (Martin & Sunley, 2003). Furthermore, ambiguity exists regarding the types of industries involved, whether they are similar or complementary, as well as the nature of their relationships. Despite these uncertainties, clusters are considered crucial elements of regional policy within various versions of new regionalism (Amin & Thrift, 1995; Amin, 1999; Cook, 2002; Cook & Morgan, 1998; Florida, 1995; Morgan & Nauwelaers, 1999; Morgan, 1997; Storper, 1997), as they are seen as key drivers for promoting innovation, the “knowledge economy”, and ultimately, the competitiveness of regions and countries.

Regardless of any conceptual ambiguities or weaknesses, the discussion regarding clusters brings to the forefront the issue of the division of labor and the interdependent nature of economic activity. In this regard, the overall economic activity functions as a system of interdependent, separate economic activities carried out by independent economic units linked through exchange relationships, either as inputs or as outputs of intermediate or final goods, means of production, or services. The intensity of these relationships is not uniformly distributed among industries but tends to concentrate around specific industries or groups of industries and has a dynamic and changing character. The geographical scale of industries' concentration, which is addressed by contemporary cluster theory, remains an open research question.

In this paper, a methodological approach for identifying and visualizing clusters is first presented. Then, in Section 3, this approach is applied, using Greece as a case study, based on the analysis of the transaction matrix from the 2010 Greek input–output tables (Eurostat, 2013), using tools from graph/network theory. In this section, the results of applying this methodology are also presented, which leads to the identification of five clusters in the Greek production system. Section 4 features a detailed discussion about the composition and internal function of these clusters, and the paper then proceeds to Section 5.²

2. Method for the Identification and Visualization of Clusters, and Data Handling

2.1. Identification of Clusters

Identifying subdivisions or clusters within a network (graph) is both conceptually and computationally complex, with numerous methods and algorithms proposed for solving this problem (Fortunato, 2010). In the context of input–output tables, the existence of functional subdivisions has been known about since the 1950s and 1960s (see Leontief, 1986), taking forms such as strategic industries, industry hierarchies, or cohesive groupings (clusters).³ The methodological approach of this study views the input–output table as a graph (or network), a perspective that aligns with a scientific trend from the early 2000s, which established network science as a separate field focused on real-world networks (social, technological, biological, cognitive) (Newman, 2010; Barabási, 2014).⁴

The transaction matrix of the input–output table is treated as the adjacency matrix of a directed, weighted network (with or without loops), allowing the use of the network's topological characteristics and associated quantitative data (weights of links). This framework enables the identification of subgroups or clusters based on the transactions between industries. The search for cohesive structures within a complex network, described by a matrix or graph, is a problem in matrix and graph theory, which is known as *partitioning*. The goal is to divide the adjacency matrix into submatrices (subgraphs) in a way that minimizes the links between them, forming groupings with more internal links (edges) than external ones.

This problem is very challenging to solve practically, even in its simplest form, which is the bisection (splitting into two equal parts) of a graph. In this seemingly straightforward case, the graph, i.e., its corresponding adjacency matrix, must be divided into two subgraphs (submatrices) with an equal number of nodes (vertices). However, the number of possible ways to bisect the graph is approximately $2^{(n+1)}/\sqrt{n}$, where n is the number of nodes/vertices (Newman, 2010, p. 359; Barabási, 2014, Chapter 9, pp. 8–9). This means that the number of solutions increases exponentially with the increase in the number of nodes of the graph, with the result being that when the number of nodes of the graph exceeds a few dozen, finding and evaluating solutions is computationally infeasible in practice. If the number of divisions is not predetermined, the number of possible solutions increases even

faster than exponentially, as described by the *Bell number*, which approximates the number of partitions (Barabási, 2014, Chapter 9, p. 9; Fortunato, 2010, p. 87).

There are numerous approaches to solving the problem of network division and numerous corresponding algorithms, as detailed in an extensive review by Fortunato (2010). The large number of methods and algorithms can be attributed not only to the computational complexity of the problem—being *NP-hard*, which undoubtedly contributes to the development of many algorithms—but also to the inherent ambiguity in defining what constitutes a cohesive subgroup. This ambiguity leads to multiple, sometimes slightly varied definitions and terms being used to describe the same phenomenon (or ontology). In the literature, terms such as *graph partitioning*, *modules*, *clusters*, and *communities* are used interchangeably or alternatively (Newman, 2010; Fortunato, 2010; Fortunato & Castellano, 2012; Barabási, 2014). The term “*communities*” is the most recent and is often preferred in approaches that identify substructures without predefining the number or other characteristics of these subgroups.

The algorithms developed from such an approach emerged primarily during the early 2000s, driven significantly by the involvement of physicists in the field. These “physicists entered the game, bringing in their tools and techniques: spin models, optimization, percolation, random walks, synchronization, etc., became ingredients of new original algorithms” (Fortunato & Castellano, 2012, p. 492). In contrast, earlier algorithms, which relied on the prior specification of certain parameters for the subdivisions of a graph or network under study, were primarily the result of research within the domain of social network analysis (Wasserman & Faust, 1994; Scott, 2000). *K-means clustering* and *hierarchical clustering* are the most commonly used algorithms in social network analysis. The first has the serious limitation that the number of clusters to be formed must be specified in advance. The second does not have this limitation but “it does not provide any way to discriminate between the many partitions obtained by the procedure, and to choose that or those that better represent the community structure of the graph” (Fortunato & Castellano, 2012, p. 498).

This differentiation among algorithms enables an initial classification of the various approaches based on a seemingly “technical” criterion. Specifically, these methods are divided into (a) those that predetermine the number of partitions or the size of the groupings (number of nodes) to be formed, or the degree centrality (number of edges or links) for each node in the subgraphs created, and (b) those that partition the graph without any prior specification of the number, size, or other characteristics of the subdivisions (Newman, 2010, pp. 354–358).

The first class of methods rely on a framework of assumptions or a model regarding the graph’s structure, expressed through parameters that define the number and features of the partitions. In contrast, the second approach does not make any assumptions about the graph’s structure or the number or size of its cohesive structures and relies solely on the graph’s inherent data, producing a solution (or solutions) by optimizing an evaluation index derived from comparisons with a “*null model*”. This null model is a random graph that maintains certain structural characteristics of the graph under study (Fortunato, 2010, p. 86).⁵ It is crucial to note that in both approaches, partitioning is based solely on topological features.

This second method uses an index called the *network modularity*, which compares the links (edges) within each subgroup (cluster/community) in a proposed partition to the number expected if the network was *random* (Newman & Girvan, 2004). Mathematically,

modularity quantifies this comparison (Fortunato & Castellano, 2012, p. 493; Barabási, 2014, Chapter 9, p. 20) as follows:

$$Q = \sum_{c=1}^{n_c} \left[\left(\frac{l_c}{m} \right) - \left(\frac{d_c}{2m} \right)^2 \right]$$

where n_c is the total number of subgroups, l_c is the number of edges within subgroup c , m is the total number of edges in the network, and d_c is the total degree of the nodes within the same subgroup c . This mathematical formulation clarifies that modularity depends on the difference between two quantities: the first is the ratio of the edges within a subgroup to the total number of edges in the network, and the second is the ratio of the expected edges within the same subgroup to the total number of edges in the network, assuming that the network's nodes are randomly connected but retain their original degree.

In this study, the method of *maximizing modularity* is used to identify clusters within Greece's production system. Despite having some disadvantages, this method has a significant advantage: it does not require any preconceived judgment or assumption about the network's structure. This is unlike many established methods from social network analysis and hierarchical clustering, which depend on such assumptions.

However, this method is not without its problems: (a) it misclassifies subgroups that are smaller than a certain resolution limit, as it cannot distinguish them from the null model (Fortunato & Castellano, 2012, p. 501), and (b) rather than having a single optimal maximum, there is often a range of near-optimal solutions forming a plateau instead of a unique peak (Barabási, 2014, Chapter 9, p. 24). Nevertheless, algorithms based on modularity maximization are generally trusted by the scientific community and it is considered that "*modularity offers a first principle understanding of a network's community structure*" (Barabási, 2014, Chapter 9, p. 24).

Modularity always takes values less than one. Positive values ($Q > 0$) indicate a good partition, with higher values representing better results. A value of zero ($Q = 0$) means there is no significant clustering, while negative values ($Q < 0$) imply that the random graph's internal connections are better than those of the given subdivision, indicating an unacceptable partition. This subdivision is considered unacceptable because a random graph yields better results. The index takes strongly negative values when each node in the network is treated as a separate subgroup. Generally, negative modularity values indicate the absence of meaningful subgroups or communities within the network structure. This is a clear signal that the division does not exhibit the expected community characteristics, implying that the network lacks cohesive internal groupings. In practice, acceptable modularity values range from 0.3 to 0.7, although higher values may occasionally appear (Newman & Girvan, 2004, p. 7).

Maximizing modularity is known to be an NP-hard problem, meaning that it can only be approximated using heuristic and approximation algorithms (Fortunato & Castellano, 2012, p. 500). Fortunato (2010), in his comprehensive review of community detection in graphs, discusses various classes of heuristic algorithms, such as greedy, genetic, simulated annealing, spectral, and tabu search, each offering different levels of success depending on the network's size and complexity.

To divide Greece's production system into clusters, two different modularity-based approaches were used: (a) the *Louvain* method reported by Blondel et al. (2008) and (b) the *Girvan–Newman* method modified by Arenas et al. (Girvan & Newman, 2002; Newman, 2004; Arenas et al., 2007, 2008). Both methods are tailored to directed, weighted networks and use the modularity index to evaluate the network partitions they produce, ultimately proposing an optimal division into clusters.⁶

The first method, *Louvain*, aggregates each node with others in the network, recalculating the modularity at each step until the division that maximizes the modularity is found (Blondel et al., 2008, pp. 3–4). The second method successively splits the network by removing edges with the highest betweenness and recalculates the modularity at every stage. These two methods differ in the algorithms they use to calculate modularity. Given that the computation of modularity falls into the category of NP-hard problems (Fortunato & Castellano, 2012, p. 500), it can only be addressed using stochastic, heuristic optimization algorithms. The Louvain method employs a greedy algorithm (Fortunato, 2010, pp. 101–102), while the modified Girvan–Newman method, as adapted by Arenas et al., uses a different optimization approach called tabu search. Even though both methods use the modularity as the criterion for evaluating network partitions, they fundamentally differ in their strategies to achieve partitioning and in how they optimize the modularity.

The Louvain method was implemented using *Pajek network analysis software 4.10* (Mrvar & Batagelj, 2016). Arenas et al.’s method—a modified version of the Girvan–Newman method—was implemented using *Radatools software suite 4.0* (Gómez & Fernández, 2016). Thus, even though both approaches seek to maximize the modularity, their methodologies and algorithmic implementations are distinct, affecting their performance and results in terms of network partitioning.

2.2. Visualization of Results

The visualization of graphs/networks, and consequently, of clusters, is an inherent advantage and key feature of network analysis. For graphs with a relatively limited number of nodes (vertices), such as a few dozen, representation can be relatively simple, often taking the form of a grid. Another option is a circular diagram, which offers an aesthetically appealing result (Krzyszewski et al., 2009; Crnovrsanin et al., 2014). However, for graphs or networks with several dozen or even hundreds of nodes, these methods become impractical. In such cases, visualization involves linking nodes/vertices with lines where links exist.

The challenge in these more complex networks is that there is no single way to represent the network graphically (Di Battista et al., 1994, p. 236). Instead, there are theoretically infinite ways to arrange the nodes and edges, as shown in the following figure. For instance, even a simple graph with four vertices and five edges can be represented in at least three equally valid ways (Figure 1). These representations maintain the relationships between nodes (vertices), as indicated by the connecting lines (edges/links), but result in visually different diagrams.

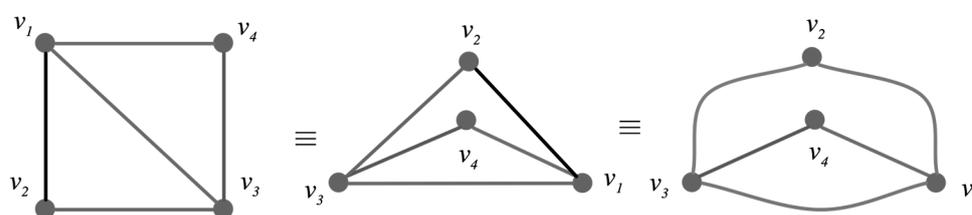


Figure 1. Different representations of the same graph.

The inherent flexibility in visualizing graphs/networks, and consequently, clusters, introduces subjectivity into how graphs/networks are represented. This characteristic of graphs certainly qualifies the value of immediacy and ease in understanding the relationships depicted through a graphical representation. The final visualization of a graph is not a single, “objective” mathematical outcome but rather a result of a creative design and, ultimately, the researcher’s intent. This flexibility can potentially lead to the “misguiding” of the reader (or even the researcher themselves) since it allows for the presentation of data

in a way that might emphasize certain aspects of the relationships—which may not be the most important ones—that are described by the graph.

This issue has led to the development of a subfield within graph theory focused specifically on visualization. This area addresses two interconnected core concerns: (a) aesthetic rules that ensure the readability and understanding of the graph and (b) the creation of algorithms for efficient computer-based graph rendering. The first aspect is directly related to the clarity and interpretability of graphs, while the second focuses on the computational efficiency of algorithms used for visualization. As [Di Battista et al. \(1999, p. 14\)](#) note, “*aesthetics* specify graphic properties of the drawing that we would like to apply, *as much as possible*, to achieve readability”. Examples of aesthetic rules include minimizing the crossing of edges, reducing the total diagram area, and ensuring uniformity in the edge length ([Di Battista et al., 1999](#), pp. 15–16).

When it comes to algorithms for implementing graph design rules, it should be noted that these are essentially optimization problems that may not be simultaneously solvable and are also computationally difficult (NP-hard). Considering the issue of computational efficiency, it becomes necessary to prioritize the aesthetic criteria for graph layout. As a result, the final output of these algorithms often involves a combination of “approximation strategies and heuristics” ([Di Battista et al., 1999](#), pp. 16–17). Despite the variety of algorithms available for graph drawing, they generally share a common foundation. Many algorithms used to achieve the final layout rely on a force-directed approach, a model inspired by the basic principles of mechanics ([Eades, 1984](#)). The core idea involves treating the edges (links) as springs, which helps to distribute the nodes (vertices) in a balanced way across a two-dimensional space, such as a computer screen, a printer, or a plotter. Variations of this approach underpin the algorithms used in modern software for social network analysis and specialized mathematical tools.

For this article, the [Fruchterman and Reingold \(1991\)](#) algorithm was used, incorporating Lombardi-style curves to aesthetically enhance the diagrams by giving the edges a curved shape ([Duncan et al., 2012](#)). The *network diagram* was created using *Gephi ver. 0.901 software* ([Bastian et al., 2009](#); [Jacomy et al., 2014](#)). The *grid-based layout* was created using *Pajek ver. 4.10 software* ([Mrvar & Batagelj, 2016](#)), and the *circular diagram* was created with *Circos Table Viewer v. 0.63-10 software* ([Krzywinski et al., 2009](#)).

2.3. Handling of Data

The data used in this study were from the *domestic input–output table for the year 2010 (product by product)* in current basic prices (in millions of EUR). This table originates from the official input–output tables for Greece in 2010 ([Eurostat, 2013](#)), provided by the European Statistical Office (Eurostat).⁷ The classification of products and industries follows the *Classification of Products by Activity-CPA 2008* ([European Union, 2008](#)) for goods and services, and the *NACE Rev. 2 Statistical classification of economic activities in the European Community* ([Eurostat, 2008](#)) for economic activities. The Eurostat data categorize 65 products/industries: 64 according to CPA/NACE classifications plus 1 additional industry, “L68A: Imputed rents of owner-occupied dwellings”.

For simplification, three industries with zero or exceptionally low values in the transactions matrix were removed, as well as five negative values that were economically meaningless, because they reversed the direction of flows and impacts. These values appeared in the output of two industries: N78 (“Employment services”) and I (“Accommodation and food services”). Specifically, the negative values amounted to EUR 0.48 million for N78 (across three entries) and EUR 1.06 million for I (across two entries). These were adjusted to zero, with a negligible overall impact, as the matrix’s total transactions amount to approximately EUR 111 billion, resulting in an effect of around 0.01%.

Additionally, three industries with negligible or zero presence were completely removed: U (“Services provided by extraterritorial organizations and bodies”), L68A (“Imputed rents of owner-occupied dwellings”), and T (“Services of households as employers; undifferentiated goods and services produced by households for own use”). These industries made no contribution to the added value and did not show any significant transactions.

Following the adjustments mentioned previously, the dimensions of the matrix became 62×62 (reduced from the 65×65 version officially published by Eurostat), containing a total of 3844 entries. Of these, 416 entries (10.8%) were zeros, compared to 780 zeros (18.5%) in the original matrix. Further simplification eliminated very small transaction values, which were replaced with zero. As a result, the number of zero entries increased to 2328 (60.6% of the total). It should be noted that this adjustment preserved 98% of the original sum of values from the 62×62 matrix before the interventions, amounting to EUR 109.077 billion out of EUR 111.614 billion. This *modified matrix* was subsequently used for cluster identification and visualization using the method described earlier.

In the presentation and commentary on the results, industries appearing in clusters were categorized by *technology level and knowledge intensity*. This categorization followed Eurostat’s guidelines (see Eurostat, 2016). The intensity of research and technological development (R&D) was used to classify two-digit manufacturing industries, using R&D expenditures as a percentage of gross value added. Four categories emerged: High Technology (HT), Medium–High Technology (MHT), Medium–Low Technology (MLT), and Low Technology (LT).

For service industries, the criterion was the percentage of employees in the corresponding two-digit economic activity industries who have a tertiary education degree. These service industries were classified in line with the two main categories in manufacturing (i.e., high and low technology) into two primary groups: Knowledge-Intensive Services (KIS) and Less-Knowledge-Intensive Services (LKIS). Furthermore, the first category (KIS) was subdivided into Knowledge-Intensive Market Services (KI_m_S), High Technology Knowledge-Intensive Services (Ht_KIS), Knowledge-Intensive Financial Services (KI_f_S), and Other Knowledge-Intensive Services (O_KIS). Less-Knowledge-Intensive Services were subdivided into Less-Knowledge-Intensive Market Services (LKI_m_S) and Other Less-Knowledge-Intensive Services (O_LKIS).

It should be emphasized that all the previous technology and knowledge intensity categories exclude the three industries of the primary sector as well as certain secondary sector industries, namely Mining (B), Electricity–Gas (D35), Water Supply (E36), Waste Management (E37–E39), and Construction (F). Due to the absence of an “official” classification from Eurostat, we designated these industries as “traditional” and marked them with the label “TR” in the related tables.

In the tables and commentary that follow, industries are identified using the NACE Rev. 2 classification codes. The description of the industries used for presentation purposes is a shortened version of their official description, which is provided in Appendix A.

3. Results

3.1. The Clusters and the Reliability of the Division

The outcome of dividing the transaction matrix into five clusters is shown in Table 1. It is important to note that, using both methods for maximizing the modularity (the Louvain method and the Girvan–Newman method modified by Arenas et al.), the initial division produced a sixth “cluster”, which consisted of the “isolated” industry *H53 Postal Services*. After a separate analysis of its connections and to achieve a more coherent presentation of the results, this industry was integrated into the “Mega-cluster”. Due to the large size of

the Mega-cluster (24 industries), incorporating Postal Services as its 25th member did not affect its overall character.

Table 1. Clusters in the production system of Greece, 2010.

Code	Description of Cluster and Industry	Code	Description of Cluster and Industry
A. AGRICULTURE–TOURISM		D. KNOWLEDGE–EDUCATION (cont.)	
1. A01	Agriculture	6. M72	Research and development
2. A02	Forestry	7. M73	Advertising
3. A03	Fishing	8. M74_M75 *	Other scientific activities
4. C10–C12	Food–Beverages	9. N78	Employment activities
5. C33	Repair/installation of machinery	10. P85	Education
6. I	Accommodation–Restaurants	11. R90–R92	Creative activities—Gambling
7. S94	Membership organizations	12. R93	Sports–Recreation
8. S96	Personal services	E. MEGA-CLUSTER	
B. ENERGY–TRANSPORT		1. C13–C15	Textiles–Apparel
1. B	Mining	2. C17	Paper
2. C19	Petroleum products	3. C20	Chemicals
3. D35	Electricity–Gas	4. C21	Pharmaceuticals
4. E36	Water supply	5. C22	Plastic products
5. H49	Land transport	6. C26	Computers–Electronics
6. H50	Water transport	7. C29	Motor vehicles
7. H51	Air transport	8. C30	Other transport equipment
8. H52	Warehousing	9. C31_C32	Furniture–Other manufacturing
9. N77	Rental/leasing activities	10. E37–E39	Waste management
C. CONSTRUCTION		11. G45	Trade and repair of motor vehicles
1. C16	Wood	12. G46	Wholesale trade
2. C23	Non-metallic mineral products	13. G47	Retail trade
3. C24	Basic metals	14. H53 **	Postal activities
4. C25	Metal products	15. K64	Financial services
5. C27	Electrical equipment	16. K65	Insurance
6. C28	Machinery	17. K66	Other financial services
7. F	Construction	18. L68	Real estate
8. M71	Architects–Engineers	19. M69_M70	Legal, accounting, management activities
D. KNOWLEDGE–EDUCATION		20. N79	Travel agencies
1. C18	Printing	21. N80–N82	Security, services to buildings
2. J58	Publishing	22. O84	Public administration, defense
3. J59_J60	Cinema–Television	23. Q86	Health
4. J61	Telecommunications	24. Q87_Q88	Social care
5. J62_J63	Computer–Information services	25. S95 *	Repair of computers and household goods

Source: Modified transaction matrix. Data processed with the Louvain and Arenas et al. methods. (*) These industries were appointed by the Louvain method: (a) M74_M75 to cluster E, (b) S95 to cluster C. (**) The industry H53 in the original divisions of both methods was a separate “cluster”.

Differences between the two methods were observed in only two cases:

1. *Industry M74_M75 Other Scientific Services*: The Louvain method placed it in the “Mega-cluster”, while the Arenas et al. method (i.e., the modified G-N method) placed it in the “Knowledge–Education” cluster.
2. *Industry S95 Repair of Computers and Household Appliances*: The Louvain method placed it in the “Construction” cluster, while the Arenas et al. method placed it in the “Mega-cluster”.

Overall, both methods produced nearly identical results, revealing the internal organization of the production system into six initial clusters, which were effectively consolidated into five cohesive groups (clusters). From a technical perspective, based on the modularity coefficient (Q), the Arenas et al. method yielded a value of $Q = 0.2923$ for the division into six clusters, while the Louvain method produced a value of $Q = 0.3005$. It should be noted that the Arenas et al. method approaches the resolution limit issue differently, arriving at an optimal solution that includes resolution considerations (Arenas et al., 2008). In contrast, the Louvain method allows for the parameterization of the resolution limit (r), which affects the results. The default value in Pajek is $r = 1$, but for this study, after extensive testing, the value $r = 0.95$ was selected, which is very close to the default.

The reliability of the division into five clusters was tested using the *E-I index* developed by Krackhardt and Stern (1988, p. 127). This index, which is used in social network analysis, compares the number of links (edges) outside the clusters (El) with those within the clusters (Ii). This index is formulated as follows:

$$E - I = \frac{El - Ii}{El + Ii}$$

The *E-I index* is the ratio of the difference between the external and internal links of the nodes (industries) within the clusters to the total number of links in the entire network (production system). To calculate the index, the underlying graph is considered without taking into account the direction of the links, effectively transforming it into an undirected network with loops. The index theoretically has a maximum value of +1 when all the links are external to the clusters, meaning that each node forms its own “cluster”, and a minimum value of −1 when all the links are internal to the clusters, indicating a fully partitioned network. Thus, the smaller the index value, the better the network is divided into cohesive subgroups, as a lower value indicates higher internal cohesion and introversion.

The results were obtained using the specific implementation of the index in the *Ucinet v.6* social network analysis software (Borgatti et al., 2002). To better interpret the results, the weights of the links were disregarded during the calculation. This means that in the adjacency matrix (transaction matrix), any values greater than zero were replaced with one. The final adjusted (rescaled) value of the index was $E - I = -0.533$. The negative value on the scale from −1 to +1 clearly indicates that the network (i.e., the production system), with the given division into five clusters, is introverted and that the clusters are significantly cohesive.

3.2. Main Characteristics of Clusters and Visualization of Results

Based on the results obtained with both methods, the Greek production system is organized into *five clusters* (Table 1, Figures 2–4). These clusters are as follows:

1. *Agriculture–Tourism Cluster*: This cluster comprises eight industries, namely the three industries of the primary sector (Agriculture, Forestry, and Fishing), the Food–Beverages industry, and Accommodation–Restaurants, which is the basic industry of Tourism.
2. *Energy–Transport Cluster*: Consisting of nine industries, this cluster includes the Electricity, Mining, and Petroleum industries. It also encompasses all the Transportation and Warehousing industries (excluding Postal Services).
3. *Construction Cluster*: This cluster includes eight industries related to the production of Metal and Non-metallic products, Machinery manufacturing, and the Construction and Architects–Engineers industries.

4. *Knowledge-Education Cluster*: Encompassing twelve industries, this cluster contains most of the knowledge-intensive industries, particularly those connected to Mass Media, Communication, Education, and Research and Development.
5. *Mega-Cluster*: This is the largest cluster, consisting of twenty-five industries. It includes Real Estate, Public Administration, Health and Social Care, Trade, Chemical, Plastic, Pharmaceutical production, the Financial industry, and various other industries. This cluster forms the core of the production system in terms of the volume of total gross value added (GVA) produced in Greece.

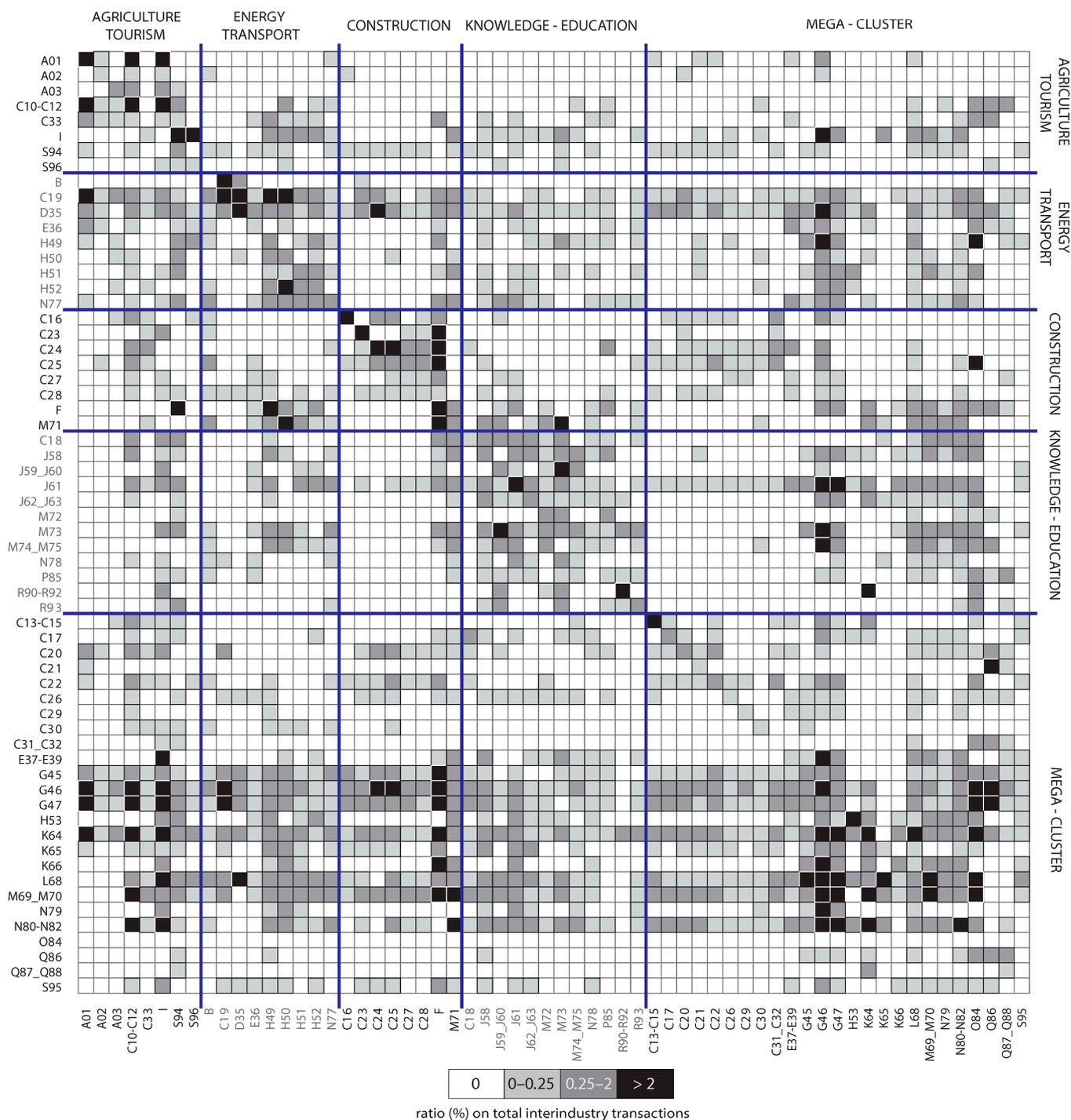


Figure 2. Visualization of the production system and its clusters as a grid.

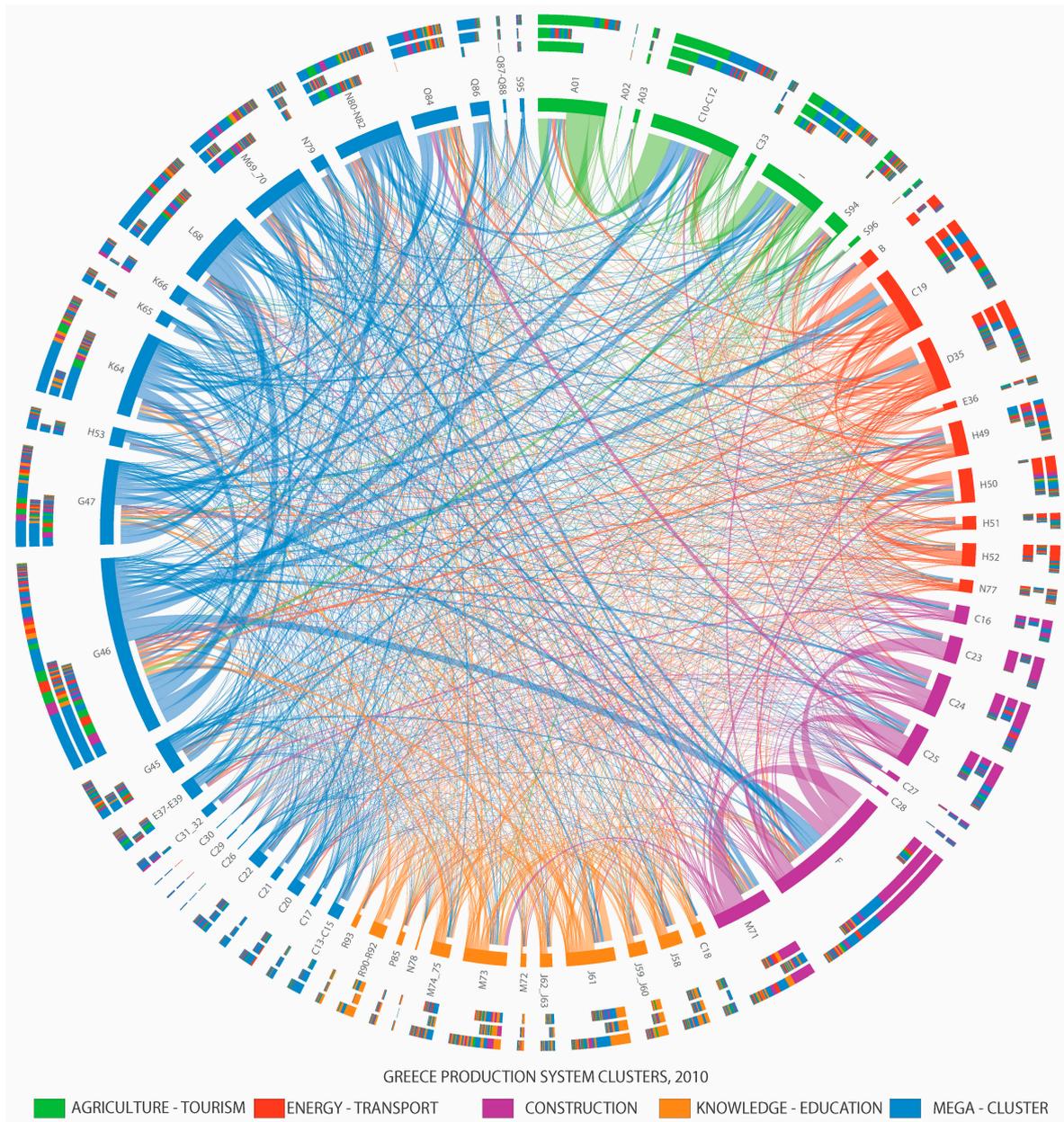


Figure 3. Circular chord diagram of the production system and its clusters.

In the *circular chord diagram* (Figure 3), industries are arranged clockwise according to their clusters, starting from the “twelve o’clock” position. Each cluster is color-coded (green for the Agriculture–Tourism cluster, red for the Energy–Transport cluster, and so on). The chords are colored based on the originating industry.

The circle’s inner perimeter is divided into arcs corresponding to the number of industries, with the length of each arc being proportional to the industry’s transaction volume (both inputs and outputs). The outer perimeter is similarly divided, with the arc lengths being proportional to the total transaction volume. The arcs are segmented into percentages, with each segment’s color indicating transactions with other industries. Moving inward, the first layer of arcs represents the industry’s outputs (to itself and others), and the second layer depicts inputs. Industries are ordered from those with the largest to the smallest transaction volume along these three perimeters.

In Figure 4, the production system is presented as a network, with clusters distinguished by different colors assigned to the nodes/vertices (industries). The lines (links) are colored according to the industry of origin (representing output), and their thickness reflects the transaction size. The size of each node and the font size of the industry labels correspond to the “influence” of the industry, measured by the *eigenvector centrality* (*PageRank*).⁸

Table 2 summarizes the main economic characteristics of the clusters. The ratio of the transaction value within the clusters to that outside them indicates the effectiveness of the division: 56% of the total transaction value occurs internally. The Mega-cluster stands out in terms of most economic metrics (except exports). Despite its large number of industries, it has significant internal cohesion, with 53% of its transaction value occurring within the cluster. It also contributes more than 53% of total gross value added of the production system, which is equivalent to the gross domestic product of the country minus taxes on products plus subsidies on products. The presence of such a large grouping, or “giant component”, in real networks such as production systems is common and can include most of the network’s nodes.⁹

Table 2. Main economic characteristics of the clusters.

Clusters	Industries (Num.)	Transactions Inside Cluster	Employment (%)	Demand (%)	Added Value		Exports	
					(%)	Technical Coefficient	(%)	Extroversion
A. Agriculture–Tourism	8	0.78	24.3	18.8	15.2	52.7	9.2	6.4
B. Energy–Transport	9	0.50	5.6	15.3	10.2	38.3	52.5	39.5
C. Construction	8	0.68	12.2	10.7	7.3	33.5	11.9	10.9
D. Knowledge–Educ.	12	0.39	12.3	10.5	13.4	66.0	3.2	3.3
E. Mega-Cluster	25	0.53	43.6	44.2	53.2	65.1	23.0	5.6
Production System *	62	0.56	98.0	99.5	99.3	55.6	99.8	11.1

Source: Domestic input–output table for Greece 2010 (Eurostat, 2013, Table 18). Labour Force Survey, 2010 (Hellenic Statistical Authority-ELSTAT, 2010). Own processing. (*) Industry “T Activities of households as employers” not included. This is why the sum of employment, demand and value added does not add up to 100%. The sum of exports is not 100% due to rounding. *Transactions inside cluster* = the ratio of the value of transactions between the industries of the cluster to the value of the sum of all the transactions of the industries of the cluster (2010). *Employment %* = Employment as a percentage of total employment (2010). *Demand %* = Demand as a percentage of total demand (final use), 2010. *Added Value %* = percentage (%) of total added value 2010. *Technical Coefficient* = GVA as a percentage total value of production (P.1), 2010. *Exports %* = the value of exports of the industries of the cluster as a percentage of total value of exports, 2010. *Extroversion* = Exports as a percentage of total value of production (P.1), 2010.

The second most significant cluster, based on several indicators, is the Agriculture–Tourism cluster, which has a comparatively much smaller number of industries (eight) but exhibits exceptional internal cohesion, with almost 80% of its transaction value occurring within the cluster. It also makes a substantial contribution to employment (24.3%) and to final demand (19%).

The Construction cluster also demonstrates high cohesion (68%) and contributes significantly to employment (12.2%) and exports (12%). On the other hand, the Knowledge–

Education cluster has the lowest cohesion (39%) and the smallest contribution to exports, despite having a relatively large number of industries (12). Nevertheless, it features the highest technical coefficient of gross value added (66%). The Energy–Transport cluster is characterized by high external orientation (extroversion 39.5%) and remarkable export performance (52.5%) but makes a lower contribution to employment. These five clusters are described in greater detail and depicted diagrammatically in the following sections.

4.2. Agriculture–Tourism Cluster

The Agriculture–Tourism cluster consists of eight industries: the primary sector industries (A01 Agriculture, A02 Forestry, A03 Fishing), C10_C12 Food–Beverages, I Accommodation and Restaurants, C33 Repair/Installation of Machinery, S94 Membership Organizations, and S96 Personal Services. This cluster therefore combines the primary, manufacturing, and service sectors. The name of the cluster underscores the prominence of agricultural production and tourism activity in the cluster, as is evident in the following paragraphs.

As shown in Table 3, the Agriculture–Tourism cluster demonstrates a high degree of cohesion, with almost 80% of its transaction value occurring within the cluster. It significantly contributes to employment (24.3%), demand (18.8%), added value (15.2%), and exports (9.2%). The technical coefficient of added value is relatively high (52.7%), while the index of external orientation (Extroversion) is low (6.4%), well below the average (11.1%).

Table 3. Agriculture–Tourism cluster: main economic characteristics.

NACE Code	Description	Technology	Transactions Inside Cluster		Empl. (%)	Demand (%)	Added Value		Exports	
			Output	Input			(%)	Technical Coefficient	(%)	Extroversion
A01	Agriculture	TR	0.97	0.47	11.9	2.0	2.5	50.1	3.2	13.0
A02	Forestry	TR	0.52	0.52	0.1	0.0	0.0	58.0	0	4.3
A03	Fishing	TR	1.00	0.33	0.4	0.4	0.4	64.6	0.9	28.9
C10–C12	Food–Beverages	LT	0.88	0.44	3.1	5.9	3.6	41.2	5.1	11.7
C33	Repair/installation of machinery	MLT	0.32	0.01	0.3	0.0	0.2	54.1	0	0
I	Accommodation–Restaurants	LKI_m_S	0.38	0.37	6.8	7.8	6.7	62.7	0	0
S94	Membership organizations	O_LKIS	0.34	0.34	0.4	1.5	0.7	33.4	0	0
S96	Personal services	O_LKIS	0.69	0.51	1.2	1.2	1.1	78.8	0	0
Total Agriculture–Tourism Cluster			0.78		24.3	18.8	15.2	52.7	9.2	6.4

The Agriculture–Tourism cluster is structured around the relationship between the industries A01, C10, C12, C33, and I. This forms a robust agriculture–food–tourism axis, complemented by inputs and outputs from industry S94 to I and from A01 and C33, as well as outputs from C33 primarily directed toward A01. Industries A02, A03, and S96 complete the cluster, with smaller transaction flows to C33 (for the first two) and to I and S94 (for S96). This composition suggests that this cluster equally produces goods and services, as seen from its added value structure. A significant share of its production is directed toward international markets, particularly those of industries A03, A01, and C10–C12, and I, although for the latter (tourism from abroad), this is not captured in the input–output tables.

From the *circular diagram* (Figure 5), it is apparent that this cluster’s structure revolves around three key industries, namely Agriculture, Food–Beverages, and Accommodation–Restaurants, with the other industries playing a complementary role. This structure is illustrated differently in the *network diagram* (Figure 6), where the importance of each industry is depicted by the size of the network nodes (vertices) and labels. This importance is measured using the eigenvector centrality index (“PageRank”), and the thickness of the lines represents the volume of transactions. The network diagram highlights the

prominence of A01 Agriculture, C10–C12 Food–Beverages, I Accommodation–Restaurants, and S94 Membership Organizations, which primarily receive outputs from industries I and C10–C12.

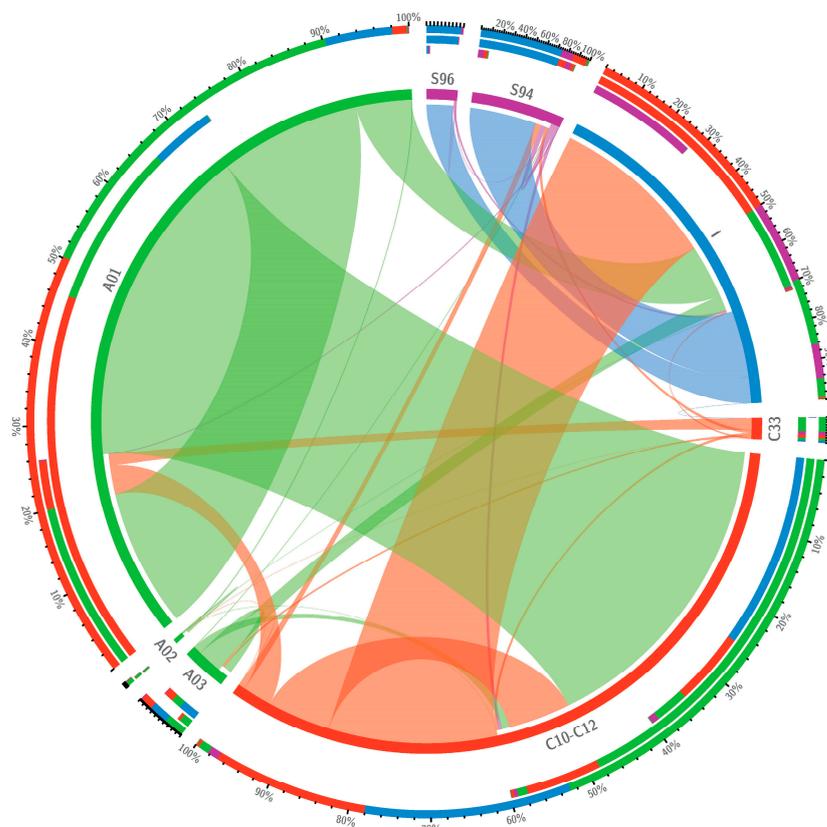


Figure 5. Circular diagram of the Agriculture–Tourism cluster.

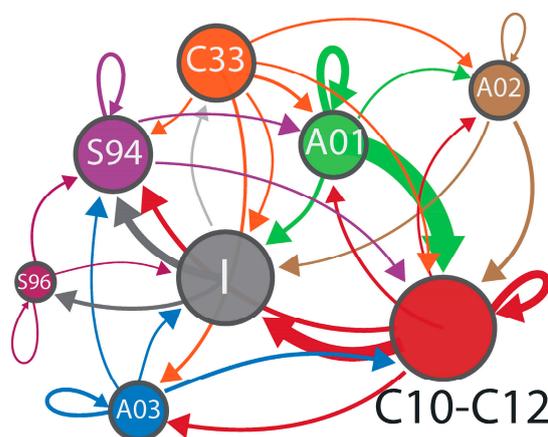


Figure 6. Network diagram of the Agriculture–Tourism cluster.

Finally, from a technological perspective, as shown in Table 3, this is a low-technology and less-knowledge-intensive cluster. Only C33 Repair/Installation of Machinery is a medium–low technology industry, while the others are either traditional (the three primary sector industries) or low-technology and less-knowledge-intensive industries.

4.3. Energy–Transport Cluster

The Energy–Transport cluster (Figures 7 and 8) consists of nine industries: B Mining, C19 Petroleum Products, D35 Electricity–Gas, E36 Water Supply, H49 Land Transport, H50

Water Transport, H51 Air Transport, H52 Warehousing, and N77 Rental and Leasing Activities. As shown in Table 4, this cluster could alternatively be described as the *Export cluster*, as it accounts for more than half of the country’s exports (52.5%). However, considering that all the transport and logistics services along with the energy production industries are found in this cluster, it is appropriate to name it the Energy–Transport cluster.

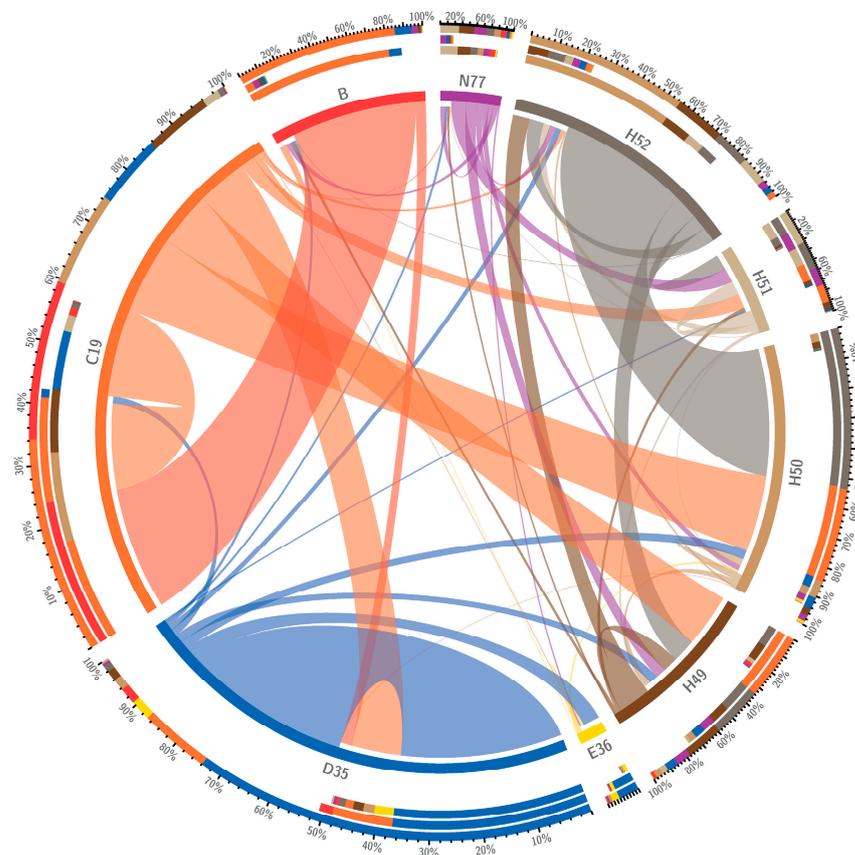


Figure 7. Circular diagram of the Energy–Transport cluster.

Table 4. Energy–Transport cluster: main economic characteristics.

NACE Code	Description	Technology	Transactions Inside Cluster		Empl. (%)	Demand (%)	Added Value		Exports	
			Output	Input			(%)	Technical Coefficient	(%)	Extroversion
B	Mining	TR	0.98	0.30	0.3	0.1	0.3	47.5	0.4	12.4
C19	Petroleum products	MLT	0.56	0.48	0.2	3.8	1.0	14.5	10.7	31.3
D35	Electricity–Gas	TR	0.42	0.72	0.6	1.8	2.3	53.8	0.5	2.2
E36	Water supply	TR	0.10	0.50	0.2	0.2	0.2	48.1	0	0
H49	Land transport	LKI_m_S	0.19	0.38	2.4	2.1	1.5	43.3	0.5	3.0
H50	Water transport	KI_m_S	0.41	0.47	0.7	6.2	3.7	47.0	37.4	96.0
H51	Air transport	KI_m_S	0.28	0.54	0.2	0.6	0.3	28.1	1	18.2
H52	Warehousing	LKI_m_S	0.80	0.45	0.9	0.3	0.6	42.0	1.9	27.6
N77	Rental/leasing activities	LKI_m_S	0.38	0.16	0.1	0.1	0.3	51.1	0.1	3.4
Total Energy–Transport Cluster			0.50		5.6	15.3	10.2	38.3	52.5	39.5

This cluster has moderate cohesion, with the value of the inter-industry transactions divided equally between internal and external transactions (50–50). At the industry level, *Mining (B)*, *Electricity–Gas (D35)*, *Petroleum Products (C19)*, and *Warehousing (H52)* display a clear “introversive” orientation, meaning that most of their transaction value occurs with other industries within the cluster rather than with the rest of the production system, as indicated in the relevant columns (Outputs, Inputs) of the table. The remaining industries in the cluster exhibit varying degrees of volume of external transactions, interacting more with industries outside the cluster.

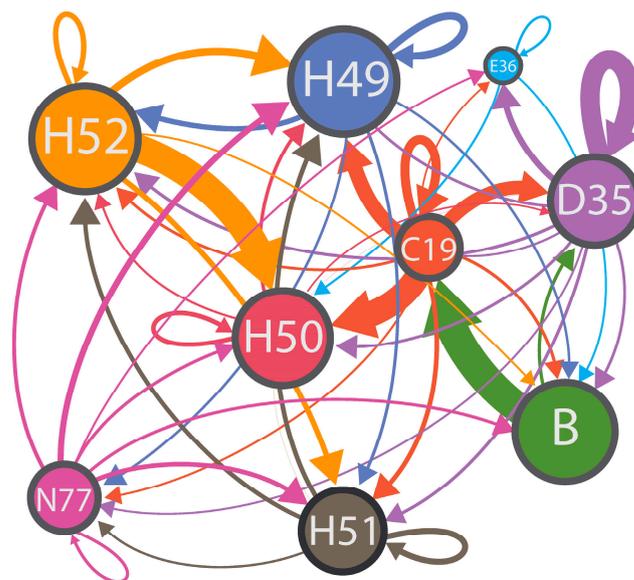


Figure 8. Network diagram of the Energy–Transport cluster.

The Energy–Transport cluster makes a relatively low contribution to employment (5.6%) and has a low technical coefficient of added value (38.3%). This indicates that this cluster is characterized by low added value or, conversely, a high intensity of intermediate inputs. Most of the industries in this cluster are classified as low-technology and less-knowledge-intensive. Only industries *H50 Water Transport* and *H51 Air Transport* are classified as knowledge-intensive (KI_m_S), while the *C19 Petroleum Products* industry is medium–low technology (MLT). In Figures 7 and 8, the cluster’s structure is illustrated, which is centered around *Mining (B)*, *Petroleum Products (C19)*, *Electricity–Gas (D35)*, and *Transportation* (primarily maritime *H50* but also land *H49*). Complementing this core structure are industries such as *H52 Warehousing*, *H51 Air Transport*, *N77 Rental/Leasing Activities*, and *E36 Water Supply*. The *D35 Electricity–Gas* industry serves as a supplier for all the other industries within the cluster, as do *C19 Petroleum Products* and *N77 Rental and Leasing Activities*. The *B Mining* industry primarily supplies *C19 Petroleum Products* and *D35 Electricity–Gas*, while *H50 Water Transport* receives inputs mainly from *H52 Warehousing* and *C19 Petroleum Products*, with minimal outputs.

Considering the overall characteristics of the Energy–Transport cluster and the industries that comprise it, this cluster emerges as a critical component of the production system, primarily due to its strong orientation toward the international market. Several of its industries are internationally competitive, notably *H50 Water Transport*, *C19 Petroleum Products*, and *H52 Warehousing*.

4.4. Construction Cluster

The Construction cluster (Figures 9 and 10) is composed of eight industries, including six manufacturing industries: *C16 Wood*, *C23 Non-Metallic Products*, *C24 Basic Metals*, *C25 Metal Products*, *C27 Electrical Equipment*, and *C28 Machinery*. It also includes *F Construction* and *M71 Architects–Engineers* from the service sector. This cluster is particularly cohesive, with over two-thirds of its transactions (0.68) occurring internally (Table 5). Most industries, except for *C28 Machinery* and *M71 Architects–Engineers*, engage in internal transactions in terms of either outputs or inputs. Its name underlines the central role of the Construction industry in the cluster.

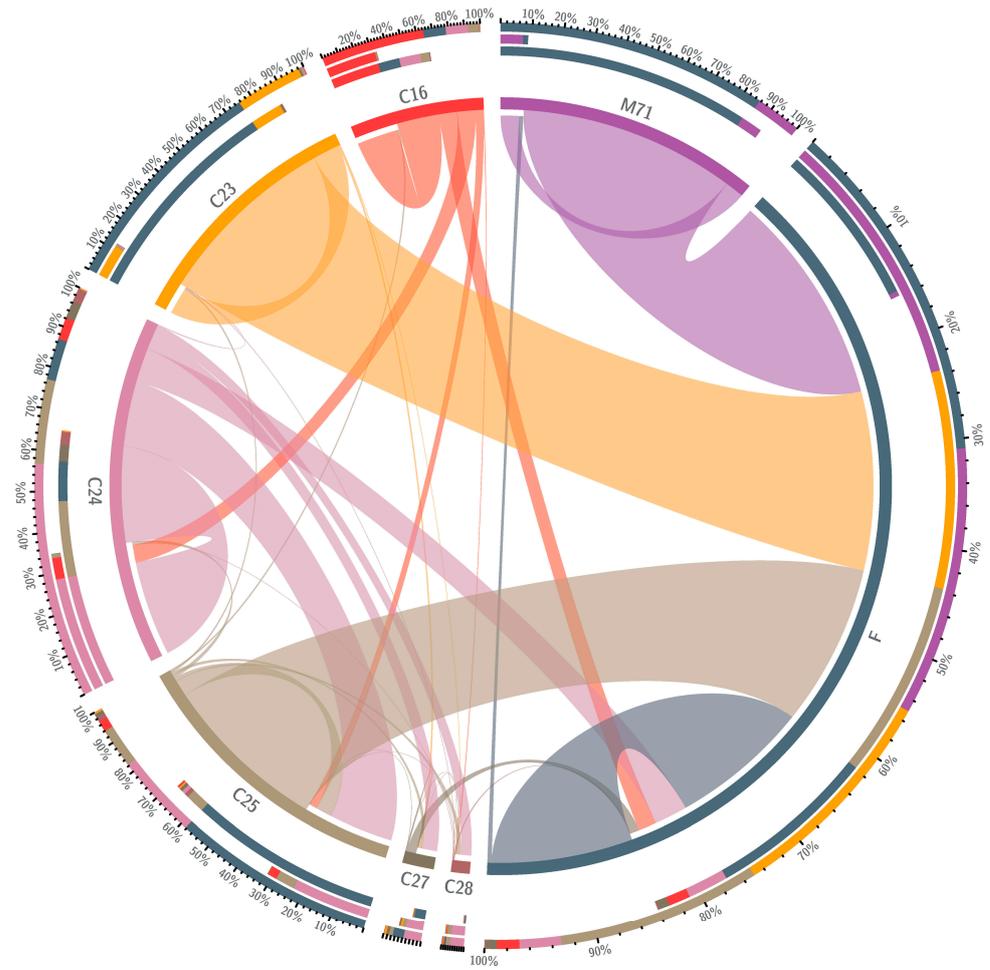


Figure 9. Circular diagram of the Construction cluster.

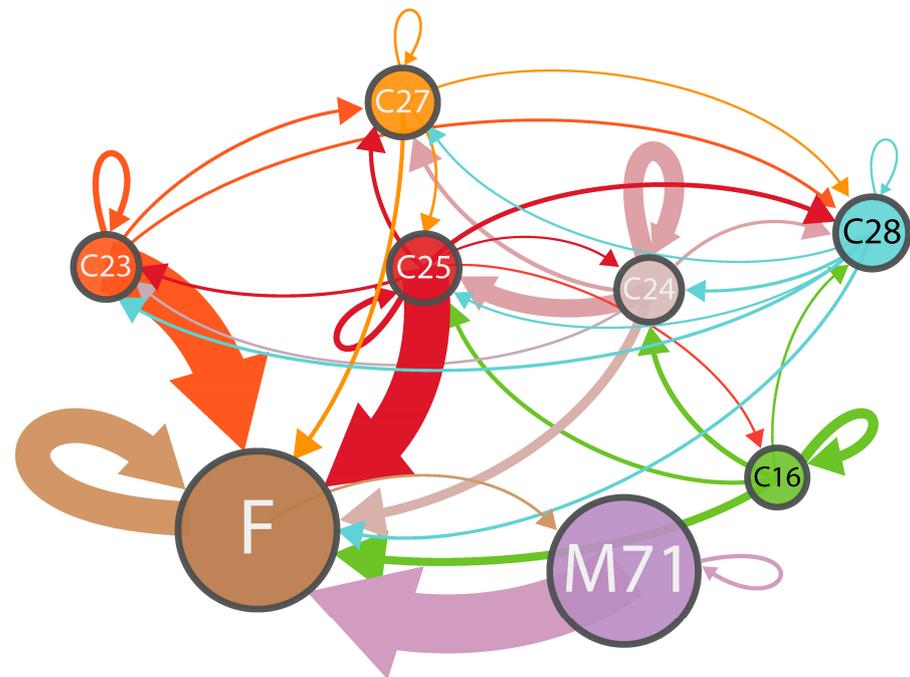


Figure 10. Network diagram of the Construction cluster.

Table 5. Construction cluster: main economic characteristics.

NACE Code	Description	Technology	Transactions Inside Cluster		Empl. (%)	Demand (%)	Added Value		Exports	
			Output	Input			(%)	Technical Coefficient	(%)	Extroversion
C16	Wood	LT	0.67	0.54	0.5	0.0	0.2	29.7	0.1	3.1
C23	Non-metallic mineral products	MLT	0.96	0.34	0.6	0.2	0.7	50.5	0.8	11.1
C24	Basic metals	MLT	0.83	0.52	0.5	0.8	0.6	24.4	5.2	43.5
C25	Metal products	MLT	0.65	0.48	1.2	0.4	0.7	33.3	0.7	6.4
C27	Electrical equipment	MHT	0.62	0.47	0.3	0.4	0.3	42.8	2.1	67.9
C28	Machinery	MHT	0.31	0.42	0.2	0.5	0.3	50.1	1.3	42.9
F	Construction	TR	0.50	0.64	7.5	8.1	3.6	31.8	1.4	2.5
M71	Architects–Engineers	KI_m_S	0.58	0.09	1.5	0.3	0.9	35.4	0.3	2.3
Total Construction Cluster			0.68		12.2	10.7	7.3	33.5	11.9	10.9

The Construction cluster is the smallest of the five clusters in terms of production volume, contributing only 7.3% of the total gross value added (GVA). Nearly half of this output (3.6%) comes solely from the Construction (F) industry. The other half comes from the other five industries, each contributing less than 1% of the total GVA of the production system. The added value technical coefficient is the lowest among all five clusters (33.5%) due to the exceptionally low values across its industries, some of the lowest in the production system.

Generally, apart from the Construction industry, this cluster consists of relatively small industries. This is reflected in the modest share of total employment (12.7%) and demand (10.7%) of the cluster, with the Construction industry accounting for the majority (7.5% in employment and 8.1% in demand). Despite the small size of its industries, the Construction cluster has a notable export contribution (11.9% of total exports of the production system), mainly from its six manufacturing industries. The *C24 Basic Metals* industry leads exports (5.2%), followed by the *C27 Electrical Equipment* industry (2.1%), with the remaining four Manufacturing industries contributing 2.9%. This export strength is evident in the high export index (Extroversion) of most Manufacturing industries in the cluster.

Technologically, most industries in the Construction cluster are of low or medium–low technology (LT, MLT), apart from M71 Architects–Engineers, which is knowledge-intensive (KI_m_S), while the Construction (F) industry is traditional (T). However, the central role of the Construction industry enables it to activate other industries in the cluster through its backward linkages, 65% of which are internal. Most industries, with the internal forward linkages ranging from 58% to 96%, are interconnected within the cluster. This means that changes in the demand for the Construction industry can propagate through inter-industry relationships and stimulate demand for higher-technology and knowledge-intensive industries, such as *C27 Electrical Equipment* (medium–high technology), *C28 Machinery* (medium–high technology), and *M71 Architects–Engineers* (knowledge-intensive).

4.5. Knowledge–Education Cluster

The Knowledge–Education cluster is composed of 12 industries; one is a Manufacturing industry and 11 are from the Service sector (Figures 11 and 12). Its name highlights two primary characteristics: the economic significance of the *Education (P85)* industry and the high concentration of service industries in this cluster, with 11 out of a total of 21 knowledge-intensive service industries in the production system being in this cluster. Alternatively, it could also be called the *Knowledge–Communication cluster*, as at least six of its industries are involved in producing, supporting, and managing traditional mass and newer Internet-based interactive communication media. These include *C18 Printing*, *J58 Publishing*, *J59_J60 Cinema–TV*, *J61 Telecommunications*, *J62_J63 Computer–Information Services*, and *M73 Advertising*. Additionally, this cluster incorporates activities from the *R90–R92 Creative Activities and Gambling* industry, which include the *R90 Creative Arts and Entertainment* industry.

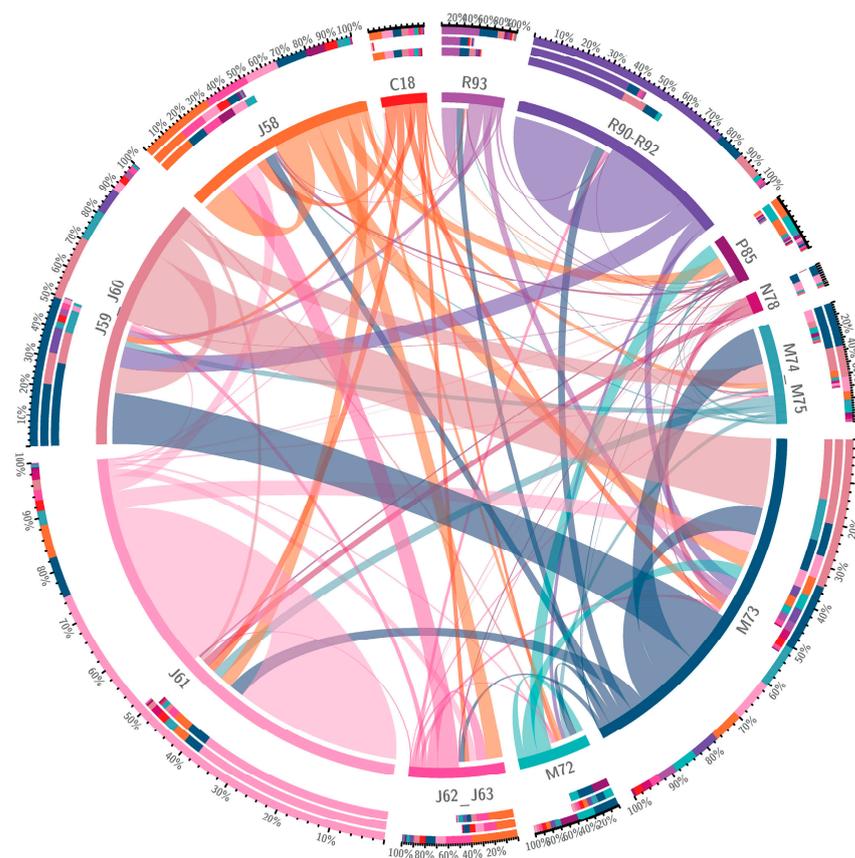


Figure 11. Circular diagram of the Knowledge–Education cluster.

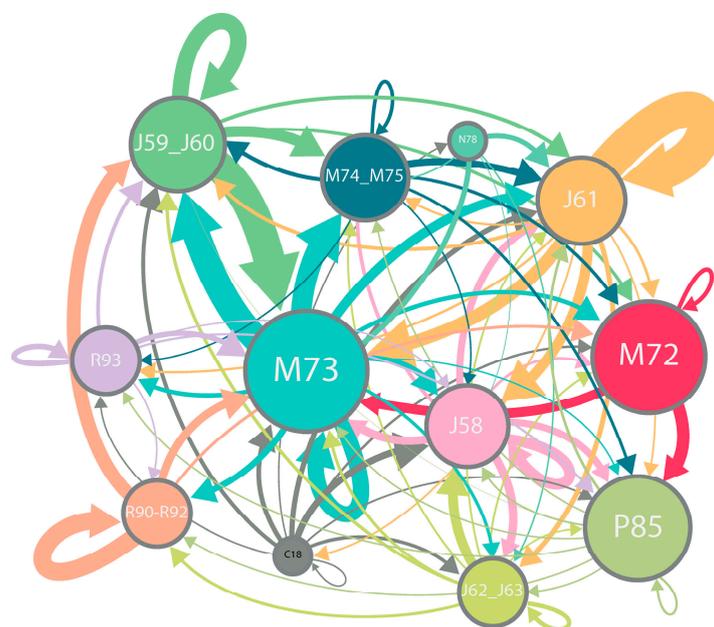


Figure 12. Network diagram of the Knowledge–Education cluster.

Many of these industries rely on telecommunications services provided by J61 Telecommunications as well as on the production and services of C18 Printing and J58 Publishing to create and manage mass communication and entertainment. These industries represent the majority of the so-called “creative industries”, which employ the members of the “creative class” (Florida, 2012, pp. 35–62). Ultimately, the name Knowledge–Education cluster was

preferred because of the economic structure of the cluster and the significance of knowledge production and dissemination, which is primarily a result of educational processes.

One distinguishing feature of the Knowledge–Education cluster, as shown in Table 6, is its relatively low cohesion (0.39) compared to the other four clusters in the production system. It also makes the smallest contribution to demand (10.5%) and is the second smallest in terms of employment (12.3%) and gross value added (13.4%). The significance of *P85 Education* is evident in its impact on these indicators, as it accounts for approximately half or more of the cluster’s total value in each case. Aside from Education, no other industry makes a notable contribution to employment, with Education itself representing 7.5%.

Table 6. Knowledge–Education cluster: main economic characteristics.

NACE Code	Description	Technology	Transactions Inside Cluster		Empl. (%)	Demand (%)	Added Value		Exports	
			Output	Input			(%)	Technical Coefficient	(%)	Extroversion
C18	Printing	LT	0.26	0.04	0.6	0.0	0.2	44.6	0.0	0.2
J58	Publishing	O_KIS	0.43	0.43	0.4	1.2	1.3	62.0	0.4	4.1
J59_J60	Cinema–Television	Ht_KIS	0.77	0.59	0.4	0.5	0.3	30.5	0.3	5.1
J61	Telecommunications	Ht_KIS	0.37	0.58	0.7	1.9	2.7	63.6	0.7	3.5
J62_J63	Computer–Information services	Ht_KIS	0.32	0.49	0.5	0.4	0.6	64.0	0.8	17.3
M72	Research and development	Ht_KIS	0.83	0.50	0.2	0.2	0.1	27.1	0.2	12.5
M73	Advertising	KL_m_S	0.34	0.49	0.4	0.1	0.2	9.8	0.3	4.5
M74_M75	Other scientific activities	KL_m_S	0.11	0.52	0.5	0.2	0.5	47.5	0.3	7.0
N78	Employment activities	KL_m_S	0.65	0.30	0.1	0.0	0.1	92.8	0.0	0.0
P85	Education	O_KIS	0.27	0.48	7.5	4.8	5.7	94.5	0.1	0.2
R90–R92	Creative activities—Gambling	O_KIS	0.64	0.94	0.7	1.2	1.6	79.8	0.1	0.7
R93	Sports–Recreation	O_KIS	0.62	0.49	0.4	0.1	0.1	34.9	0.0	0.2
Total Knowledge–Education Cluster			0.39		12.3	10.5	13.4	66.0	3.2	3.3

This is a cluster that operates with a very high technical coefficient of added value (66%), the highest among the five clusters and above the overall production system average (55.6%). According to the detailed industry-specific data in Table 6, this high coefficient arises from the extremely high values in certain industries. Most industries in this cluster use minimal intermediate inputs, and in some cases, such as *J61 Telecommunications*, *J58 Publishing*, and *R90–R92 Creative Activities–Gambling*, a significant portion of their transactions are intra-industry.

On the other hand, *M73 Advertising* (9.8%) and *M72 Research and Development* (27.1%) have relatively high volumes of inputs. This cluster performs particularly poorly in exports (3.2%), with the highest export-contributing industry, *J62_J63 Computer–Information Services*, contributing only 0.8% to the total exports of the production system. Similarly, this cluster has a low external orientation (Extroversion) index (3.3%), with nearly all its industries, except for *M72 Research and Development* (12.5%) and *J62_J63 Computer–Information Services* (17.3%), having significantly lower values than the production system average (11.1%). This indicates that while the cluster is composed of knowledge-intensive services, it lacks an export orientation. The exceptions are *M72 Research and Development* and *J62_J63 Computer–Information Services*, which show potential for exports.

4.6. Mega-Cluster

The Mega-cluster, as suggested by its name, is the largest cluster in the production system in terms of almost all aspects except for exports (Table 7). It consists of 25 industries in total: 10 from the secondary sector (8 of which are manufacturing) and 15 from the service sector. It includes some of the largest industries by employment, such as *G47 Retail Trade* (12.3%), *O84 Public Administration* (8.5%), and *Q86 Health* (4.7%), as well as some of the strongest in terms of demand and added value, like *L68 Real Estate* (10.3% and 15.1%, respectively), *O84 Public Administration–Defense* (9.9% and 8.7%), and *G46 Wholesale Trade* (6.3% and 6.0%).

Table 7. Mega-cluster: main economic characteristics.

NACE Code	Description	Technology	Transactions Inside Cluster		Empl. (%)	Demand (%)	Added Value		Exports	
			Output	Input			(%)	Technical Coefficient	(%)	Extroversion
C13–C15	Textiles–Apparel	LT	0.83	0.85	1.1	0.8	0.5	42.9	2.9	45.5
C17	Paper	LT	0.57	0.85	0.2	0.3	0.2	29.5	0.3	11.1
C20	Chemicals	MHT	0.52	0.70	0.3	0.5	0.3	27.6	2.2	45.5
C21	Pharmaceuticals	HT	0.97	0.78	0.4	0.5	0.5	58.6	1.9	45.7
C22	Plastic products	MLT	0.50	0.79	0.3	0.2	0.1	18.1	1.0	24.9
C26	Computers–Electronics	HT	0.37	0.76	0.1	0.1	0.1	58.4	0	0
C29	Motor vehicles	MHT	0.87	0.69	0.1	0.1	0.1	48.0	0.1	15.7
C30	Other transport equipment	MHT	0.18	0.64	0.2	0.1	0.1	65.0	0.1	14.0
C31_C32	Furniture—other manufacturing	LT	0.92	0.52	1.0	0.5	0.3	33.6	0.5	11.7
E37–E39	Waste management	TR	0.58	0.40	0.5	0.4	0.7	58.1	0.6	9.4
G45	Trade and repair of motor vehicles	LKL_m_S	0.32	0.77	2.0	1.9	2.3	66.4	1.2	6.6
G46	Wholesale trade	LKL_m_S	0.38	0.69	3.7	6.3	6.0	46.3	6.2	9.5
G47	Retail trade	LKL_m_S	0.40	0.68	12.3	3.3	3.7	55.2	3.2	9.4
H53	Postal activities	O_LKIS	0.65	0.83	0.5	0.0	0.3	37.4	0.0	1.1
K64	Financial services	KL_f_S	0.61	0.64	1.8	1.2	3.6	69.3	0.8	3.1
K65	Insurance	KL_f_S	0.39	0.90	0.4	0.5	0.4	44.6	0.8	18.2
K66	Other financial services	KL_f_S	0.62	0.74	0.4	0.0	0.6	76.4	0	0
L68	Real estate	LKL_m_S	0.69	0.61	0.1	10.3	15.1	93.2	0	0
M69_M70	Legal, accounting, management activities	KL_m_S	0.57	0.62	2.4	0.4	2.1	62.2	0.8	4.5
N79	Travel agencies	LKL_m_S	0.58	0.59	0.3	0.4	0.3	31.6	0	0
N80–N82	Security, services to buildings	LKL_m_S	0.55	0.53	1.2	0.2	1.7	53.0	0.2	1.2
O84	Public administration, defense, social security	O_KIS	1.00	0.59	8.5	9.9	8.7	71.8	0	0
Q86	Health	O_KIS	0.86	0.87	4.7	5.5	4.6	67.6	0.1	0.3
Q87_Q88	Social care	O_KIS	0.81	0.48	0.9	0.4	0.3	55.8	0	0
S95	Repair of computers and household goods	LKL_m_S	0.35	0.77	0.3	0.3	0.4	81.6	0.1	4.8
Total Mega-Cluster			0.53		43.6	44.2	53.2	65.1	23.0	5.6

In terms of exports, the Mega-cluster ranks second (23.0%), but this is largely due to the sheer number of its industries rather than the strength of any individual export industry. It is a cohesive cluster, the third highest in terms of cohesion among the five clusters, with 53% of its transaction volume occurring internally. This cohesion persists despite the cluster having twice or even more than triple the number of industries (25) compared to the other clusters (8 to 12). Almost all of its industries have a transaction index for both inputs and outputs that exceeds 0.5.

The relatively high degree of cohesion makes further division attempts unreliable. When the cluster was subjected to the same division process as the overall network (a production system composed of 62 industries), using the same method (modularity optimization algorithms including the Louvain and Arenas et al. based on the modified G-N method), the results were inconsistent. The Louvain method produced three new sub-clusters: one with a single isolated industry (*C13–C15 Textiles–Apparel*), a second with six industries that could be referred to a “healthcare-pharmaceutical sub-cluster” (including *C20 Chemicals*, *C21 Pharmaceuticals*, *C22 Plastics*, *C31_C32 Furniture*, and healthcare and social welfare services *Q86 Health*, *Q87_Q88 Social Care*), and a third sub-cluster containing the remaining 18 industries. The Arenas et al. method resulted in five sub-clusters, with only the isolated *C13–C15 Textiles–Clothing* sub-cluster matching the Louvain results. The remaining four sub-clusters varied, with two containing four industries each and two containing nine industries each.

The significant variation in the results between the two methods indicates that further division of the Mega-cluster is particularly unreliable. The outcome from the Louvain method seems to make more economic sense, as it identifies a grouping centered around healthcare and social welfare services, along with the pharmaceutical industry, drawing in related industries like chemicals and plastics. Additionally, this division has a higher modularity index ($Q = 0.2681$) compared to the second method ($Q = 0.1575$). It should be noted, however, that the modularity values in both cases are significantly lower than those for the main division, which were $Q = 0.3005$ for the Louvain method and $Q = 0.2923$ for the Arenas et al. method. Overall, these results are insufficient to confidently

claim that the production system consists of seven or, even more unlikely, nine clusters. Nevertheless, these findings can guide a better understanding of how the Mega-cluster functions, especially when combined with diagrammatic representations.

The diagrams reveal the density of the inter- and intra-industry relationships within the Mega-cluster, contributing to its relatively high cohesion index. In the circular diagram (Figure 13), the quantitative prominence of the Trade industries (*G45, G46, G47*) is evident, marked with brown-shaded arcs and connections, both forward and backward. The second most significant group is the Financial sector (*K64 Financial Services, K65 Insurance, and K66 Other Financial Services*), depicted in gray shades. *Business service providers (M69_M70 and N80–N82)* and *N79 Travel Agencies*, marked in shades of blue, form another major group with strong ties to both the Trade and Financial sectors.

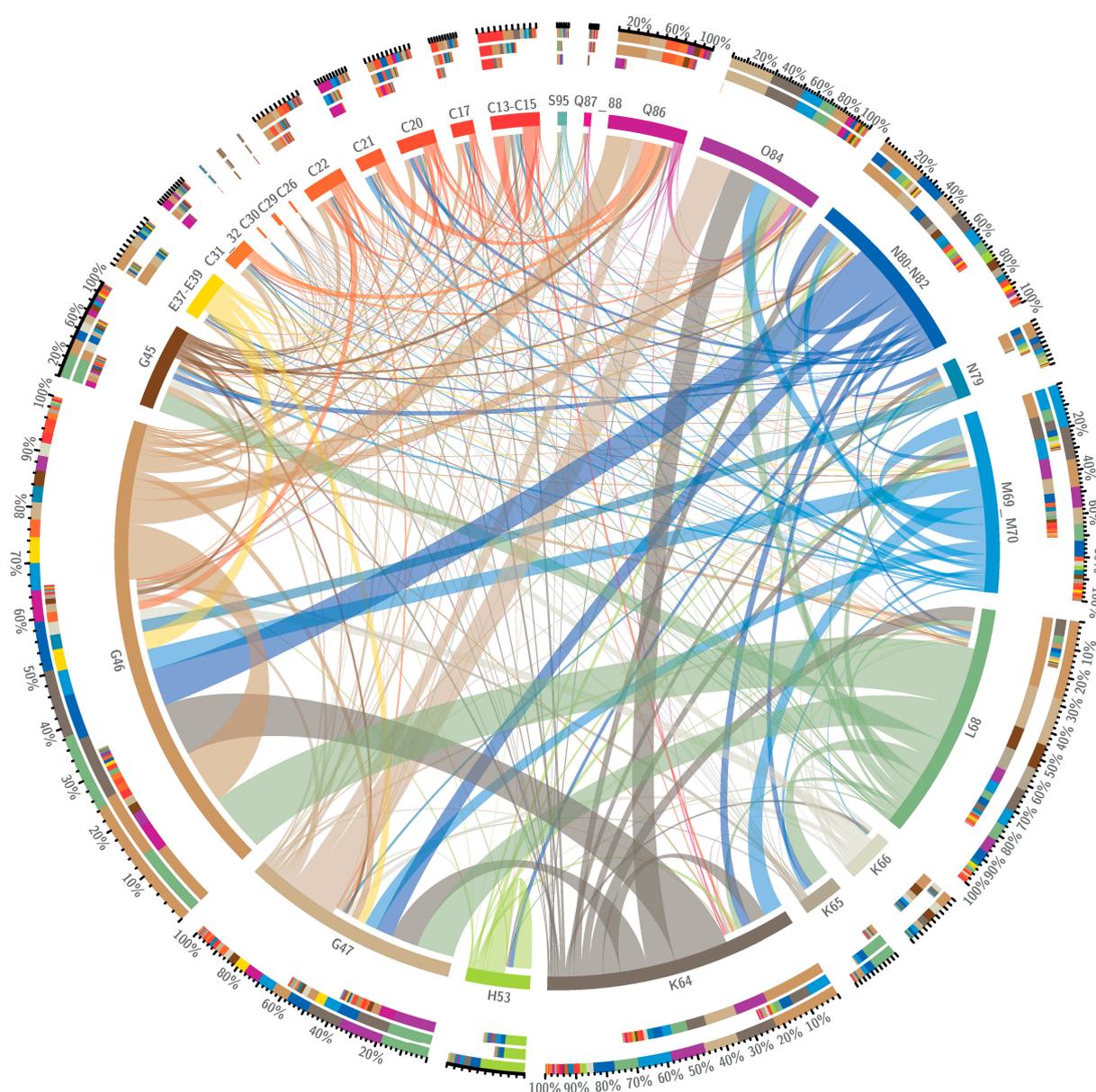


Figure 13. Circular diagram of the Mega-cluster.

The *L68 Real Estate* industry, shown in dark green, also has notable links with Trade and Finance. Public sector industries (*O84 Public Administration, Q85 Health, and Q86_Q87 Social Care*), shaded in purple, mainly serve as recipients of forward linkages from other industries within the cluster. The linkage between *Q86 Health* and *C21 Pharmaceuticals*

and C31_C32 Furniture is notable, which justifies their appearance as a separate “healthcare-pharmaceutical sub-cluster” in the Louvain results. The Manufacturing industries, marked in red, have a relatively small size but maintain a significant number of inter-industry linkages within the cluster. Lastly, the diagrams show that H53 Postal Activities and C13-C15 Textiles–Apparel have a higher volume of intra-industry linkages compared to inter-industry ones, explaining their isolation as individual clusters in the initial production system division and the Mega-cluster sub-division attempts.

The network diagram (Figure 14) of the Mega-cluster emphasizes the topological significance of industries rather than the volume of inter-industry relations highlighted in the previous circular chord diagram. In this visualization, as with the corresponding diagrams for the other clusters, the size and placement of the industries (nodes/vertices) indicate their importance or “influence” within the network (cluster). This influence is summarized by the eigenvector centrality (PageRank), which considers both the number and strength of the linkages as well as the significance of the connected industries.

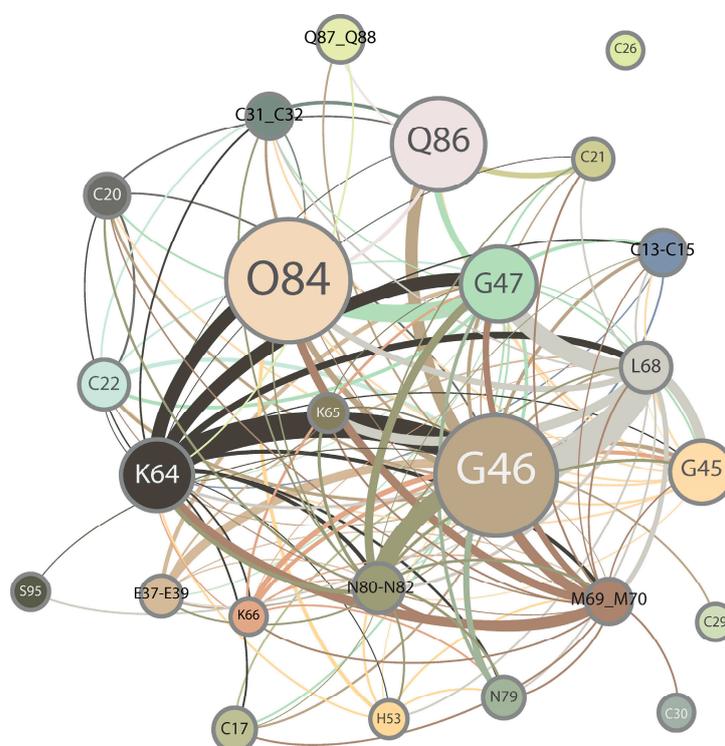


Figure 14. Network diagram of the Mega-cluster.

The network diagram of the Mega-cluster reveals three groups of industries:

1. *Public Sector Industries:* Including O84 Public Administration and Defense and Q86 Health.
2. *Trade Industries:* Comprising G46 Wholesale Trade, G47 Retail Trade, and G45 Automotive Trade and Repairs.
3. *Financial Sector Industries:* Consisting of K64 Financial Services and K65 Insurance.

The L68 Real Estate industry is less prominent in this network view compared to the previous circular diagram, while the M69_M70 Legal–Accounting Services and N80–N82 Protection and Other Services industries, despite being positioned peripherally, have some influence on the cluster’s dynamics. Notably, C21 Pharmaceuticals and C31_C32 Furniture, located near Q86 Health at the top of the diagram, and the nearby Q86_Q87 Social Care, C20 Chemicals, and C22 Plastics form the “healthcare-pharmaceutical sub-cluster” previously identified.

The Mega-cluster exhibits a balance between high-technology and knowledge-intensive industries on the one hand and low-technology and less-knowledge-intensive industries on the other. Specifically, this cluster includes five high- and medium-high-technology industries and five low- and low-medium-technology industries (including *E37–E39 Waste Management*). In the service sector, there are eight knowledge-intensive industries and seven less-knowledge-intensive ones, totaling 13 high-technology and knowledge-intensive industries versus 12 low-technology and less-knowledge-intensive industries.

Despite this numerical balance, the outcomes of the cluster favor low-technology and less-knowledge-intensive production. High-technology (HT and MHT) and knowledge-intensive industries (KI_f_S and O_KIS) contribute 21.5% to the total gross value added (GVA) of the production system, compared to 31.7% for low-technology (LT, MLT and TR) and less-knowledge-intensive industries (LKI_m_S and O_LKIS). Similarly, in terms of employment, high-technology (HT and MHT) and knowledge-intensive industries (KI_f_S and O_KIS) account for 20%, while less-intensive ones account for 23.6%. For the overall demand, the figures are 19.2% versus 25%, and for exports, they are 6.8% versus 16.2%, respectively. Thus, despite the numerical balance, the Mega-cluster operates as a low-technology and less-knowledge-intensive cluster.

The Mega-cluster contributes 43.6% of the total employment in the production system, making it the second most labor-intensive cluster after the Agriculture–Tourism cluster. However, the employment distribution is highly uneven among its industries. *G47 Retail Trade* alone accounts for 12.3% of employment, and when combined with *G46 Wholesale Trade* (3.7%) and *G45 Trade and Repair of Motor Vehicles* (2.0%), the Trade industries collectively contribute 18.0%. The next most significant industry is *O84 Public Administration and Defense*, contributing 8.5%, while the whole public sector, i.e., including *Q86 Health* (4.7%) and *Q87_Q88 Social Care* (0.9%), contributes 14.1% of employment.

The remaining employment in this cluster is distributed mainly across the industries of the secondary sector, including the nine manufacturing industries and *E37–E39 Waste Management* (4.2%), along with business support services (3.9%) and the financial sector (2.6%). Finally, *L68 Real Estate*, *H53 Postal Services*, and *S95 Computer Repairs* contribute minimal employment shares at 0.1%, 0.5%, and 0.3%, respectively.

This cluster's share in adding to the total demand is equally significant as in employment, reaching 44.2%. Of this total, almost a quarter (10.3%) is attributed to the *L68 Real Estate* industry. The *O84 Public Administration* industry has a similar share of 9.9%, and when combined with the other public sector industries, *Q86 Health* (5.5%) and *Q87_Q88 Social Care* (0.4%), the total demand of the public sector reaches 15.8%.

The Trade industries collectively contribute to the total demand with a smaller but still substantial share of 11.5%, distributed among *G46 Wholesale Trade* (6.3%), *G47 Retail Trade* (3.3%), and *G45 Trade and Repair of Motor Vehicles* (1.9%). Manufacturing industries, along with *E37–E39 Waste Management*, provide a combined 3.6%, while the remaining eight industries together add 3.0%. Notably, *K64 Financial Services* stands out among these, with a contribution of 1.2%.

The 25 industries within the Mega-cluster collectively contribute more than half (53.2%) of the gross value added (GVA) of the production system. The most significant contributor is the *L68 Real Estate* industry, which accounts for 15.1% of the total GVA. The *O84 Public Administration and Defense* industry is the second most significant, contributing 8.7%, while the entire public sector (including *Q86 Health* at 4.6% and *Q87_Q88 Social Care* at 0.3%) collectively contributes 13.7%.

The Trade industries collectively provide 12.0% of the GVA, with *G46 Wholesale Trade* standing out at 6.0%. The nine Manufacturing industries have a relatively weak presence, contributing only 2.1% in total. Interestingly, the *M69_M70 Legal and Accounting Services*

industry alone makes the same contribution of 2.1%. Lastly, the Financial sector contributes 4.7%, with *K64 Financial Services* accounting for 3.7 percentage points of this total.

The Mega-cluster functions with a very high value added technical coefficient (65.1%), making it the second “high-value-added” cluster of the production system, with the Knowledge–Education cluster being the first. This high coefficient is due to the significant value added contributions from some of its main industries. Notably, the *L68 Real Estate* industry has a value added technical coefficient of 93.2%, that of *O84 Public Administration and Defense* stands at 71.8%, that of *Q86 Health* is 67.6%, *K64 Financial Services* has a value added technical coefficient of 69.3%, and that of *G45 Trade and Repair of Motor Vehicles* is at 66.4%.

Exports are the only economic category in which the Mega-cluster does not rank first among the production system’s clusters, despite having the largest number of industries. It holds the second largest share of exports (23.0%), following the Energy–Transport cluster (52.5%). However, it also has the second lowest export orientation (Extroversion) index (5.6%), just ahead of the Knowledge–Education cluster (3.3%). This is the reason why, considering its size, its export volume appears relatively low. Notably, only 9 out of the 25 industries in the cluster have an export orientation index (Extroversion) equal to or higher than the production system average (11.1%).

The very low export performance of the cluster should be, to some extent, expected given the nature of several industries in the cluster, which are almost exclusively domestic-market-oriented (e.g., *L68 Real Estate*, *O85 Public Administration and Defense*, *Q87_Q88 Social Care*). Even though most manufacturing industries in this cluster are export-oriented, their small size results in a limited overall contribution to exports (9.0%). By contrast, the Trade industries, despite their very low export orientation indices, contribute a significant 10.6% to exports due to their size.

In summary, the Mega-cluster is a central structural element of the production system, not only due to the number of industries it encompasses but also because of the scale of its economic outcomes, particularly in terms of employment, demand, and most significantly, the creation of added value. It is a cohesive cluster structured around three main groups of industries: the Public sector, Trade, and the Financial sector. Except for its Manufacturing industries, the rest of this cluster does not exhibit a significant outward orientation, leading to relatively low export performance. Finally, while it operates at high levels of added value, the economic impact of the Mega-cluster is predominantly driven by low-technology and less-knowledge-intensive industries, despite a numerical balance between high-technology and knowledge-intensive and low-technology and less-knowledge-intensive industries.

5. Conclusions

The aim of this article was to present a method for identifying and visualizing clusters, as well to apply this method, using Greece as a case study. This was achieved by treating the transaction matrix of the input–output table as a graph (or network) and employing graph-theoretical division methods and visualization techniques. The modularity method of network analysis yielded reliable results. As demonstrated, the domestic input–output table of the production system of Greece reveals five functional internal industry groupings (clusters). It is important to note that these five clusters appear to follow an economic logic, with all of them being organized cohesively around the key industries that define their main characteristics.

The Agriculture–Tourism cluster is built around the primary production industries (Agriculture, Forestry, and Fishing), the Food–Beverages industry, and the Accommodation–Restaurants industry. The Energy–Transport cluster is structured around the Mining, Petroleum, Electricity, and Transport industries. The Construction cluster consists of

various manufacturing industries that all interact significantly with the Construction sector, and it also includes services related to Architecture and Engineering. The Knowledge–Education cluster is mainly composed of service industries tied to knowledge creation and dissemination (such as Research and Development and Education) and all types of communication (print, publishing, television, film, etc.). The Mega-cluster, the fifth identified cluster, serves to validate the division’s effectiveness, as, according to the relevant literature, large clusters of this kind frequently appear in real networks. This cluster is organized around three distinct axes: public sector industries (Public Administration, Defense, and Health), Trade, and Financial Services. Additionally, there is evidence of a potential functional Health–Pharmaceutical sub-cluster.

From the overall study of the structure of the clusters, the weak presence of manufacturing industries in the production system is evident. Although there is complete diversification, i.e., all the industries of the NACE Rev. 2 classification are present in the production system of Greece, most manufacturing industries make a low contribution to the majority of indicators in the production system. Furthermore, the overall picture is that the production system lags behind in terms of technology and knowledge.

This article’s approach to clusters prioritizes functional–economic rather than geographic proximity. However, given Greece’s geographical scale and the spatial structure of its economy, there are also geographic dimensions too. It is well known that economic activity in Greece is heavily concentrated in two major urban centers (Athens and Thessaloniki) and that tourism is prominent in certain island and coastal regions of the country. The existence of regional clusters could be a fruitful future research direction, supported by regional input–output tables and other regional economic data. Furthermore, future updated research using the latest available data could show if, how, and to what extent the economic crisis in Greece affected the structure and functionality of the clusters in the production system.

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Conflicts of Interest: The author declares no conflicts of interest.

Appendix A. NACE Rev. 2 Classification Codes and Descriptions of Industries

	NACE Rev.2 Codes	Short Description	Description
1	A01	Agriculture	Crop and animal production, hunting and related service activities
2	A02	Forestry	Forestry and logging
3	A03	Fishing	Fishing and aquaculture
4	B	Mining	Mining and quarrying
5	C10–C12	Food–Beverages	Manufacture of food products, beverages and tobacco products
6	C13–C15	Textiles–Apparel	Manufacture of textiles, manufacture of wearing apparel and manufacture of leather and related products
7	C16	Wood	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
8	C17	Paper	Manufacture of paper and paper products
9	C18	Printing	Printing and reproduction of recorded media
10	C19	Petroleum products	Manufacture of coke and refined petroleum products
11	C20	Chemicals	Manufacture of chemicals and chemical products
12	C21	Pharmaceuticals	Manufacture of basic pharmaceutical products and pharmaceutical preparations
13	C22	Plastic products	Manufacture of rubber and plastic products
14	C23	Non-metallic mineral products	Manufacture of other non-metallic mineral products
15	C24	Basic metals	Manufacture of basic metals
16	C25	Metal products	Manufacture of fabricated metal products, except machinery and equipment
17	C26	Computers–Electronics	Manufacture of computer, electronic and optical products
18	C27	Electrical equipment	Manufacture of electrical equipment
19	C28	Machinery	Manufacture of machinery and equipment n.e.c.

NACE Rev.2 Codes		Short Description	Description
20	C29	Motor vehicles	Manufacture of motor vehicles, trailers and semi-trailers
21	C30	Other transport equipment	Manufacture of other transport equipment
22	C31_C32	Furniture—other manufacturing	Manufacture of furniture, other manufacturing
23	C33	Repair-installation of machinery	Repair and installation of machinery and equipment
24	D35	Electricity–Gas	Electricity, gas, steam and air conditioning supply
25	E36	Water supply	Water collection, treatment and supply
26	E37–E39	Waste management	Sewerage, waste management and remediation activities
27	F	Construction	Construction
28	G45	Trade and repair of motor vehicles	Wholesale and retail trade and repair of motor vehicles and motorcycles
29	G46	Wholesale trade	Wholesale trade, except of motor vehicles and motorcycles
30	G47	Retail trade	Retail trade, except of motor vehicles and motorcycles
31	H49	Land transport	Land transport and transport via pipelines
32	H50	Water transport	Water transport
33	H51	Air transport	Air transport
34	H52	Warehousing	Warehousing and support activities for transportation
35	H53	Postal activities	Postal and courier activities
36	I	Accommodation–Restaurants	Accommodation and food service activities
37	J58	Publishing	Publishing activities
38	J59_J60	Cinema–Television	Motion picture, video and television program production, sound recording and music publishing activities; Programming and broadcasting activities
39	J61	Telecommunications	Telecommunications
40	J62_J63	Computer–Information services	Computer programming, consultancy and related activities; Information service activities
41	K64	Financial services	Financial service activities, except insurance and pension funding
42	K65	Insurance	Insurance, reinsurance and pension funding, except compulsory social security
43	K66	Other financial services	Activities auxiliary to financial services and insurance activities
44	L68B	Real estate	Real estate activities
45	L68A	Imputed rents of owner-occupied dwellings	Imputed rents of owner-occupied dwellings
46	M69_M70	Legal, accounting, management activities	Legal and accounting activities; Activities of head offices; management consultancy activities
47	M71	Architects–Engineers	Architectural and engineering activities; technical testing and analysis
48	M72	Research and development	Scientific research and development
49	M73	Advertising	Advertising and market research
50	M74_M75	Other scientific activities	Other professional, scientific and technical activities; Veterinary activities
51	N77	Rental/leasing activities	Rental and leasing activities
52	N78	Employment activities	Employment activities
53	N79	Travel agencies	Travel agency, tour operator and other reservation service and related activities
54	N80–N82	Security, services to buildings	Security and investigation activities; Services to buildings and landscape activities; Office administrative, office support and other business support activities
55	O84	Public administration, defense, social security	Public administration and defense; compulsory social security
56	P85	Education	Education
57	Q86	Health	Human health activities
58	Q87_Q88	Social care	Residential care activities; Social work activities without accommodation
59	R90–R92	Creative activities–Gambling	Creative, arts and entertainment activities; Libraries, archives, museums and other cultural activities; Gambling and betting activities
60	R93	Sports–Recreation	Sports activities and amusement and recreation activities
61	S94	Membership organizations	Activities of membership organizations
62	S95	Repair of computers and household goods	Repair of computers and personal and household goods
63	S96	Personal services	Other personal service activities
64	T	Activities of households as employers	Activities of households as employers of domestic personnel; Undifferentiated goods- and services-producing activities of private households for own use
65	U	Extraterritorial organizations	Activities of extraterritorial organizations and bodies

Source: (Eurostat, 2008) and own elaboration.

Notes

- ¹ In the intervening period, clusters were introduced in the form of “growth poles” by [Perroux \(1950, Perroux, 1970\)](#) and [Boudeville \(1966\)](#), only to be abandoned some years later, along with spatial Keynesianism, in the 1970s. However, clusters reappeared in the same decade and into the early 1980s, occasionally either under their current name (clusters) or as “industrial complexes” ([Czamanski, 1971](#); [Czamanski & Ablas, 1979](#); [Loviscek, 1982](#); [Huallachain, 1984](#)).
- ² This article draws from [Foutakis \(2019\)](#).
- ³ Examples include [Rasmussen \(1957\)](#), [Hirschman \(Hirschman, 1960\)](#), and [Chenery and Watanabe \(1958\)](#). For an in-depth discussion, see [Sonis and Hewings \(2009\)](#) and [Miller and Blair \(2009\)](#).
- ⁴ Applications in input–output analysis have emerged over the past 15 years ([Muñiz et al., 2011](#); [Miller & Blair, 2009](#); [Montesor & Marzetti, 2008](#)), especially for Greece, see [Aroche-Reyes and Garcia-Muniz \(2018\)](#) and [Tsekeris \(2017\)](#).

- ⁵ A random graph (or network) is an unstructured graph, first studied by Erdős and Rényi in 1959. In such a graph, “the probability of having an edge between a pair of vertices is equal for all possible pairs”, whereas “real networks are not random graphs, as they display big inhomogeneities, revealing a high level of order and organization”. Additionally, “the distribution of edges is not only globally, but also locally inhomogeneous, with high concentrations of edges within special groups of vertices, and low concentrations between these groups. This feature of real networks is called *community structure*, or *clustering*” (Fortunato, 2010, pp. 76–77). Comparing a real network with its null model confirms whether a true community structure exists. For more on random networks, see (Fortunato, 2010; Newman, 2010, Chapters 12–13).
- ⁶ A more recent method, as suggested by anonymous reviewer two, whom we thank, is the Leiden algorithm (Traag et al., 2019), which is considered by its authors to be an improvement over the Louvain method. We intend to test it in future research.
- ⁷ The link provided in the references section (Eurostat, 2013) is no longer available from Eurostat. The original Eurostat tables for Greece are available from the author on demand.
- ⁸ The PageRank eigenvector centrality index (Brin & Page, 1998) was used, implemented in the network analysis software *Gephi 0.901*, which was also used to create the network visualizations of the production system. The concept behind the eigenvector centrality is that the “a vertex’s importance in a network is increased by having connections to other vertices that are themselves important [...] eigenvector centrality gives each vertex a score proportional to the sum of the scores of its neighbors” (Newman, 2010, p. 169). For a detailed discussion and presentation of eigenvector centrality, including PageRank, see (Newman, 2010, pp. 169–181).
- ⁹ For more on giant components in networks, see Newman (2003, 2010) and Barabási (2014).

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