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Business Dynamics in Recovery Times: A Comparative Perspective on Manufacturing Firms' Performance in the European Union

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Abstract: Our paper investigates the gaps in performance in the manufacturing sector between Western and Eastern European countries and attempts to analyze how enterprises from these two parts of Europe have tackled recovery after the Global financial crisis of 2007-2009. We uncover the patterns of performance in the after-crisis period and offer insights into the prospects of the manufacturing sector in the European Union, faced nowadays with a new recovery, after the coronavirus crisis. Moreover, we study these patterns in industries with different technological levels. We have selected five performance variables, namely Turnover growth rate, Turnover per employee, Wage-adjusted labor productivity, Gross operating rate, and Investment rate, and employed statistical cluster analysis, which is a multivariate data analysis technique that can detect these patterns in performance, in both its approaches: hierarchical and k-means clustering. Our findings show that the almost perfect groupings of businesses from Western, more developed economies, and Eastern, less developed ones, in all industries, with the notable exception of Portugal, are rather striking, regardless of the technological level of industries. We show that Eastern EU businesses were not the worst performers in the after-crisis period, but rather on the contrary. Certainly, they are smaller in size but have enjoyed higher labor productivity and profitability, as well as higher investment rates in all industries. This points towards a higher dynamism of smaller-sized businesses in general, and Eastern EU located ones, in particular, in the years after the Global financial crisis, which has been reflected in superior performance.

Keywords: cluster analysis; manufacturing; high-tech industries; European Union; performance.

Introduction

Since the Industrial Revolution, the manufacturing sector has played an essential role in the economic growth of developing countries. In European countries, this sector represents one of the oldest and most dominant sectors, with a share in GDP of 14.5% approximately at the end of 2019 (World Bank). For the largest European countries, namely Germany, the United Kingdom, France, and Italy, the manufacturing sector represents a key area on which their economy is based, but the same is true for the former communist countries in Central and Eastern Europe. At the same time, the manufacturing contribution to the EU's GDP is declining, as well as its share in global manufacturing, which raises concerns about the EU competitiveness against China, Japan, or the United States (Marchinski & Martinez Turegano, 2019).

Recently, the manufacturing sector entered into a declining stage caused by the proliferation of new technology and also by the trend of the Western European countries toward moving to a more service-based economy. On the other hand, while some Western

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European countries have reduced the importance of this sector, other countries have improved it. Czechia, Poland, and Slovakia represent the best examples for this fact, considering that in the last years, they became notable contributors to the EU manufacturing sector (EURAXIND, 2017). According to World Bank data, in the case of Czechia, the manufacturing value-added as a percent of GDP was reported at 22.38 % in 2019. For the same year, Poland reported 16.64 % and Slovakia 18.14%. Moreover, the manufacturing firms in these countries had the biggest range of R&D spend in 2014 (see Figure 1).

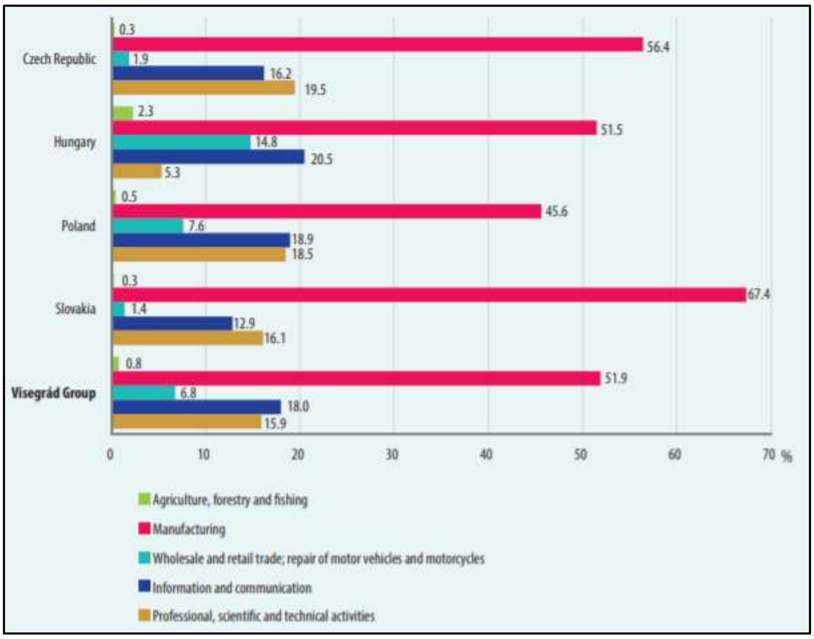

Figure 1. Share of R&D business expenditures by main sections, 2014
(Hungarian Central Statistical Office, 2018)

Even if the manufacturing sector goes through a period of decline, this sector is still one of the EU's strongest economic sectors. In 2017, this sector employed more than 28.5 million people in the EU countries, although differences exist from one country to another, as illustrated in Figure 2 (Eurostat, 2020). Moreover, 8.8% of all enterprises (almost 2 million) in the non-financial economy in the EU-27 economies were found in the Manufacturing sector at the end of 2017, which generate an added value of EUR 1,820 billion. Considering these dimensions, the manufacturing sector was the second-largest contributor to employment in the EU-27 (22.8%) but the largest contributor to the value-added in the non-financial business economy, with almost one-third of the total – 29.3% (Eurostat, 2020).

The Global financial crisis of 2007-2009 represented a significant negative event in the Manufacturing sector's life in the EU, with a significant drop in employment and value-added growth. But, as Veugelers (2017) notes, the sector's recovery after the crisis was quick, which shows the significant resilience of manufacturing enterprises. Nevertheless, the speed of recovery in the two parts of the EU, the Western one formed of more developed economies, and the Eastern one formed of emerging economies, was different, reflected in key differences between performance indicators such as profitability or labor productivity.

The manufacturing sector has been one of the most affected by the COVID-19 pandemic. At the outset of this crisis, as supply chains ground to a halt and demand dropped severely, the factories either decelerated production or closed the doors. The consequence was widespread job losses across many industrial sectors or diminished working hours for many employees. In the last months, many industrialized countries have already been moving forward making great efforts to reorient business models, but developing countries persist to experience greater constraints when it comes to finance and technical capacity. With no end to the COVID-19 crisis in sight, manufacturing companies will need ongoing financial assistance and support from the government (UNIDO, 2020). In an environment of high uncertainty, maybe it is too early to talk about a real recovery, but manufacturing companies need to consider a recovery plan.

Figure 2. Number of persons employed by enterprise size class in 2017 (% of total employment)
(Eurostat, 2020)

Considering that governments across the world scramble to respond appropriately to the devastating effects of the COVID-19 pandemic, it may be useful to look back at how the world responded to similar global systemic shocks in the past and learn from what worked and what did not. The global financial crisis of 2008-2009 may be the most relevant in shaping the economic response to Covid-19. To protect workers and household incomes, a wide range of work subsidization and social protection programs must be expanded or rolled out. For instance, schemes to subsidize temporary leave or short-time for workers such as those used in Germany and Poland during the global financial crisis demonstrated that they can be effective and enable a faster recovery in employment following a return to growth (Revenga & Galindo, 2020).

European Union has long emphasized the role of high-tech industries and knowledge-intensive services in boosting competitiveness and development (Kok Report, 2004) and included the progress of advancement of these industries as a critical component of its Lisbon Strategy and Europe 2020 Strategy (Horobet et al., 2020). At the end of 2014, though, high-tech industries and knowledge-intensive services-intensive services held together only 5.9% of turnover and 9.6% of value-added generated by EU enterprises, according to Eurostat data. Moreover, for many EU countries, particularly Eastern ones, low-tech industries, such as food and beverage processing or textile manufacturing, hold important shares in employment. It is also noteworthy to mention that multinational companies, many headquartered in Western EU countries, have considerably contributed to the development of these lower-tech industries in Eastern EU countries.

In this framework, our research addresses these gaps in performance in the manufacturing sector between Western and Eastern countries and attempts to observe how enterprises from the two parts of Europe have tackled the after-crisis recovery. Specifically, we are interested in uncovering patterns of performance in the after-crisis period (between 2010 and 2017) that offer insight into the prospects of the manufacturing sector in the EU, faced now with a new recovery, after the coronavirus crisis. For this research aim, we use statistical cluster analysis, which is a multivariate data analysis technique that can detect these patterns in performance, in both its approaches: hierarchical and k-means clustering.

This paper is organized as follows. The following section offers insights into the research directions and results in the existing literature. The next section presents the data and the methodology used. Then, the following section discusses our most relevant results, and the last section concludes and provides directions for future research.

Literature review

Until now, the existing empirical literature on firms' performance and competitiveness has been mostly concentrated at the microeconomic level, more precisely, on firm-specific characteristics frameworks that justify their performance as well as the competitiveness. Considering the ever-expanding digital economy, the inclusion of businesses' idiosyncrasies in terms of industry and location is necessary for the interpretation of possible differences in competitiveness across firms or industries. From this point of view, competitiveness has been used, as a concept, in the last decades together with the economic performance of industries or countries. Therefore, a progressively interdependent globalizing economic environment has amplified the interest of analysts and policymakers in the international competitiveness of firms, industries, and countries, which began to be addressed jointly.

Regarding the studies that investigate business performance, some of them suggested that ownership type, i.e., foreign or domestic, represents an explanatory factor for business performance. For instance, Bobenič, Hintošová, and Kubíková (2016) discovered that a higher involvement of foreign ownership tends to improve the firms' performance in Slovakia. On the other hand, Barbosa and Louri (2005) demonstrate that foreign ownership does not generate a notable difference in performance for firms in Portugal and Greece. Later, Horobet (2018) investigated the competitiveness of foreign- and locally-owned companies in eleven Central and Eastern European countries and suggested that, depending on the country and indicators used, the discrepancies are not always in support of foreign-owned firms.

The empirical research studies that examined the differences between companies from high- and low-tech industries take into consideration both the number and the type of innovations implemented or how firms handle the process of commercialization. For instance, Covin and Prescott (1990) demonstrated that low-tech product innovators differed from the high-tech ones when it comes to structure, market orientation, or the need for external financing. Moreover, Raymond and St-Pierre (2010) suggested that high-tech firms' higher investment propensity into product R&D and low-tech firms' higher investments in process R&D may not be considered a beneficial approach to innovation for SMEs. Reboud, Mazzarol, and Soutar (2014) analyzed companies with both high and low levels of innovation intensity from Australia and France and found that SMEs that may not be officially considered high-tech firms, could be strongly interested in innovation commercialization practices.

In the matter of driving factors of performance of businesses from high- and low-tech industries, the literature is quite poor, to the best of our knowledge. Among these papers, Hamilton, Shapiro, and Vining (2002) investigated whether the growth of Canadian high-tech firms is constant across size or is correlated with the business demographic factors. The authors suggested that the higher growth of Canadian high-tech firms is not due to foreign ownership. Later, Cozza et al. (2012) examined the impact of product innovation on the economic performance of Italian firms from medium- and high-tech industries and found notable differences between innovative and non-innovative firms regarding profitability and growth rates. They discovered that the differences in the matter of profitability become notable when considering micro- and small-sized companies, while these differences become to fade when considering medium and large firms. Another study belongs to Reichert and Zawislak (2014) who analyzed the link between technological capability and firm performance employing data of Brazilian firms and discovered that industries of lower technology intensity do not need investments in technological capabilities for obtaining superior economic performance. Also, Hirsch-Kreinsen (2008) demonstrated that the performance of medium low-tech and high-tech industries is strongly connected, but, on the other hand, the innovative competence of the high-tech industries relies on their narrow relationship with medium low-tech industries. In other words, the performance of these two industries is inextricably linked. High-tech industries are considered the ones that continue to develop unequivocally in international trade and their dynamism influences the whole sector on its evolution regarding performance together with the performance of all the other sectors and, thus, the economy in general (Ecevit Sati, 2014).

To the best of our knowledge, there are only a few studies that discuss the recovery processes of the manufacturing sector after the global financial crisis of 2008-2009. They have in common a general point of view regarding this subject, which is that manufacturing companies have discovered ways to enhance production efficiency during the recovery periods. In a study of the European Commission (2010), it is mentioned that the EU manufacturing production stabilized and started to recover in the second quarter of 2009, which is impressive considering that manufacturing remains the most negatively affected sector with announced job losses between September 2008 and November 2009. Wellener et al. (2019) determine signals and patterns in US manufacturing economic and financial data from past recessions and recoveries and indicate approaches that manufacturing firms could take into consideration to create resilience ahead of future downturns. They performed a linear discriminant analysis on more than 700 industrial manufacturing companies and their approaches for these companies include the following aspects: preventing liquidity crisis by increasing insights into cash flow, making targeted capital investments to increase asset efficiency and productivity, investing in process-related innovation, implementing digital initiatives which may help to build resiliency.

Concerning research studies where the authors used similar methodologies to ours in attempting to capture differences between firms in the manufacturing sector, there are only several, as far as we are aware. Arvanitis and Hollenstein (1998) investigated Swiss manufacturing companies and, using cluster analysis, found specific patterns regarding innovative activities and firms' use of external sources of knowledge. They revealed that the mixture of these two clusters yielded five innovation types and only two of them appear to be moderately superior to the others in the matter of economic performance. In other words, the link between specific industries and innovation types is not straightforward and the Swiss manufacturing firms appear, therefore, to decide freely which innovation strategy to select. Recently, Gkotsis, Pugliese, and Vezzani (2018) employed this type of technique to identify clusters of EU firms competing in comparable technological markets and demonstrate that overall, their clusters managed to capture differences among firms. Concretely, the authors found that the magnitude of R&D investments, the R&D intensity, the technological specialization, and the technological concentration vary between and within cluster families. Moreover, Karaca (2018) applied the k-means clustering algorithm to establish how the manufacturing industries in Turkey are clustered. Using the number of local units and the number of employees in the

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manufacturing industries, the author discovered that the optimal number of clusters is three.

Summarizing the main literature findings, one can state that there is room for research on the performances of companies from industries with different technological levels, i.e., high-tech versus low-tech industries. Moreover, investigating the patterns of firms and industries' performance over time and in various countries might offer insight into their idiosyncrasies that, in their turn, may serve as a starting point for a wider understanding of within European Union economic heterogeneities, despite the long-time integration process. This is beneficial both from the firms' perspectives, but also from macroeconomic and regional perspectives. In this framework, our paper is a follow-up of the analysis undertook by Horobet et al. (2020) that investigated the main firm-related driving factors behind profitability in high-tech versus low-tech industries in Europe.

Data and research methodology

We have selected four industries from the European Union manufacturing sector, with different degrees of technological level, based on the High-tech classification of manufacturing industries based on NACE Rev.2 2-digit codes. Thus, the four industries were: C21 (Manufacture of basic pharmaceutical products and pharmaceutical preparations) – high-tech (HT); C29 (Manufacture of motor vehicles, trailers, and semi-trailers) – medium high-tech (MHT); C25 (Manufacture of fabricated metal products, except machinery and equipment) – medium low-tech (MLT); C10 (Manufacture of food products) – low-tech (LT). For each industry we have collected from Eurostat - Structural Business Statistics data on several performance variables – size, operational profitability, costs management, labor productivity, etc. – between 2010 and 2017. Due to the altered industry dynamics during the years of the 2007-2009 Global financial crisis, we have decided to exclude them from our sample. Five variables have been selected for analysis, as follows: (1) Turnover growth rate (TURNGR), which is a measure of industry dynamics; (2) Turnover per employee (TURNEMP), which proxies companies' average size; (3) Wage-adjusted labor productivity (WALP), which is a measure of labor productivity adjusted to salaries' level; (4) Gross operating rate (GOR), which is a measure of industry profitability, calculated as the ratio between operating surplus (or profit) and turnover; and (5) Investment rate (INVR), which is a measure of investment intensity, calculated as the ratio between gross investments and value-added at factor costs.

Our sample included 12 countries that were European Union members at the end of 2017: Austria, Czech Republic, France, Germany, Hungary, Italy, Netherlands, Poland, Portugal, Romania, Spain, and United Kingdom. Although not all EU member countries were included in the analysis, our sample is representative of the included industries at the EU level, since the four manufacturing industries in the twelve countries held, collectively, between 65 to 85% in EU turnover at the end of 2017 (Eurostat). For each industry and indicator, the number of observations, depending on data availability, ranges between 100 and 108. Table 1 presents a brief descriptive statistic of variables, complemented by the box-plots for each variable in Figure 3.

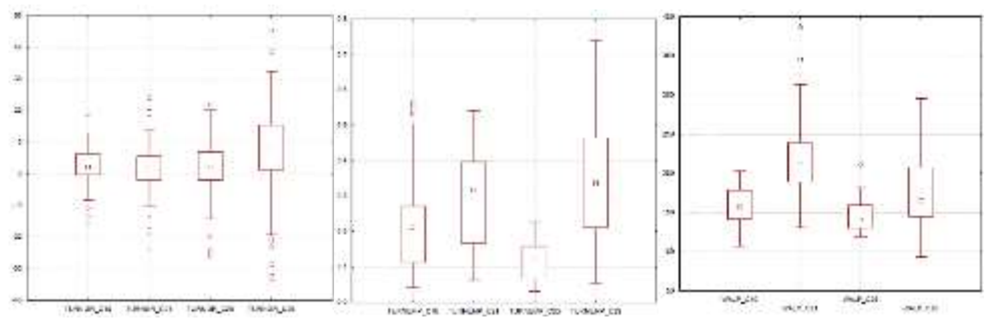
Across countries and years, the industries' performance is variable, but the degree of variability is different depending on the specific variables. Moreover, the technological level of the industries is not always a guarantee of superior performance. Thus, industry C29 shows the highest median turnover growth rate of the four industries, but also the most dispersed in terms of years and countries, while the lowest turnover growth rate (as the median) is recorded in industry C10. When enterprises' size is considered, the highest-sized businesses are in industries C29 (also the most spread among countries and years) and C21, and the smallest in industry C25 (approximately three times smaller in median terms). This is not a surprising result, given the differences in these industries; food manufacturing can take place in smaller enterprises, with a lower number of employees, while motor vehicle production requires larger facilities and higher personnel numbers.

The high-tech industry, C21, records the highest mean labor productivity (WALP), although performance measured by WALP is more spread across countries and years. At the other end, C25 is the industry with the lowest median labor productivity. As in the case of labor productivity, C21 is the industry with the highest profitability, measured by GOR, and C10 with the lowest. At the same time, industries' profitability over time varies from one country to the other; this variability is more pronounced also in industry C29 while being the lowest in C10. Last, but not least, the industry with the highest median investment rate is also C29, and C21 has the lowest median investment rate over years and countries. A rather common attribute of the five measures of performance is the presence of outliers, but no specific pattern can be detected considering years or countries.

Table 1. Descriptive statistics of variables

	Mean	Median	Minimum	Maximum	Lower quartile (25%)	Upper quartile (75%)	Standard deviation
TURNGR_C10	2.143	2.214	-15.847	18.777	-0.429	6.145	5.819
TURNEMP_C10	0.208	0.211	0.043	0.564	0.113	0.271	0.120
WALP_C10	161.074	156.400	106.600	202.900	141.700	178.700	23.442
GOR_C10	7.632	7.350	0.900	14.000	6.500	8.500	2.228
INVRATE_C10	20.294	17.900	9.300	57.600	15.000	23.450	8.475
TURNGR_C21	1.359	1.499	-58.764	24.065	-1.941	5.464	9.719
TURNEMP_C21	0.285	0.318	0.061	0.542	0.166	0.397	0.135
WALP_C21	219.884	211.650	130.600	412.300	189.300	239.300	47.037
GOR_C21	18.837	17.900	5.800	41.500	15.200	21.600	6.156
INVRATE_C21	13.776	12.600	0.000	29.400	10.500	17.300	5.533
TURNGR_C25	1.422	2.117	-32.230	21.891	-1.986	6.976	10.715
TURNEMP_C25	0.119	0.125	0.030	0.227	0.068	0.158	0.056
WALP_C25	143.658	139.900	119.200	211.000	129.700	159.200	18.778
GOR_C25	11.436	11.150	4.700	20.000	9.950	13.000	3.094
INVRATE_C25	15.671	13.100	5.700	39.800	10.050	18.850	7.564
TURNGR_C29	10.907	7.630	-33.118	448.428	1.150	15.322	44.923
TURNEMP_C29	0.337	0.336	0.054	0.740	0.211	0.464	0.151
WALP_C29	175.124	164.300	93.400	295.100	145.300	207.100	43.993
GOR_C29	7.463	7.850	-1.300	18.300	5.550	9.950	3.357
INVRATE_C29	24.354	20.900	6.400	102.500	15.800	29.050	13.606

Source: STATISTICA output and authors' calculations



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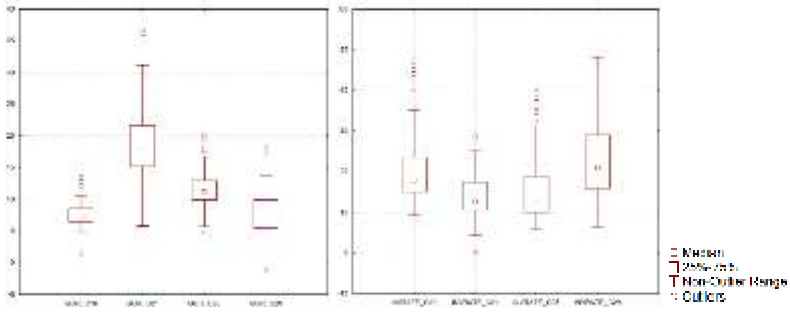

Figure 3. Box-plots of variables

Note: Whiskers show the 25%-75% quartiles and outliers have been defined as observations outside the interval [Mean - Standard deviation; Mean + Standard deviation]
(Authors' calculations and STATISTICA output)

We have applied t-statistic tests for the differences in variables' means between the four industries and they have shown that means are statistically significant different between all industries for turnover per employee, labor productivity, and investment rate. On the other hand, industries C10 and C29 do not differ in mean profitability and the same is true for C10 against C21 and C29, and for C21 against C25.

Clustering represents a common technique for statistical data analysis and is used in many domains, such as machine learning, data mining, business intelligence, image pattern recognition, and so on. This technique is represented by the process of grouping related objects into different groups, or, more accurately, it implies the partitioning of a data set into subsets according to some similarities. The main goal of clustering is to determine groups of related objects and to detect interesting patterns in the data (Kaufman & Rousseeuw, 2009).

There are many clustering algorithms used in the literature. Some examples are represented by the partitioning methods, hierarchical methods, density-based methods, or grid-based methods. Regarding the first type of methods, most partitioning ones are distance-based (Blashfield & Aldenderfer, 1988). Given *k*, which represents the number of partitions to construct, this method produces an initial partitioning. Next, it applies an iterative relocation technique, which attempts to refine the partitioning by shifting the objects from one group to another. The common criterion of a good partitioning implies that the objects in the same cluster are close or related to each other, while the objects in different clusters are far apart or remarkably different. Moreover, there are various criteria for determining the quality of the partitions. The traditional partitioning methods can be extended for subspace clustering, rather than looking for the full data space. This approach is helpful when there are numerous attributes considered and the data are sparse. Obtaining global optimality when it comes to partitioning-based clustering is frequently computationally prohibitive, possibly demanding an exhaustive enumeration of all the possible partitions. Alternatively, most applications employ popular heuristic methods, i.e. greedy approaches like the k-means and the k-medoids algorithms, that gradually improve the clustering quality and approach a local optimum. Another type of clustering algorithm used in the literature is represented by the hierarchical method, which produces a hierarchical decomposition of the given set of data objects. This type of method can be classified as being either agglomerative or divisive, in reliance on how the hierarchical decomposition is constituted. The agglomerative approach also named the bottom-up approach, initiates with each object creating a separate group. Thus, it successively merges the objects or groups close to one another, until all the groups become merged into one, or a termination condition holds. The divisive approach, also named the top-down approach, starts with all the objects in the same cluster. In each successive iteration, a cluster is split into smaller ones, until, eventually, each object is in one cluster, or a termination condition holds (Han, Pei, & Kamber, 2012; Gülagiz & Sahin, 2017).

The most well-known and widely applied partitioning method is the k-means clustering algorithm. This algorithm takes the input parameter, *k*, as well as partitions a set of *n* objects into *k* clusters in such a way that the resulting intra-cluster similarity is high and the inter-cluster similarity becomes low. Cluster similarity is measured considering the mean value of the objects in a cluster that can be perceived as the cluster's centroid or center of gravity. Firstly, it randomly selects *k* of the objects, each of which in the first place represents a cluster mean or center. For each of the remaining objects, an object is assigned to the cluster to which it is the most similar, in accordance with the distance between the object and the cluster mean. After that, it creates the new mean for each cluster. This procedure iterates until the criterion function converges (Ali & Kadhum, 2017).

For this research, we have used both hierarchical and k-mean clustering algorithms to determine the appropriate cluster numbers and to identify the characteristics for each cluster within each industry. The cases or objects included in the clustering algorithm were identified by two attributes: country and year. The number of cases in each clustering amalgamation was 96 (12 countries and 8 years). The next section presents and discusses the main results.

Results

We present in Figure 4 the results of the hierarchical clustering algorithm for the four industries. The four tree diagrams (or dendrograms) show our observations (an observation is defined by a country and a year between 2010 and 2017) grouped in various clusters, based on the linkage distances between the five variables' standardized values.

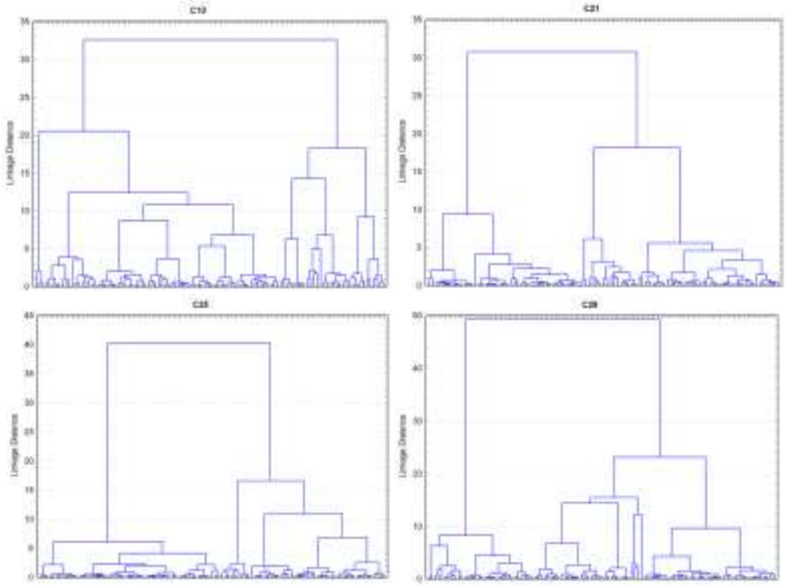

Figure 4. Tree diagrams for the four industries
(Authors' calculations and STATISTICA output)

For each industry, several clusters are identified by the hierarchical algorithm, but no specific indication of the optimal number of clusters exists. Thus, depending on how much flexibility we allow for within-cluster homogeneity versus between-cluster heterogeneity, the number of clusters evidenced in Figure 4 varies between a few important ones, but more heterogeneous, and many smaller ones, but more homogeneous. Nevertheless, the average linkage distance between observations shows us that the clustering that results in the most homogeneous groups is for industry C25 (average linkage distance is 1.344), while the one resulting in the most heterogeneous groups is C10 (average linkage distance is 2.275).

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To identify the optimal number of clusters for each industry we applied the k-means clustering algorithm, in the modified machine-learning-based version. Table 2 shows the distribution of observations in clusters for each industry. There are 3 clusters found for C21 and C25, indicating that they are more homogeneous than the other two industries that have either 4 clusters (C29) and even 6 clusters (C29). The number of observations included in each cluster varies across amalgamations, but we note that, except cluster 2 in the C10 clustering, all clusters include at least 5% of the observations for each industry.

Table 2. Clusters' attributes

Cluster	TURNGR	TURNEMP	WALP	GOR	INVRATE	Number of cases	Percentage (%)
Industry: C10							
1	0.574	-0.079	0.496	-0.362	-0.499	6	5.66
2	-0.566	-0.082	0.548	-0.149	-0.520	2	1.89
3	0.656	-0.097	-0.693	-0.602	-0.539	16	15.09
4	-0.120	-0.103	1.105	1.102	0.070	26	24.53
5	0.071	-0.106	-0.148	-0.541	0.941	27	25.47
6	-0.341	-0.097	-0.281	-0.070	-0.380	29	27.36
Industry: C21							
1	-0.242	-0.153	-0.240	-0.200	0.097	17	17.17
2	-0.111	-0.144	0.086	-0.052	-0.293	44	44.44
3	0.006	-0.160	0.598	0.577	0.274	38	38.38
Industry: C25							
1	-0.319	-0.245	-0.235	-0.268	-0.450	35	33.33
2	-0.163	-0.263	0.546	-0.019	0.982	41	39.05
3	-0.210	-0.236	0.352	0.055	-0.616	29	27.62
Industry: C29							
1	-0.056	-0.107	0.949	1.592	-0.692	8	7.62
2	-0.138	-0.278	-0.059	-0.106	1.630	14	13.33
3	-0.127	-0.156	-0.376	-0.548	-0.474	57	54.29
4	-0.212	-0.240	1.191	0.919	0.227	26	24.76

Note: Variables' values for each cluster are normalized means.
Source: STATISTICA output and authors' calculations

The formed clusters are as heterogeneous as possible between them and the number of clusters found by the clustering algorithm has been verified by the ANOVA procedure. ANOVA shows that existing clusters are statistically significant different from each other and all variables contribute to cluster formation, for each industry. The only exception is TURNGR for industry C29, which suggests that industry performance from the perspective of turnover growth rate has been quite homogeneous across countries and years. Table 3 shows the distances between clusters' centroids for each industry – the smaller these distances are, the more similar the clusters are, and the reverse is true for higher distances. Considering the average distance between clusters, industry C21, the high-tech one, presents the highest similarity between formed clusters (average distance of 0.479), while industry C10, the low-tech one, shows the lowest similarity between clusters (average distance of 0.585). When observing pairs of clusters for each industry, the smallest distances are between clusters 1 and 2 (0.217) and 3 and 6 (0.237) in industry C10, but the highest distances are also found for C10 clusters: 0.891 for clusters 1 and 5, and 0.822 for clusters 1 to 4. Coupled with the previous observation, this implies that businesses' performance in the food industry (C10) was rather volatile over the years and diverse on a country basis, at least when compared to the other three industries.

Table 3. Distances between clusters' centroids for each industry

C10	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Cluster 1	0.000	0.217	0.681	0.822	0.891	0.624
Cluster 2	0.217	0.000	0.653	0.716	0.815	0.528
Cluster 3	0.681	0.653	0.000	0.704	0.424	0.237
Cluster 4	0.822	0.716	0.704	0.000	0.538	0.538
Cluster 5	0.891	0.815	0.424	0.538	0.000	0.382
Cluster 6	0.624	0.528	0.237	0.538	0.382	0.000

C21	Cluster 1	Cluster 2	Cluster 3
Cluster 1	0.000	0.380	0.392
Cluster 2	0.380	0.000	0.664
Cluster 3	0.392	0.664	0.000

C25	Cluster 1	Cluster 2	Cluster 3
Cluster 1	0.000	0.669	0.450
Cluster 2	0.669	0.000	0.706
Cluster 3	0.450	0.706	0.000

C29	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Cluster 1	0.000	0.780	0.524	0.491
Cluster 2	0.780	0.000	0.534	0.449
Cluster 3	0.524	0.534	0.000	0.575
Cluster 4	0.491	0.449	0.575	0.000

Source: STATISTICA output and authors' calculations

The higher dissimilarity between the six clusters identified for industry C10 is also easy to observe in Figure 5, which shows clusters' normalized means for each industry. We further discuss these attributes and link them to clusters' composition.

For industry C10, clusters 1 and 2, which are quite similar, include only businesses from the Netherlands, but from different years: cluster 1 includes years 2011-2013 and 2015-2017, while cluster 2 includes years 2010 and 2014. Interestingly, the most important differences between the two clusters come from TURNGR – cluster 1 has a high turnover growth rate, but cluster 2 has the lowest turnover growth rate of all clusters. For the remaining variables, there are no significant differences between the two clusters. Cluster 3, which has the highest TURNGR, although not far from cluster 1, and the lowest labor productivity and the lowest investment rate, is formed only of businesses from four countries (Germany, France, Italy, and Austria) and mostly years 2011-2013. The remaining Western and more developed countries and years – except Portugal and the United Kingdom – are grouped in cluster 6, jointly with Spain (all years). This is the cluster with average to low performance as described by all variables, indicating that the food industry in these countries has underperformed in the years after the global financial crisis, compared to Eastern European countries and Western countries such as the Netherlands, Portugal, or the United Kingdom. Clusters 4 and 5 include all Eastern EU countries and the above-mentioned Western countries are showing the best performance in terms of labor productivity and profitability, although there are important differences from one cluster to the other. Thus, businesses included in cluster 4 – from Hungary (2009-2010 and 2014-2016), Poland (all years), Romania (2009-2010, 2014), and the United Kingdom (all years) – had the highest labor productivity and profitability, while enjoying average investment rates. Interestingly, these businesses are rather small, as indicated by the low values of TURNEMP, and this is a feature shared with cluster 5, which has the lowest TURNEMP normalized mean. On the other hand, cluster 5, which includes Czech Republic (2010-2017), Hungary (2011-2013, 2017), Romania (2011-2013, 2015-2017), and Portugal (all years), benefits from the highest investment rate, suggesting that businesses in the food industry in these countries have taken recovery seriously and

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decided to increase their investment rate over the years, at least compared to their Western counterparts. This may be also linked to the higher importance of the food industry in these economies, considering its contribution to GDP and share in number of employees.

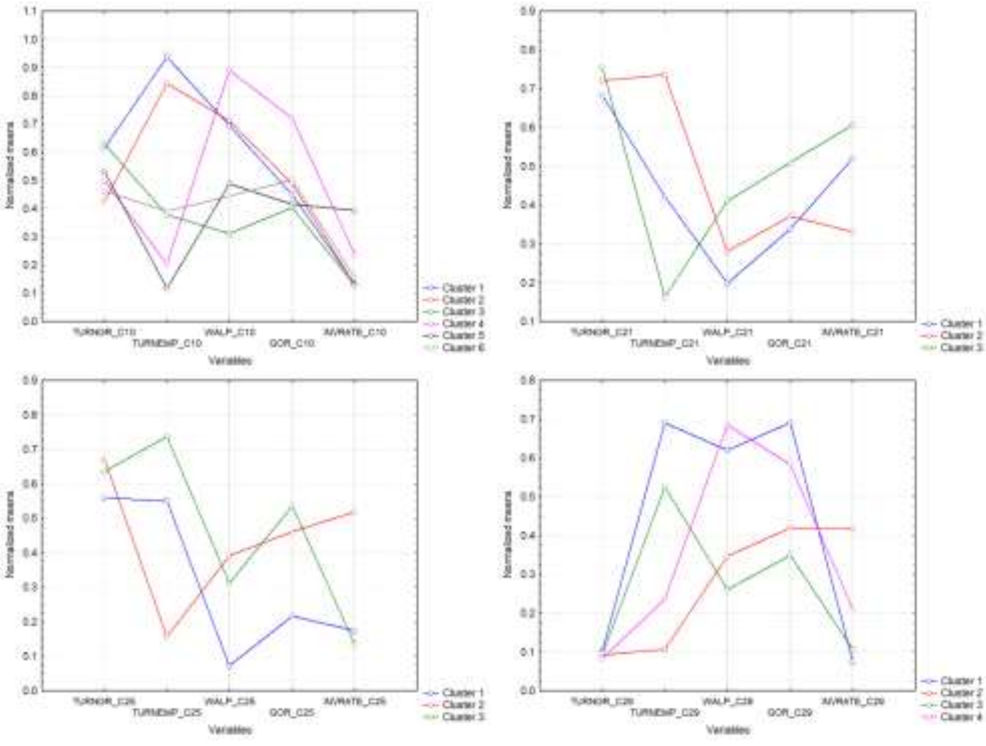

Figure 5. Clusters' normalized means
(Authors' calculations and STATISTICA output)

In the case of high-tech industry C21(pharmaceuticals), there were only three clusters identified, implying an overall higher similarity between the businesses in the industry compared to C10. The performance pattern revealed by the analysis of clusters in industry C10 is confirmed by groups in industry C21. Thus, cluster 3 includes the best performing businesses – highest turnover growth rate, labor productivity, profitability, and investment rate – that has the smallest size; these businesses represent Czech Republic, Hungary, Poland, and Romania, from all years. At the other end, cluster 1, which groups businesses from Spain (2011 and 2017), Austria, Portugal, United Kingdom, and Poland (only 2016), is the underperformer in this industry. This cluster has the lowest turnover growth rate, labor productivity, and profitability. Cluster 2, which groups the highest size businesses from Western EU countries (Germany, Spain, France, Italy, the Netherlands, Austria, and the United Kingdom), shows the lowest investment rate accompanied by low profitability and average labor productivity and turnover growth rate.

For industry C25 (metal products manufacturing), classified as medium high-tech, the three clusters show diverse performance, but clusters 2 and 3 dominate cluster 1 in all variables. At the same time, the major differences between clusters 2 and 3 are based on businesses' size and investment rate; thus, cluster 2 has the lowest size and highest investment rate, while cluster 3 has the highest size but lowest investment rate businesses. In terms of cluster composition, cluster 2 includes Czech Republic, Poland, and Romania (all years for these countries), along with Hungary (2010-2017), but also Portugal (2009-2010 and 2014-2017), thus being a cluster focused on Eastern EU countries. Cluster 3, on the other hand, includes only Western EU countries: Austria (all years), United Kingdom (all years), Netherlands (all years), Italy (only 2015-2017), and Germany (2011). Cluster 1 is the underperformer in this industry, with the lowest labor productivity and profitability, accompanied by a low turnover growth rate and investment rate obtained by average-size businesses. They come from Western EU countries (Germany, Spain, France, Italy, and Portugal) and Hungary (but only 2009).

In industry C29 (motor vehicles manufacturing), considered medium high-tech, businesses are more diverse across years and countries compared to the previous two industries, as indicated by the creation of 4 clusters. Here, Western and Eastern countries were grouped in two clusters each, based mostly on size and investment rate. We remind readers that turnover growth rate is not a cluster differentiating factor for this industry, as mentioned above. Clusters 1 and 3 include, except Portugal, only businesses from Western EU countries; the two clusters are separated by labor productivity – in cluster 1 are included businesses with high WALP, but in cluster 3 there are businesses with lowest WALP -, profitability – highest for cluster 1 and lowest for cluster 3. They both have low investment rates. The countries included in the two clusters are Netherlands and United Kingdom – cluster 1, and the remaining Western countries – Germany, Spain, France, Italy, Austria, and Portugal – in cluster 3. Eastern EU countries and Portugal are grouped in clusters 2 and 4, mainly differentiated also by labor productivity and profitability. Businesses in cluster 4, of average size over the years, enjoyed the highest WALP in this industry and high profitability but also had average investment rates: Czech Republic, Hungary, and Poland. In cluster 2 are included the smallest businesses from Romania and Portugal (all years), and Hungary (2012), that enjoyed the highest investment rates, but had low WALP and GOR.

Conclusions

Our research investigated the differences in performance in four industries in the EU manufacturing sector, with various technological levels, to shed light on the patterns of recovery after the 2007-2009 Global financial crisis. The quantitative analysis method used was the clustering algorithm, in two forms: hierarchical and k-means.

The almost perfect groupings of businesses from Western, more developed economies, and Eastern, less developed ones, in all industries, with the notable exception of Portugal, is rather striking, regardless of the technological level of industries. It should be noted, though, that Eastern EU businesses are not the worst performers, as one may think at first sight. Certainly, they are smaller in size but have enjoyed higher labor productivity and profitability, as well as higher investment rates in all industries, although with differences from one country to the other. This points towards a higher dynamism of smaller-sized businesses in general, and, in particular, of Eastern EU located ones, in the years after the global financial crisis, which has been reflected in superior performance. From a managerial perspective, our results suggest that bigger is not always necessarily better, as the flexibility associated with reduced business size was valuable in the after-crisis years. Moreover, smaller firms in the manufacturing industry in Eastern Europe also demonstrated a higher propensity towards investments compared to their Western counterparts (here, it is possible to observe this trend due to multinational companies' investments in this part of the EU), further reflected in better operational profitability and labor productivity. However, the nature of the data we have used in this research does not make it possible to differentiate between the performance of locally-owned versus foreign-owned companies, which might offer more insight into the contribution of multinational companies to the better performance of Eastern businesses. We will consider this direction of research in our future endeavors, which will also include more industries and sectors.

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