# Optimization for Partitional Time-Series Clustering

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***Abstract***

Time-series clustering is a convenient tool for analysing hidden structures in data. However, as is the case with clustering, it is possible to encounter a number of complications, especially with regards to the sensitivity to the initial algorithm conditions and the subjective choice of the number of groups. The aim of this article is to conduct an experiment using real life data of housing prices in the EU to suppress subjectivity, whether in terms of finding subgroups in the data or the validation of the result for partitional clustering. The proposed procedure is based on a modified bootstrapping principle, where the principle of stability via repetition is applied to the algorithm and its results. As such, this method is applied both to the group selection by monitoring the Calinski-Harabasz index and the final assignment of the resulting classification of clustered objects. The result of this process is a structure that has a better informative value about the relationships in the data.

| ***Keywords*** | ***DOI*** | ***JEL code*** |
| --- | --- | --- |
| *Partitional clustering DTW distance, k-means algorithm, time-series* | *https://doi.org/10.54694/stat.2025.47* | *C15, C18, C38* |

## INTRODUCTION

The necessity of working with large quantities of volatile high-dimensional datasets containing a wide range of key information needed for the smooth operation of established processes is an issue many fields are facing. Common examples of such data are time-series, the specific nature of which allows for versatile use beyond the basic definition of a sequence of values for a selected statistical feature over time (Liao, 2005). Given this diversity, many tools have been developed to extract said information from time-series, with time-series clustering being one of many different emerging fields offering a versatile method looking for hidden structures inside data. Especially useful is the ability for identification of different subgroups of time-series in a large set of subjects and the subsequent description of group characteristics, e.g. for revealing subphenotypes of patients with infection (Bhavani et al., 2023).

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Clustering analysis has been widely researched and is an attractive method from the point of view of statistical analysis. But many issues arise in its specifications, especially in the clustering of time-series. The core of the issue stems from the reality that time-series does not represent points of n-dimensional space, but rather an entire sequence. At the same time, the complication of time itself influences the monitoring of the development. As such, it is necessary to consider both the issue of possible dependence between values and their time shift. The need to solve these complications leads to a combination of the field of statistical analysis of time-series with recently developed options for information mining methods (Aghabozorgi et al., 2015).

Current knowledge about time-series clustering often adapts already established clustering algorithms with a new similarity measure, the application of which is suitable for dynamic data (Aghabozorgi et al., 2015). The classification of possible clustering methods for time-series clustering is thus not new, where a large part of the methods used are hierarchical or partitional algorithms, which comprise a significant portion of the most frequently used algorithms.

Partitional methods in the field of time-series are predominantly based either on a suitable prototype function or the choice of an appropriate group representative (Biehl et al., 2016; Petitjean et al., 2011). This builds the basis for the optimal solution search in an iterative manner. As is the case with conventional clustering, and especially in the case of time-series, where the situation is further complicated by the volatility of the time-series itself, the vast majority of partitional methods are sensitive to the choice of initial parameters. Suppression of the subjectivity for the final results thus represents a key problem where the usual validation of the clustering results is made more difficult (Ben-David et al., 2006).

The field of data mining offers tools for the application of some methods that allow for a much more accurate view of the real clustering result (e.g. bootstrap). These methods can be utilized in order to point out the shortcomings of the resulting solution or, in some cases, its disputability. The aim of this article is therefore to point out the possibilities of optimizing partitional clustering, specifically, the evaluation of subjectivity suppression of the results for partitional clustering methods applied to time-series and their later validation.

## 1 LITERATURE SURVEY

Literature about clustering analysis is a diverse set of sources that describe in detail various areas of clustering, such as hierarchical clustering (Murtagh and Contreras, 2017; Ran et al., 2023), partitional clustering (Celebi, 2016), the use of neural networks (Du, 2010) as well as specialized procedures (Barton et al., 2019). It is possible to find extensive overviews comparing individual methods (Ezugwu et al., 2022). Similarly, there exists a wide range of literature related to machine learning, particularly on the usage of clustering methods in the field of classification and prediction (Kotsiantis et al., 2006), or description of bootstrapping methods for validation (Schumacker, 2014).

Contrarily, the amount of literature dealing with the issue of time-series clustering is low. One of the most important publications dealing with time-series clustering is published by Aghabozorgi et al. (2015), which contains an exhaustive summary of methods and procedures implemented in the field of time-series clustering up until 2015. Since then, several textbooks for time-series clustering have been published, e.g. the textbook created by Maharaj et al. (2019), which summarizes the development of traditional and fuzzy clustering methods, including approaches based on observations, features, models and machine learning methods.

The main issue which arises during literature review for time-series clustering is that a high percentage of existing articles focus on the development of their own procedures for time-series clustering, applied only on simulated data, which leads to overfitting and other issues concerning the wider application of these methods and validation of their results (Bagnall et al., 2017).

Block bootstrapping in the context of time-series is a tool used to estimate standard errors, confidence intervals and other relevant statistics. It allows the enhancement of predictions by evaluating the forecasts' uncertainty in chosen econometric models. Conceptually, this method is a non-parametric resampling technique applied to a single time-series, where instead of resampling individual points, resampling results in several blocks of observations. There are two main variants of this application, one assuming the resulting blocks are non-overlapping or overlapping (Hall, 1985). However, block bootstrapping can be very fastidious in terms of real application, as the convergence of errors is rather slow (Härdle, 2003).

Despite the method's imperfections, most of the currently available tools trying to improve upon the results of the block bootstrapping do not achieve significantly better results. The issue worsens when one tries to apply this principle on time-series clustering, as there is little to no literature about its effectiveness nor results.

## 2 MATERIAL FRAMEWORK

Statistical clustering attempts to classify similar objects based on given characteristics under the assumption of homogeneity to their own group members and heterogeneity to other group members. Differences in definition of similarity used in clustering can lead to significant variability of the results, depending on the chosen approach. This applies both to the classic application of clustering and to its modification for time-series. Another difficulty from the point of view of time-series arises from the fact that the distance measure must not only comply with the chosen concept for the definition of similarity but also be able to deal with the issues of multidimensionality and volatility connected to the nature of working with time-series.

### 2.1 Methodology

For the purposes of this article, a standard combination of time-series clustering methods will be used, namely the Dynamic time warping (DTW) distance (Vintsyuk, 1968; Sakoe and Chiba, 1978) and the k-means algorithm. The DTW distance as a similarity measure is currently considered to be one of the most successful metrics for time-series clustering usage, as it is very suitable for working around time distortions.

Suppose that to calculate the distance of two time-series $X = (x_1,..., x_T)$ and $Y = (y_1,..., y_T)$ the Euclidean distance would be used, defined as:

$$Euclidean\left(X,Y\right)=\sqrt{\sum_{i=1}^{T}\left(x_i-y_i\right)^2}\,. \tag{1}$$

The given definition of distance for time-series brings with it two main complications:

- The time-series being compared must be of the same length,
- The individual events of the time-series being compared must occur at the same point in time, otherwise their resulting distance will be noticeably higher even though both time-series undergo similar development.

The DTW distance essentially provides an optimization of the Euclidean distance, the goal of which is to find such an assignment of points in a pair of time-series that would lead to the minimization of the resulting total distance. For the Euclidean distance, the optimization problem can be written as follows:

$$DTW\left(X,Y\right)=\min_{\pi\in A(X,Y)}\left(\sum_{(i,j)\in\pi}Euclidean\left(X_i,Y_j\right)\right), \tag{2}$$

where the optimal assignment $\pi$ of length $k$ is a sequence of $k$ indexed pairs of time-series values $X$ and $Y$. The set $A(X,Y)$ contains all possible assignment paths. In essence, the optimization problem can also be illustrated as finding the optimal path of the original distance matrix using the Euclidean distances. From the definition of the DTW distance, it is obvious that the main issue of its calculation is its computational complexity. Even with a small increase in the number of the time-series, the quantity of possible sorting combinations increases drastically. There are ways to simplify the calculation, but for the purposes of this article we will use the basic definition of the DTW distance.

The k-means algorithm is an unsupervised clustering algorithm based on the idea of the similarity of neighboring points (MacQueen, 1967). Its application to time-series is in practice the same as its common application to classic data sets. In other words, time-series clustering mainly differs in the method of calculating the distance, where it is possible to subsequently use common, well-known clustering algorithms. There are also specific clustering algorithms targeted at time-series, e.g. k-Shape (Paparrizos and Gravano, 2016).

### 2.2 Validation

Calinski-Harabasz (CH) index was chosen for the purpose of validation for both the intermediate results from the optimization process introduced in this article and the final clustering results themselves. In general, the CH index quantifies the ratio between-cluster separation to the within-cluster dispersion (Calinski and Harabasz, 1974). It is a popular metric commonly used to evaluate the quality of clustering results in unsupervised learning.

The core idea behind the CH index is to examine how distinct the clusters are (high inter-cluster variance) and how tightly grouped the data points are within each cluster (low intra-cluster variance). The mathematical formulation for this principle is as follows:

$$CH = \frac{\left(B_k / \left(k-1\right)\right)}{\left(W_k / \left(n-k\right)\right)}, \tag{3}$$

where $B_k$ is the between-cluster separation and $W_k$ is within-cluster dispersion, both normalised by the corresponding degrees of freedom.

A higher CH index indicates better-defined clusters, meaning the clusters are well separated and the objects within the cluster are similar. However, a lower score suggests overlapping or poorly defined clusters. Because the index depends on the number of clusters, it is often used to determine the optimal in clustering tasks. While the CH index performs well for convex, spherical clusters, it may not be as effective for complex, non-linear cluster shapes.

### 2.3 Optimization

When applying partitional clustering to time-series, there are many practical issues related to the selection of an appropriate number of clusters and their result. Since most real time-series data do not have a predetermined group assignment, it is necessary to consider a procedure that would allow for the effective detection of hidden structures in the data. However, partitional methods themselves assume that the number of clusters is predetermined, which makes the selection of an appropriate parameter a key step in the entire process.

One possible approach to automate and refine this process is to repeatedly apply the algorithm with different initial conditions. The results obtained this way can then be consolidated into a single, less subjective solution that better reflects consistent patterns in the data rather than their individual runs. This principle assumes that repeated application of clustering helps to suppress random effects and better captures persistent structures in the data.

To identify the structure, further processing of the results of repeated clustering was proposed. A set of 100 outputs for the selected optimal number of clusters was used to construct the co-association matrix (Zhong et al., 2019). This matrix of dimensions  (corresponding to the number of time-series analyzed) captures the intensity with which individual pairs of time-series were assigned to the same cluster across individual runs of the algorithm. Specifically, if two time-series were assigned to the same cluster in any run, value 1 is added to the corresponding cell of the matrix (defined by the row and column corresponding to both time-series). The given matrix was further modified with the following notation:

$$x_{pairs_{ij}} = 1 - \frac{x_{ij}}{100} \,. \tag{4}$$

After processing all 100 repetitions, the matrix contains values in the range $\langle 0,1 \rangle$, which represents the degree of co-association of the given time-series in the same cluster, so that lower values signal a smaller distance between time-series and therefore significant similarity. This information provides a comprehensive view of the resulting structure in the data as well as the degree of similarity between individual pairs of time-series and serves as a basis for further consolidation of the results. Additionally, the given matrix can be interpreted as a distance matrix, which may be used to determine the resulting classification of time-series based on the result of 100 different runs of the algorithm.

#### *2.3.1 Number of clusters*

The final number of clusters was selected based on repeated partitional clustering for different values of the parameter $k$, specifically in the range from 2 to $T - 1$ (where T is the number of time-series). For each value of $k$, the clustering was repeated 100 times with different random initializations of the starting point, which resulted in a total of $(T - 1) \times 100$ runs of the algorithm.

Each individual solution was subsequently evaluated using the CH index. For each value of $k$, the average, maximum and median index values from the respective 100 runs were calculated. A higher index value indicates a better-quality clustering structure.

#### *2.3.2 Bootstrapping*

We can further modify the aforementioned method via the application of bootstrapping. The principle used in the article combines the general usage of bootstrapping with the idea proposed by block bootstrapping. Since the time-series data are notoriously challenging to analyze due to the issue of correlation and volatility, the proposed approach remains intentionally simple.

Given a dataset of $n$ time-series of length $T$, $n$ new datasets were generated, each created by omitting one of the original time-series. For each of these modified datasets, the clustering procedure proposed earlier was repeated. This resulted in $n$ co-association matrices, one per modified dataset. Finally, by aggregating these matrices into a single, more robust co-association matrix, we hope to achieve a distance matrix that better captures the underlying structure of the data.

### 2.4 Data

Real estate prices are an important indicator of economic development and the standard of living for the population of any country. Eurostat regularly publishes detailed data on the development of residential real estate prices across the Member Countries and selected non-EU countries. This data allows not only the monitoring of long-term trends in housing, but also the comparison of different regions of the EU.

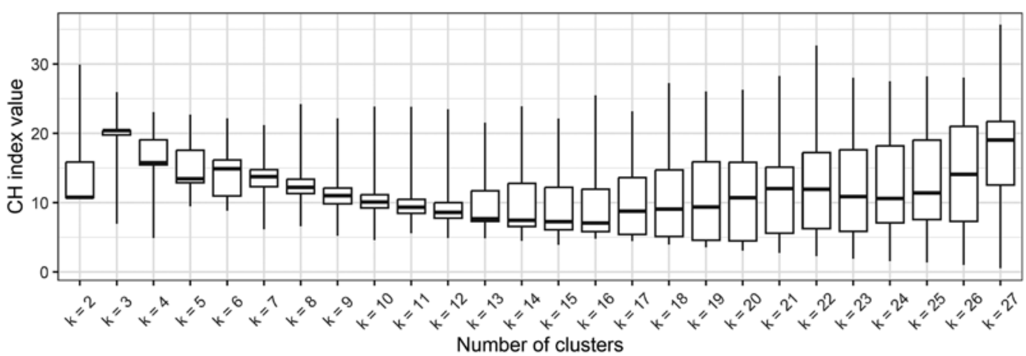
The dataset used in the article contains a total of 28 selected European and non-European countries, recording 59 observations of quarterly house price indices from the first quarterof 2010 to the third quarter of 2024 (Eurostat, 2025). Given that the main principle of time-series clustering is based on the comparison of shape and structure in the time-series development, many of the methods behave better when they are not applied directly on the raw data. One of the possible and simplest methods for data preprocessing used for time-series clustering is standardisation, where the transformation of a time-series means rescaling the values in a way where the mean is equal to zero and standard deviation is equal to one. This can be achieved by a simple subtraction of the sample mean from the observed values and division by the standard deviation. Rather than be bottled down by the differences in values,by rescaling the time-series to a common range, we can focus more on the actual comparison of shapes, something that often contributes to cleaner and more concise results for time-series clustering. However, this method introduces a certain degree of bias into the data which should be handled carefully.

Processing of the data and the results was done by using the R programming language (R Core Team, 2025) with several key libraries, specifically the package *caret* (Kuhn, 2024) for data-preprocessing, *TSclust* (Montero and Vilar, 2014) and *dtwclust* (Sardá-Espinosa, 2019) for time-series classification and *clusterCrit* (Desgraupes, 2024) for clustering validation.

## 3 RESULTS

The first step of the analysis consists of choosing an appropriate number of clusters. Based on the analysis of the resulting values, it was found that the first significant and stable value of the CH index occurs at point $k = 3$, which indicates the existence of three significant subgroups in the data (Figure 1). After this point, the index decreases and starts to increase again only when the parameter  is greater than 18. From the point of view of clustering needs, the given index values are already too high, and the results cannot be interpreted as meaningful. For these reasons $k = 3$ was chosen as the optimal number of clusters.

**Figure 1** Values of the CH index for values of *k* 2 to T-1




**Source:** Author's calculations

Based on the above procedure, a rough estimate of the optimal number of clusters was obtained, which serves as a starting point for further analysis. However, it is necessary to once again emphasize that the results of individual runs of partitional clustering can vary significantly depending on the initial conditions of the algorithm. This variability is evident with the given parameter $k = 3$, where it is possible to observe significantly different index values across repeated runs. At the same time, it is evident that some solutions are repeated multiple times based on the same index value. This implies the need to further analyse the clustering output in a way that achieves consistent and interpretable results.

Based on the resulting co-association matrix (Table 1), it is evident that some countries were often classified into the same cluster within the repeated runs of the algorithm, in some extreme cases the value being equal to zero, meaning that in all 100 iterations these countries were classified into the same cluster. This phenomenon points to the existence of a strong structural similarity of the development within the analyzed time-series.

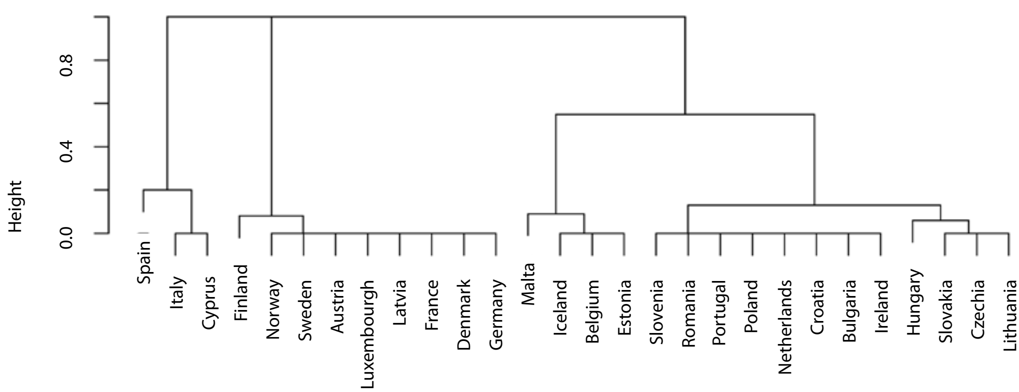
**Table 1** Co-association matrix for the first five countries (full matrix in Table A1)

| | Bulgaria | Czechia | Denmark | Germany |
|---|---|---|---|---|
| Belgium | 0.55 | 0.42 | 0.44 | 0.44 |
| Bulgaria | | 0.13 | 0.99 | 0.99 |
| Czechia | | | 0.86 | 0.86 |
| Denmark | | | | 0.00 |

**Source:** Author's calculations

The algorithm of the farthest neighbor method was then used to search the matrix. Resulting classification can therefore be illustrated in Figure 2. Based on the image it can be argued that most analyzed countries display a strong tendency to be classified together and form smaller groups on the lowest level of the resulting dendrogram.

**Figure 2** Initial resulting ranking of European and other selected countries

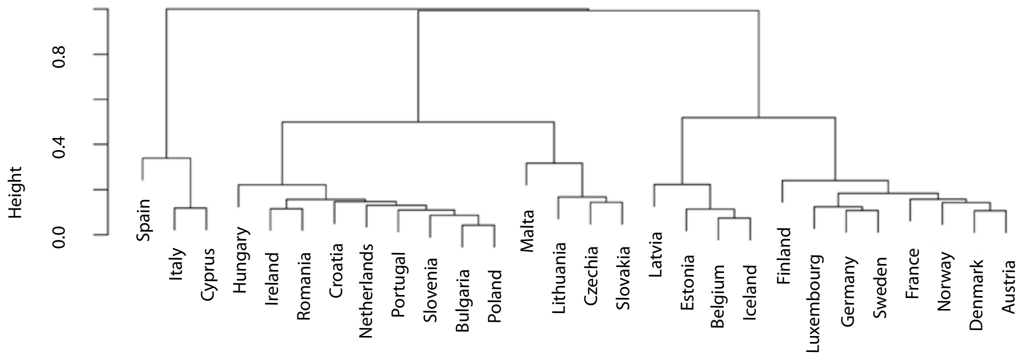



**Source:** Author's calculations

Further possible modification is in the application of machine learning validation procedures. For each variant, 100 iterations of partitional clustering assuming $k = 3$ have been performed, similarly to the previous cases. The resulting aggregated co-association matrix will thus capture not only the variability caused by the choice of the starting point of the algorithm, but also the sensitivity of the model to the presence of individual countries in the input data.

This modification led to a solution that remains largely stable in its basic layout (see Figure 3). Again, a smaller cluster consisting of Cyprus, Italy and Spain appears, followed by a cluster comprising mainly Western European and Scandinavian countries, and finally a diverse, heterogeneous cluster comprised of, among others, Croatia, Poland and Slovenia. The most significant difference from the initial result is the new assignment of countries such as Latvia, Estonia and Belgium. The assignment stayed otherwise consistent.

**Figure 3** Modified result of time-series clustering




**Source:** Author's calculations

## 4 DISCUSSION

Approximately three main clusters can be identified (Figure 4). The smallest and most clearly defined cluster is the third cluster formed by Southern European countries, namely Spain, Italy and Cyprus, whose real estate price dynamics show a high degree of similarity in their development.

The second, larger cluster mainly consists of Northern and Western European countries, its first subgroup including countries such as Finland, Norway, Austria and Germany. These countries are characterized by relatively stable development and common economic features as well as high economic prosperity, which may also be reflected in the time-series of real estate prices. Second subgroup consists of countries

**Figure 4** Assignment of housing prices for chosen countries based on the modified results

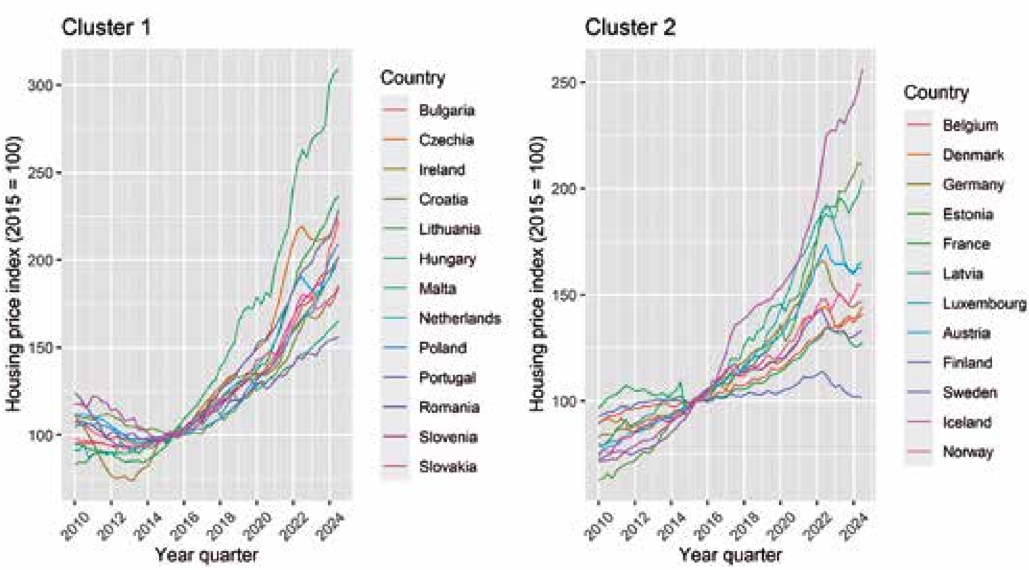
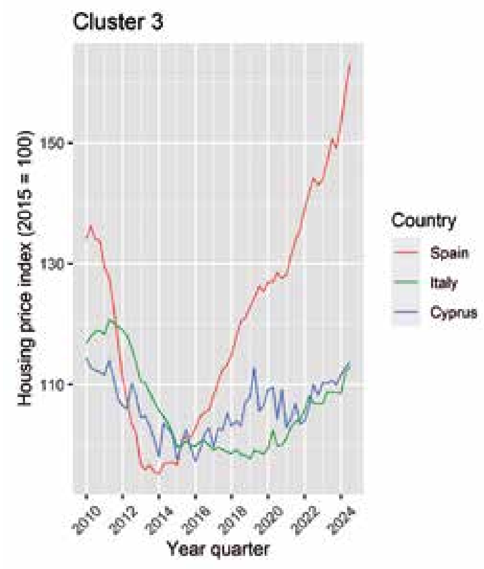


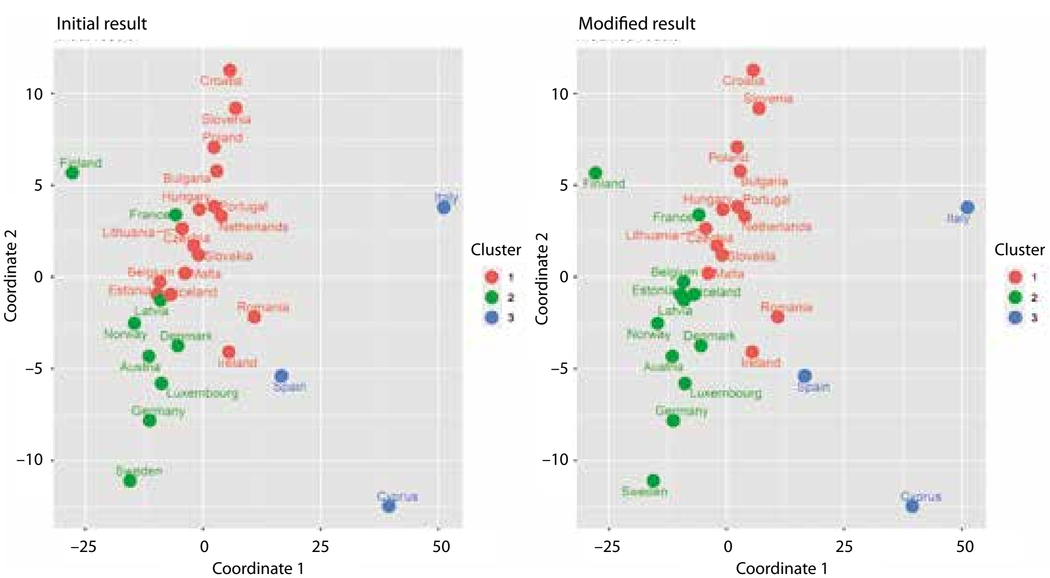
**Figure 4** continuation




**Source:** Eurostat

Latvia, Estonia, Belgium and Iceland. These countries are all small, open, high-income European economies that depend on services, trade and external markets. It is important to note that Belgium, Estonia and Iceland are on a border between two of the main big clusters suggesting a shared structure with both of the groups (Figure 5).

**Figure 5** Multidimensional scaling of the initial and modified solutions




**Source:** Author's calculations

Last cluster consists mainly of countries of Central and Eastern Europe, which could also be divided into two smaller subgroups. One group encapsulates Malta, Lithuania, Czechia and Slovakia, while the other subgroup focuses on countries like Poland, Croatia and Romania. Main feature of this cluster is a noticeably lower economic prosperity, especially compared to the countries of the other big final cluster.

## CONCLUSION

Time-series clustering allows not only the assessment of individual development of time-series, but also the comparison of broader datasets and the uncovering of common features or tendencies that may indicate the existence of hidden influences. It is also possible to assume that these influences may act differently within identified groups of time-series and thus have a significant, albeit different impact on their dynamics. In this sense, clustering can be perceived as a means of exposing the hidden structure in the data, which can then be visualized and interpreted. At the same time, it is necessary to emphasize that time-series clustering contains a significant degree of subjectivity. The results are sensitive to the choice of algorithm, parameter settings, definition of the distance metric and the choice of initial conditions, as well as the interpretation itself. Although subjectivity can be partially limited by using different methods and comparing their outputs, e.g. bootstrapping, it cannot be completely eliminated. For this reason, it would be misleading to claim that the obtained results are absolutely accurate.

However, the analysis conducted in this study using real life data of housing prices in EU showed that despite the aforementioned limitations in most cases a somewhat consistent structure can be observed in the data. This fact supports the idea that the greatest benefit of time-series clustering lies in the discovery and description of these hidden structures rather than in a fixed and unambiguous classification. From a practical point of view, it is therefore appropriate to direct further research towards methods that will enable this latent structure to be revealed more clearly and made visually accessible. For example, it could be beneficial to link clustering with methods for visualizing high-dimensional data or with advanced dimensionality reduction techniques. Such an approach could lead to a deeper understanding of the internal relationships between individual time-series and at the same time provide tools for a more robust interpretation of the results.

Overall, it can be concluded that time-series clustering represents a valuable analytical framework, the strength of which does not lie in achieving complete unambiguousness of the results, but in the ability to reveal stable, recurring patterns and structures in the data. Their detailed investigation and description can bring new insights into the dynamics of the observed phenomena and open the way to their deeper interpretation and predictive modelling.

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# APPENDIX

**Table A1** Full co-association matrix

| COUNTRY | Belgium | Bulgaria | Czechia | Denmark | Germany | Estonia | Ireland | Spain | France | Croatia | Italy | Cyprus | Latvia | Lithuania | Luxembourg | Hungary | Malta | Netherlands | Austria | Poland | Portugal | Romania | Slovenia | Slovakia | Finland | Sweden | Iceland |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Bulgaria | 0.55 | 0.42 | 0.44 | 0.44 | 0.00 | 0.55 | 1.00 | 0.44 | 0.55 | 1.00 | 1.00 | 0.44 | 0.42 | 0.44 | 0.48 | 0.09 | 0.55 | 0.44 | 0.55 | 0.55 | 0.55 | 0.55 | 0.42 | 0.52 | 0.44 | 0.00 | 0.44 |
| Czechia | | 0.13 | 0.86 | 0.99 | 0.55 | 0.00 | 0.73 | 0.99 | 0.00 | 0.93 | 0.93 | 0.99 | 0.13 | 0.99 | 0.07 | 0.46 | 0.00 | 0.99 | 0.00 | 0.00 | 0.00 | 0.00 | 0.13 | 1.00 | 0.99 | 0.55 | 0.99 |
| Denmark | | | 1.00 | 0.86 | 0.42 | 0.13 | 0.86 | 0.86 | 0.13 | 1.00 | 1.00 | 0.86 | 0.00 | 0.86 | 0.06 | 0.33 | 0.13 | 0.86 | 0.13 | 0.13 | 0.13 | 0.13 | 0.00 | 0.94 | 0.86 | 0.42 | 0.86 |
| Germany | | | | 0.00 | 0.44 | 0.99 | 1.00 | 0.00 | 0.99 | 1.00 | 1.00 | 0.00 | 0.86 | 0.00 | 0.92 | 0.53 | 0.99 | 0.00 | 0.99 | 0.99 | 0.99 | 0.99 | 0.86 | 0.08 | 0.00 | 0.44 | 0.00 |
| Estonia | | | | | 0.44 | 0.99 | 1.00 | 0.00 | 0.99 | 1.00 | 1.00 | 0.00 | 0.86 | 0.00 | 0.92 | 0.53 | 0.99 | 0.00 | 0.99 | 0.99 | 0.99 | 0.99 | 0.86 | 0.08 | 0.00 | 0.44 | 0.00 |
| Ireland | | | | | | 0.55 | 1.00 | 0.44 | 0.55 | 1.00 | 1.00 | 0.44 | 0.42 | 0.44 | 0.48 | 0.09 | 0.55 | 0.44 | 0.55 | 0.55 | 0.55 | 0.55 | 0.42 | 0.52 | 0.44 | 0.00 | 0.44 |
| Spain | | | | | | | 0.73 | 0.99 | 0.00 | 0.93 | 0.93 | 0.99 | 0.13 | 0.99 | 0.07 | 0.46 | 0.00 | 0.99 | 0.00 | 0.00 | 0.00 | 0.00 | 0.13 | 1.00 | 0.99 | 0.55 | 0.99 |
| France | | | | | | | | 1.00 | 0.73 | 0.20 | 0.20 | 1.00 | 0.86 | 1.00 | 0.80 | 1.00 | 0.73 | 1.00 | 0.73 | 0.73 | 0.73 | 0.73 | 0.86 | 1.00 | 1.00 | 1.00 | 1.00 |
| Croatia | | | | | | | | | 0.99 | 1.00 | 1.00 | 0.00 | 0.86 | 0.00 | 0.92 | 0.53 | 0.99 | 0.00 | 0.99 | 0.99 | 0.99 | 0.99 | 0.86 | 0.08 | 0.00 | 0.44 | 0.00 |
| Italy | | | | | | | | | | 0.93 | 0.93 | 0.99 | 0.13 | 0.99 | 0.07 | 0.46 | 0.00 | 0.99 | 0.00 | 0.00 | 0.00 | 0.00 | 0.13 | 1.00 | 0.99 | 0.55 | 0.99 |
| Cyprus | | | | | | | | | | | 0.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.93 | 1.00 | 0.93 | 0.93 | 0.93 | 0.93 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Latvia | | | | | | | | | | | | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.93 | 1.00 | 0.93 | 0.93 | 0.93 | 0.93 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Lithuania | | | | | | | | | | | | | 0.86 | 0.00 | 0.92 | 0.53 | 0.99 | 0.00 | 0.99 | 0.99 | 0.99 | 0.99 | 0.86 | 0.08 | 0.00 | 0.44 | 0.00 |
| Luxembourg | | | | | | | | | | | | | | 0.86 | 0.06 | 0.33 | 0.13 | 0.86 | 0.13 | 0.13 | 0.13 | 0.13 | 0.00 | 0.94 | 0.86 | 0.42 | 0.86 |
| Hungary | | | | | | | | | | | | | | | 0.92 | 0.53 | 0.99 | 0.00 | 0.99 | 0.99 | 0.99 | 0.99 | 0.86 | 0.08 | 0.00 | 0.44 | 0.00 |
| Malta | | | | | | | | | | | | | | | | 0.39 | 0.07 | 0.92 | 0.07 | 0.07 | 0.07 | 0.07 | 0.06 | 1.00 | 0.92 | 0.48 | 0.92 |
| Netherlands | | | | | | | | | | | | | | | | | 0.46 | 0.53 | 0.46 | 0.46 | 0.46 | 0.46 | 0.33 | 0.61 | 0.53 | 0.09 | 0.53 |
| Austria | | | | | | | | | | | | | | | | | | 0.99 | 0.00 | 0.00 | 0.00 | 0.00 | 0.13 | 1.00 | 0.99 | 0.55 | 0.99 |
| Poland | | | | | | | | | | | | | | | | | | | 0.99 | 0.99 | 0.99 | 0.99 | 0.86 | 0.08 | 0.00 | 0.44 | 0.00 |
| Portugal | | | | | | | | | | | | | | | | | | | | 0.00 | 0.00 | 0.00 | 0.13 | 1.00 | 0.99 | 0.55 | 0.99 |
| Romania | | | | | | | | | | | | | | | | | | | | | 0.00 | 0.00 | 0.13 | 1.00 | 0.99 | 0.55 | 0.99 |
| Slovenia | | | | | | | | | | | | | | | | | | | | | | 0.00 | 0.13 | 1.00 | 0.99 | 0.55 | 0.99 |
| Slovakia | | | | | | | | | | | | | | | | | | | | | | | 0.13 | 1.00 | 0.99 | 0.55 | 0.99 |
| Finland | | | | | | | | | | | | | | | | | | | | | | | | 0.94 | 0.86 | 0.42 | 0.86 |
| Sweden | | | | | | | | | | | | | | | | | | | | | | | | | 0.08 | 0.52 | 0.08 |
| Iceland | | | | | | | | | | | | | | | | | | | | | | | | | | 0.44 | 0.00 |
| Norway | | | | | | | | | | | | | | | | | | | | | | | | | | | 0.44 |

**Source:** Author's calculations