Quarterly Journal of Quantitative Economics(JQE) (2026) **23(1) 99-132**

Shahid Chamran University of Ahvaz

Quarterly Journal of Quantitative Economics

Journal Homepage: www.jqe.scu.ac.ir
Print ISSN: 2008-5850
Online ISSN: 2717-4271



Directional Volatility Spillovers-based Fuzzy Clustering for Financial Time Series: Evidence from Stocks of Companies Listed on the Tehran Securities Exchange

Elham Farzanegan *

** Assistant Professor of Economics, Department of Economics and Social Sciences, Nahavand Higher Education Complex, Bu-Ali Sina University, Hamedan, Iran. (Corresponding Author)*
Email: *e.farzanegan@basu.ac.ir*
0000-0002-3725-3189
Postal address*: Shahid Mostafa Ahmadi Roshan, Nahavand Higher Education Complex, Bu-Ali Sina University, Hamedan,Iran. Postal code: 6517838695.*

ARTICLE HISTORY	JEL CLASSIFICATION	KEYWORDS
Received: 27 December 2023 Revision: 07 May 2024Acceptance: 05 June 2024	***C34, C61, G12***	***Fuzzy Partitioning Around Medoids, Directional Volatility Spillovers, Weighted Dissimilarity Measure, Exponential Distance, Tehran Securities Exchange***

Acknowledgments: we appreciate the Reviewers' insightful suggestions on improving the quality of the research.
Conflict of Interest: The author declare no conflict of interest.
Funding: The author received no financial support for the research, authorship, and publication of this article.

How to Cite:
Farzanegan, Elham. (2026). Directional volatility spillovers-based fuzzy clustering for financial time series: evidence from stocks of companies listed on the Tehran Securities Exchange. *Quarterly Journal of Quantitative Economics (former Economics Studies)*, 23 (1), 99-132.
10.22055/jqe.2024.45633.2597

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Quarterly Journal of Quantitative Economics
(former Economic Studies)

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EXTENDED ABSTRACT

INTRODUCTION

Clustering is an unsupervised learning technique for detecting similarities or differences between financial time series. One of the important aspects of clustering is how dissimilarities can be measured. To obtain meaningful clusters, stylized empirical facts of time series should also be included in the definition of dissimilarities.

From the methodological point of view, similarity can be measured using distance measures; the traditional Euclidean distance which is a measure of how close the observations are, can not be a desirable metric for measuring the similarity between time series as it does not make any assumptions about important characteristics of data.

In literature, when actual financial time series are considered, properly defining dissimilarity also becomes more complicated. Some characteristics previously used for clustering of financial time series are return volatilities, long-term memory, auto-correlation, heterogeneity variance, higher order moments, asymmetry, and fat trails of empirical densities (Jondeau & Rockinger, 2012; Soltyk & Chan, 2023).

One of the empirical stylized features that has not been studied for clustering is the volatility spillover effects (Cerqueti et al., 2023; D'Urso et al., 2016). Identifying the clusters in volatility spillovers between assets leads to a deep insight into the financial market microstructure, which would have implications for portfolio managers and policymakers to make decisions in periods of financial crises and uncertainty about the economy in general, particularly when directional volatility spillovers have been taken into account (Diebold & Yilmaz, 2009, 2012).

This paper presents an innovation in research methodology using directional volatility spillovers in fuzzy clustering C-medoids. The reviews of the literature reveal that this approach has not yet been applied to emerging markets. So, this research seeks to complement the existing studies by providing empirical findings for the Tehran Stock Exchange.

METHODOLOGY

As the main objective of this research is to cluster data sets based on the directional volatility spillovers - "From" and "To" others, firstly, the stock return volatilities are computed using the Parkinson estimator (Parkinson, 1980). Then, the directional volatility spillover indices are measured based on the H-step ahead generalized forecast-error variance decompositions (GFEVD) in a VAR model (Pesaran & Shin, 1998). Therefore, stocks are partitioned in terms of magnitude as well as directions of volatility spillovers. In other words, dissimilarities are measured according to the contribution of each stock to produce spillover to others and to receive it from them. For this purpose, the dissimilarity between the directional volatility spillovers is calculated by the Euclidean distance based on the weighted combination of "From" and "To" spillovers. In this research, an objective weighting system is adopted which assigns weights to the dimensions of spillovers depending on the specific market under consideration (Cerqueti et al., 2023; D'Urso et al., 2016).

Further, following Wu and Yang (2002) and D'Urso et al. (2016), the weighted Euclidean distance is converted using an exponential function. The exponential weighted Euclidean distance is robust against noise and outliers in the volatility spillovers (D'Urso et al., 2016; Wu & Yang, 2002). Then, these weighted dissimilarity measures are used for fuzzy clustering models. This paper adopts two approaches of fuzzy partitioning around medoids (Fuzzy PAM), namely, the Fuzzy C-Medoids model based on the Volatility Spillover (VS-FCMdd) and the Exponential Fuzzy C-Medoids model based on the Volatility Spillover (VS-E-FCMdd) are considered, which iteratively calculate the optimal weights. Accordingly, the importance of dimensions of directional volatility spillovers in clustering, the medoids of each cluster, and stock membership degrees of each cluster are found. Finally, to determine the optimal number of clusters and to validate these clustering models, the Xie-Beni index is employed (Xie & Beni, 1991).

For this purpose, a daily stock return time series concerning 30 stocks from 28 industries of the Tehran Stock Exchange, from 2008/8/26 to 2023/8/27, has been investigated.

FINDINGS

For the present investigation, the directional volatility spillover indices are estimated for Horizon, $H = 10$, and optimal lag, $P = 5$ for the VAR model; from depicting the estimated values of "From" and "To" spillover indices, the outliers with higher values of spillovers and lower values than others are

Shahid Chamran University of Ahvaz
Quarterly Journal of Quantitative Economics
(former Economic Studies)

identified. Moreover, at cluster 2, the Xie-Beni index value reaches the minimum value.

From the empirical evidence, it is found that all the membership degrees of VS-E-FCMdd are lower than those of VS-FCMdd for both clusters. In particular, VS-FCMdd assigns outliers to the cluster with higher membership degrees, but the robust VS-E-FCMdd assigns them with cluster membership degrees near 0/5.

The findings also show that the VS-FCMdd model produces the partition that confirms the high against low "From" volatility spillover pattern; However, some extreme observations remain that have been wrongly assigned to clusters. In contrast, the partitions obtained by the VS-E-FCMdd algorithm imply the low against high volatility spillover pattern; but it excludes the extreme events from this clustering. Therefore, one can obtain a more reliable partition in terms of low and high (i.e. spillovers) clusters. In addition, unlike the VS-FCMdd model, stocks identified in each cluster, are more tight around the medoid of the cluster belonging to it. The empirical results show that the robust clustering model seems to have better performance in clustering the dataset.

CONCLUSION

Empirical findings show that the VS-FCMdd and VS-E-FCMdd clustering models similarly identify a two-group structure in the dataset, i.e. "high" and "low" levels of volatility spillovers. Due to the presence of outliers, the VS-E-FCMdd produces more fuzzy partitions and is effective in clustering the stock volatility spillovers of the Tehran Stock Exchange. The results demonstrate that the VS-E-FCMdd model assigns a higher weight to the "From" volatility spillover. Moreover, the stocks listed on the Tehran Stock Exchange are differentiated mostly in terms of "From" volatility spillover, i.e., the amount of volatility spillover that each stock receives from all other stocks. Particularly, cluster 1 includes the stocks which, in comparison to others, receive more "From" spillovers, but transfer fewer "To" spillovers.

For future research, it is recommended that the dynamic volatility spillover indices be calculated on the rolling time window technology basis, and the new clustering algorithms are generalized based on this alternative measure. Moreover, one could modify the the robust VS-E-FCMdd model to the new robust fuzzy clustering algorithms. Finally, different models for robust fuzzy clustering could be generalized for classifying the nonstationary and nonlinear time series.

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