Is This Time Different? Reconsidering Inflation Hedged Portfolios Through Community Detection and Fuzzy Network

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Abstract

The resurgence in inflation that started in 2021 made asset allocation suddenly more complicated. In past high inflationary episodes, the academic literature has shown that investors found success in investing in assets such as commodities, real estate, and certain types of stocks, notably in the energy and materials sectors. However, those options may not necessarily outperform in different macro and geopolitical environments, making it more difficult to build robust inflation hedged portfolios. To address this challenge, we first leverage fuzzy clustering and community detection to identify diversified clusters of industries indexes during historical high inflation regimes. Then, we build optimized portfolios of industries for each cluster and compare their performance in the recent inflationary episode. Finally, we assess the performance of "inflation-clustered" portfolios against traditional hedges, like commodities, to test if optimized stocks allocation in high inflation regimes is a better alternative for investors. We find that leveraging historical inflation information through clustering has been remarkably profitable during the recent period.

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1. Introduction

During the past fifteen years, most developed countries have pursued aggressive quantitative easing policies to support their economies. These unprecedented measures and the recent spikes in oil and gas prices triggered by the Ukrainian war, have pushed inflation levels back to 40-year highs. As a result, investors ought to reconsider their strategies to effectively hedge against inflation and generate positive real returns. A stream of research in the field of portfolio optimization has focused on the use of commodities such as gold and oil (Tang and Xiong, 2012; Baur and Lucey, 2010), while others have explored the role of real estate as inflation hedges (Chaudhry and Myer, 1996; Case and Shiller, 1989). Brière and Signori (2012) argues that investors should invest in cash when the investment horizon is short and increase their allocation to inflation linked bonds and precious metals when horizon increases. However, Li (2019) shows that price indexation lags may lead to mispricing and alter the optimal portfolio composition, typically requiring a higher allocation to inflation-linked bonds to hedge against the delayed price adjustments.

In times of high inflation, investing in traditional markets is more critical though: stocks, even those with high betas, may underperform (Ang *et al.*, 2012), while treasuries are likely to decrease in prices (as yields go up), which makes longer-term bonds risky to hold in the short term (Dalio *et al.*, 2022). Fama and Schwert (1977) examines the impact of inflation on stock returns and finds that during periods of high and unexpected inflation, real stock returns are indeed lower. Modigliani and Cohn (1979) argues that high inflation leads to higher nominal discount rates, which decreases the valuation of companies' future cash flows. Inflation also increases input costs for companies, such as raw materials and labor. As a result, higher inflation may compress profit margins, leading to lower earnings and profitability levels (Solnik, 1983). However, Schotman and Schweitzer (2000) concludes that the negative inflation hedge can become positive over longer investment horizons, particularly if inflation persistence is high.

Having said that, industries that produce essential goods and services, such as utilities or consumer staples, may have the ability to pass on increased costs to consumers due to the inelastic demand for their products. Sharma (2011) shows that firms with more pricing power tend to outperform during periods of rising prices. Bampinas and Panagiotidis (2016) finds that companies within resource-based industries, particularly from the Energy and Industrials sectors, can benefit from rising commodity prices, and even provide effective long-run hedges against inflation. However, their hedging ability is subject to significant time variation, influenced by broader economic conditions. Adcock, Bessler and Conlon (2022) evaluates the relationship between characteristic-sorted portfolios and macroeconomic variables, focusing on decomposing the contributions of these variables to portfolio returns. The authors conclude that while macroeconomic variables statistically influence characteristic-sorted portfolios, their economic significance is more limited than expected. Likewise, Bouaddi and Taamouti (2013) evaluates portfolio selection in a data-rich environment and argue that the best portfolios in terms of maximizing expected returns are the ones that contain economic factors. However, their results highlight the importance of considering dynamic and non-linear exposures to better understand macroeconomic influences on portfolio returns.

To uncover these nuanced relationships, network and cluster analyses have long been used to classify stock market multivariate time series (Pattarin *et al.* (2004), Dose and Cincotti, 2005). Recent advances in network theory offer promising avenues for enhancing portfolios construction, resulting in more diversified and better risk-adjusted performances compared to the Global Minimum Variance (GMV) and Equally Weighted (EW) portfolios. Peralta and Zareei (2016) constructs financial networks where the edges represent the strength of connections between assets, determined by their return correlations. Clemente, Grassi and Hitaj (2022) proposes "smart network-based portfolios", where the optimization problem minimizes the portfolio variance while considering individual volatilities and asset interconnections, using a modified clustering coefficient. Giudici, Polinesi and Spelta (2022) explores how network models can inform robo-advisors to craft portfolios that better capture the interdependencies between assets, potentially leading to more robust investment strategies.

In this article, we also leverage network theory to identify which industries are most likely to perform well in the latest inflationary environment. Notably, we ask the following questions: Is the most recent « high inflation » period different from previous « high inflation » episodes with regards to investing? Would the dynamics between inflation and industries stocks after the Second World War and over the 1973-1982 decade have helped equity investors to outperform during the period 2021-2023?

To answer those questions, and unlike the above literature on portfolio allocation, we propose to build inflation hedged portfolios in three steps. Firstly, we uncover regimes of inflation using three-state Markov Switching (MS) models on CPI data over almost 80 years, following Guidolin and Timmermann (2007), Guidolin and Hyde (2012), which have shown the importance of using regime switching models for portfolio selection. Secondly, we build diversified clusters of industries and identify which ones share similar dynamics with inflation when the latter is characterized by a high regime. To this aim, we use two methodologies: K-means coupled with the Louvain method developed by Blondel *et al.* (2012), and the Dynamic Time Warping (DTW)-based fuzzy clustering method, proposed by Krishnapuram *et al*. (2001) and Izakian *et al.* (2015). The Louvain method is a community detection algorithm that optimizes modularity to identify community structures and is well suited when dealing with large networks. Fuzzy clustering techniques, such as Fuzzy centroid methods, can detect natural groups in time series, even in the presence of outliers and noisy data, and are particularly robust when combined with advanced distance measures like DTW (D'Urso *et al*., 2023). In a third step, we build optimized portfolios of industries for each cluster found in high regime samples and assess their performance over the most recent inflation period (2021-2023). Genetic algorithm is notably used to obtain diversified portfolios. Finally, we assess the performance of our inflation-clustered portfolios against inflation hedged (commodities-based) portfolios.

The remainder of the article proceeds as follows. Section 2 identifies and discusses historical inflation regimes. Section 3 describes the notions of community detection and fuzzy network. Section 4 provides the results of our two clustering methods for different historical periods, with a focus on high inflation regimes. Section 5 addresses optimal portfolio weights based on the clustered analysis and presents out-of-sample portfolios results during the latest inflationary episode (2021-2023). Section 6 compares optimized commodities-based portfolios to our cluster-based portfolios. Finally, Section 7 concludes and outlines future research ideas.

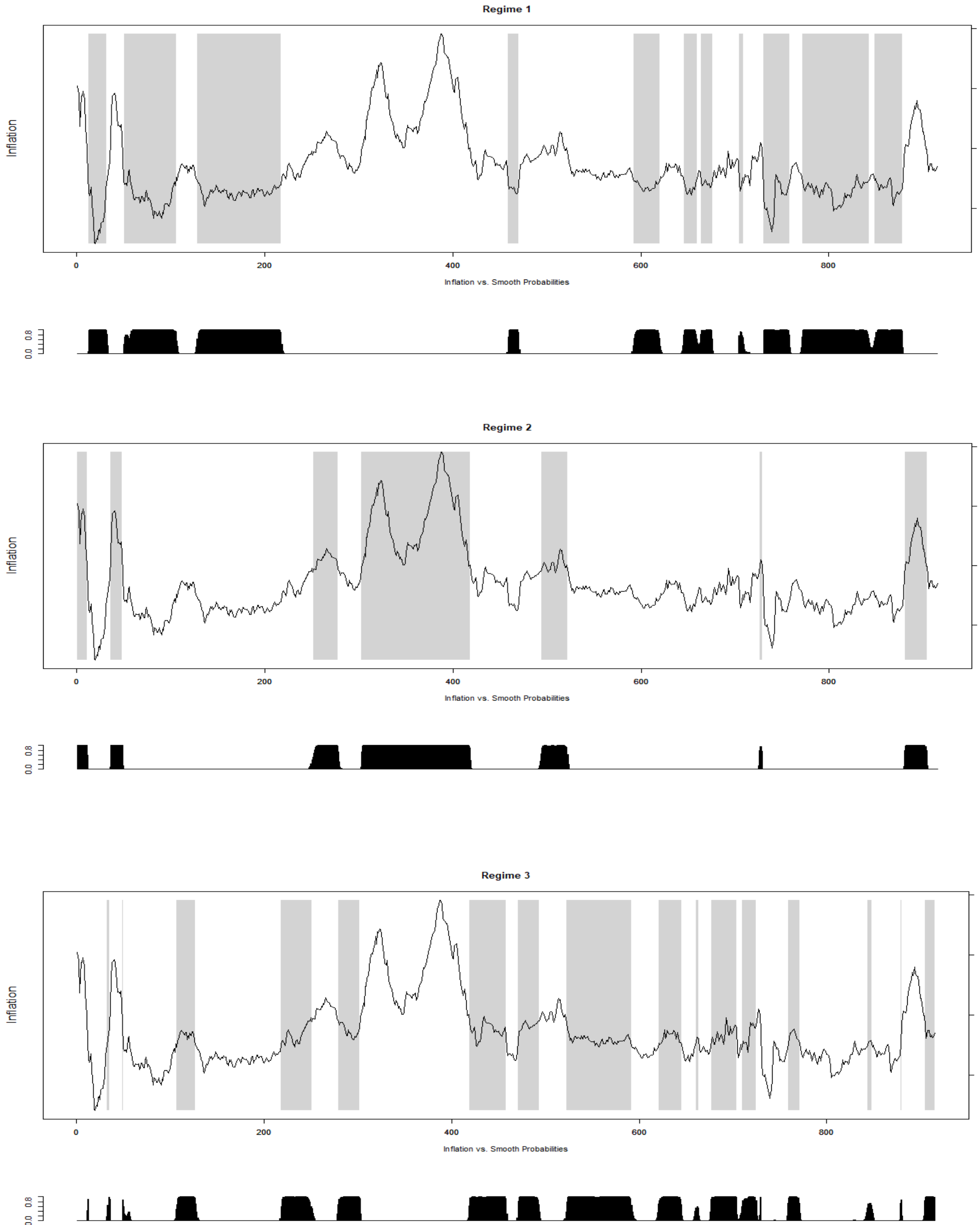
2. Inflation Regimes

Regime switching models are often used to capture changes in economic conditions and have shown their importance for portfolio selection (Guidolin and Timmermann, 2007, Guidolin and Hyde, 2012). A regime switching model with two states is a model that assumes two underlying regimes in the data generating process. These two regimes can be thought of as high and low states, or as expansionary and contractionary states (see Hamilton, 1990, 1994). Another key aspect of Markow Switching (MS) models is their ability to handle non-linear dynamics, which is a common feature during periods of high volatility. However, as advocated by Filardo (1994), a three state MS model is most likely to give more consistent results, particularly in capturing the subtleties of economic transitions. This additional state allows to gain flexibility and may provide a more accurate estimation of inflation dynamics, thus leading to better identification of clusters sharing similar properties. Hence, we estimate the following three-state Markov Switching model:

$$X_t = \mu_{S_t} + \ \varepsilon_t \ \ \varepsilon_t \sim N(0, \sigma^2_{S_t}) \tag{1}$$

X_t is the time column vector of observations, S_t = 1, 2, 3 represents the regime in time *t*, μ_{S_t} collects the regime dependent intercepts, and $N(0, \sigma^2_{S_t})$ denotes a normal distribution with mean 0 and variance $\sigma^2_{S_t}$. These unobservable states are generated by a discrete-sate irreducible and ergodic first-order Markov Chain: $Pr(S_t = j | S_{t-1} = i) = p_{ij}$ where p_{ij} is the element of a *3*3* transition matrix, *P*. These parameters are estimated using Maximum Likelihood (ML), with the use of the Expectation-Maximization (EM) algorithm for handling the latent variables. Figure 1 shows the Consumer Price Index (CPI) year-on-year changes, together with the macroeconomic regimes estimated with the above three-state switching model.

Figure 1: Three-State Markov Switching Regimes



Source: FRED and authors' calculations: y-o-y inflation rates are calculated using the Consumer Price Index (CPI) published by the US Bureau of Labor Statistics (BLS). Markov Switching model with three states. State 1 captures a low inflation regime, State 2 a high inflation regime, and State 3 a medium inflation regime.

The model captures three persistent inflation regimes, namely low, medium, and high. The low inflation regime (Regime 1) prevails before the two oil crises and most of the time during the period 2009-2021, starting with the end of the Great Financial Crisis that brought a short deflation episode. The medium inflation regime (Regime 3) occurs notably throughout two decades, starting after the second oil shock in 1983. Finally, the high regime (Regime 2) captures several windows, where inflation reached the 5 percent threshold or higher. This occurred in 1946-48 after the Second World War, and after a period of low inflation (Regime 1), again for two years in 1950-51. The next and longest high inflation period started with the first oil crisis in 1973 and ended in 1982. More recently, the model picks the year 2008 as a high regime that was triggered by the temporary upsurge in oil prices, and finally the most recent period, from April 2021 to May 2023.

Given those periods of high inflation, we will now assess if the dynamics between inflation and industries after the Second World War (first period) and during the 1973-1982 decade (second period) would have helped equity investors to outperform during the period 2021-2023 (third period) by investing in assets that historically have performed well during the first two periods. The results of our investigation are then contingent upon similarities, in terms of economic and financial conditions, between the post-World War II, the two oil crises of the 70's, and the current environment. For example, the post-war period was characterized by reconstruction, supply chain reestablishment, and significant policy changes, which may have parallels to the post-pandemic economic recovery. Having said that, the sharp fluctuations in inflation rates between 1948 and 1950 could have led to an inconsistent performance of stocks that typically benefited from inflation. Such volatility in inflation could have resulted in similarly high volatility in stock prices, especially for sectors sensitive to inflation rates. Meanwhile, the inflationary periods of the 1970's share many similarities with the commodities shocks in the aftermath of the Russian invasion. Then, industries that benefited from inflation in the 1973-1982 period might exhibit similar (over)performance during the years 2021-2023. However, the economic environment has evolved in 40 years, with modern markets being more globalized and interconnected, thus the industries selected based on their performance during the 1973-1982 period may not be as resilient to economic factors influencing markets from 2021 onwards, which, besides the energy crisis, are more centered around monetary policy adjustments and geopolitical tensions.

Moreover, if stocks selected based on their past performance might still offer resilience due to their historical inflationary advantage, they may also face new challenges such as digital transformation, regulatory changes, and shifts in consumer behavior. All in all, a sector that was considered a safe-haven in one period could be a high-risk sector in another, depending on sector-specific risks and opportunities besides the underlying inflation drivers. To explore the interconnectedness between inflation and industries, the next section describes the methodology to classify our assets universe in clusters.

3. Clustering and Communities

Clustering is an unsupervised learning technique used to uncover similarities across statistical series, and recently, time series clustering has been gaining much attention in finance (Peralta & Zareei, 2016). A crucial aspect of clustering is how similarity/dissimilarity across units is computed, where the choice of a robust distance metrics is needed. Community detection methods, such as the Louvain method, address some of the limitations of K-means clustering by focusing on finding densely connected subgraphs or communities within a network. Meanwhile, similar to other fuzzy methods, Fuzzy C-medoids provides a degree of membership for each data point in multiple clusters, and therefore, gives a more nuanced view of cluster membership, with an assessment of the uncertainty attached to each assignment. We now delve into the details of our two methodologies, i.e. K-means Community Detection and Fuzzy C-Medoids Clustering.

3.1 Distance Measures

It is well known that the definition of a proper (dis)similarity measure becomes more complicated when one deals with financial time series. Selecting a distance function to evaluate similarities/dissimilarities of time series has a significant impact on the clustering algorithms and their results (Izakian *et al.,* 2015). This selection may depend upon the nature of the data and the specificities of the application. In most partition-based time series data clustering techniques, the Euclidean distance is commonly used. While a large panel of distance metrics is now available in the literature (see Javed *et al*, 2020), Dynamic

Time Warping (DTW) is recognized as one of the most accurate measures for time series (Johnpaul *et al*., 2020). The latter method calculates the distance and the alignment path between two time series and is likely to be more accurate than the Euclidean distance as the sequences may not share the same number of values. The DTW algorithm first divides the two sequences into equal points and defines the so-called Accumulated Cost Matrix or Global Cost Matrix, where each grid point *(i, j)* contains the Euclidean distance. The elements in the Global Cost Matrix, *D*, are defined by the following equation:

$$DTW_{(i,j)} = D_{(i,j)} = \min\{d_{(i-1,j-1),} d_{(i-1,j),} d_{(i,j-1)}\} + d_{(i,j)} \quad with\ i \in (1,n), j \in (1,m) \tag{2}$$

Where $d_{(i-1,j-1),}$ $d_{(i-1,j),}$ $d_{(i,j-1)}$ represent the Euclidean distances.

Then, to be considered admissible, an alignment path should satisfy the following conditions:

$$\pi_0 = (0,0) \tag{3}$$

$$\pi_K = (n,m) \tag{4}$$

Where the beginning and ending of time series are matched together. The sequence is also monotonically increasing in both *i* and *j*, and the time series indexes should appear at least once:

$$i_{k-1} < i_k < i_{k-1} + 1 \tag{5}$$

$$j_{k-1} < j_k < j_{k-1} + 1 \tag{6}$$

Once the optimal path $\pi_k^*,\ k \in (1,K)$ is identified, based on the neighbor with a minimal value, the normalized distance is written as:

$$D = \frac{\sum_{i=1}^{K} d(k)}{\sum_{i=1}^{K} k} \tag{7}$$

The smaller the distance obtained from the DTW model, the closer in distance the two sequences are. Thus, if two series are more associated with each other, the distance will be low, in turn, series are less associated when the distance is high.

3.2 Network Construction

A network is a widespread mechanism to represent objects and their interactions or relations. Formally, a network *G(V, E)* is composed by a set of *N* vertices $V = \{v_1, ..., v_N\}$ and a set of *M* edges defined as $E = \{(v_i, v_j) \mid v_i, v_j \in V\}$, where (v_i, v_j) is an edge that connects two vertices v_i and v_j.

When representing a network graph, one goal could be to minimize the number of edges that cross from one subgroup of vertices to another, therefore putting limits on the number of groups as well as to the relative size of the groups. Essentially, the goal of clustering is to divide the data set into clusters such that the elements assigned to a particular cluster are connected in some predefined sense (such as with a distance measure). One must select a clustering algorithm, which usually depends on the strategy used to maximize the intra-group similarity and minimize the inter-group similarity. The most common approaches are hierarchical and partitional clustering (Liao, 2005). Partitional algorithms and notably K-means, optimize clustering by minimizing the distance between each cluster center (a.k.a. centroid) and the data points within that cluster. K-means is one of the most popular methods and represents each series as a vertex connected to its K-Nearest Neighbor (KNN) network. The crucial parameter is *k*, which is the number of nearest neighbors to build clusters from. A large value of *k* reduces the impact of noise on classification, making boundaries between classes less distinct, i.e. decreasing the number of clusters.

3.3 Community Detection

Community detection methods, such as the Louvain method, address some of the limitations of K-means clustering[1] by focusing on finding densely connected subgraphs or communities within a network. While K-means assumes that clusters are roughly spherical and have equal sizes, community

[1] Notably the sensitivity to noise and outliers.

detection can handle data with non-globular or irregularly shaped clusters more effectively (Blondel *et al.*, 2012). The algorithm operates in two phases: first, it iteratively optimizes modularity locally by moving nodes to neighboring communities that yield the highest gain. Second, it aggregates nodes into a super-node, forming a new network where each node represents a community. These phases are repeated until no further modularity gain is possible. Thus, community detection methods often determine the number of communities automatically based on the network's topology and connectivity patterns and alleviate the need for subjective decisions regarding k. The Louvain method is known for its efficiency and ability to handle very large networks, making it suitable for a wide range of applications. The modularity to be optimized is a scalar value between -1 and 1 that measures the density of links inside communities as compared to links between communities. Given a weighted network, modularity is then defined as:

$$Q = \frac{1}{2m} \sum_{i,j} \left[A_{i,j} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j) \tag{8}$$

where A_{ij} represents the weight of the edge between i and j, $k_i = \sum_j A_{ij}$ is the sum of the weights of the edges attached to vertex i, c_i is the community to which vertex i is assigned and $m = \sum_{ij} A_{ij}$. The function $\delta(u, v)$ is equal to 1 if $u = v$ and 0 otherwise. The Louvain method has hyperparameters, such as resolution, which adjust the balance between the importance of smaller, more fine-grained communities and larger, more coarsely defined communities. The granularity of community detection may be challenging to determine, potentially leading to different clusterings. Therefore, to guide the Louvain community in detecting the most suitable clusters, we use the connectivity matrix (the binary matrix specifying if two vertices are connected or not) from the K-means algorithm as an input to the community detection algorithm in order to help algorithm convergence.

3.4 Fuzzy C-Medoids

A medoid is a representative object from a cluster whose average distance to all other objects in the same cluster is minimal. Since the medoid object is always an element of the original data, i.e. the cluster centers (medoids) are selected among the initial time series and then fully interpretable, they are also less influenced by outliers compared to K-means (Izakian *et al.*, 2015). Implementing the fuzzy C-medoids clustering algorithm implies to minimize the following objective function:

$$q = arg\ min \sum_{p=1}^{N} u_{pc}^{m}\ d_{pc}^{2}\left(X_i, X_j\right) \tag{9}$$

$$u_c = X_q \tag{10}$$

$$\sum_{c=1}^{k} u_{pc} = 1,\ u_{pc} \geq 0 \tag{11}$$

Where X_q denotes a randomly initialized column vector of observation, $d_{p,c}$ represents the DTW distance between the *p-th* member of the data and the *c-th* fuzzy centroid selected. For each member of the data, the degree of belongingness is constrained so that its sum equals to 1 across all clusters. Therefore, if there are N objects in the data and k clusters are desired, a $N \times k$ membership matrix u can be created, where all the rows must sum to 1. The exponent m is known as the fuzziness exponent and should be greater than 1[2].

The above algorithm, however, is not guaranteed to find the global minimum, and Fuzzy partitions usually have no ground truth associated with them. As suggested by Krishnapuram *et al.* (2001), several random initializations should be carried out to increase the reliability of the results. Moreover, we select the number of clusters c by using internal Cluster Validity Indices (CVI) from Wang and Zhang (2007)[3]. Once we find the number of clusters that optimize a majority of our selected CVIs, we change the fuzzy partition to a sharp one by assigning the respective series to a corresponding cluster (taking the highest probability among all), and then validate the choice if the output yields a sufficient number of series by cluster, otherwise, we repeat the process with a different random start.

[2] Izakian *et al.* (2015) sets the coefficient equal to 2, while Krishnapuram *et al.* (2001) recommends a value between 1 and 1.5.

[3] Internal CVIs only consider the partitioned data and try to define a measure of cluster purity, whereas external CVIs compare the obtained partition to the correct one. Thus, external CVIs can only be used if the ground truth is known.

4. Clusters Results

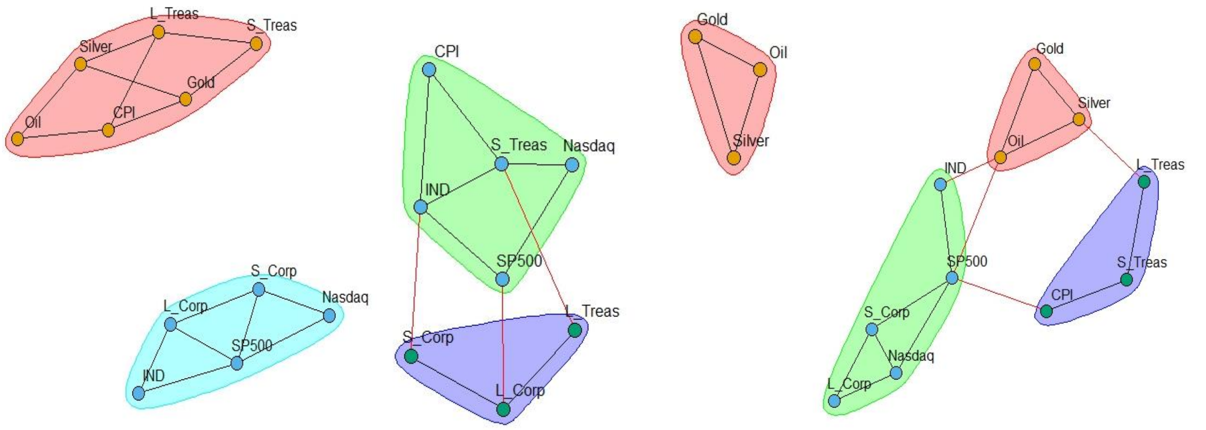
4.1 Asset Classes

To bring perspective on our methodologies, we first implement our clustering approach with broader asset classes. Our first set includes traditional stock indices (S&P500 and NASDAQ), the short and long end of the US yield curve, corporate bonds (long and short dated), commodities (oil, gold, silver) and also include industrial production along with CPI inflation. Following the regimes found in Figure 1, we break down the whole sample in three periods, 1973-1982, 1983-2008, 2009-2021[4], and display the networks of clusters found using Community Detection Method. The Louvain communities are based on network inputs, with $k = 2$, i.e. allowing for maximum granularity.

Figure 2 displays the clusters for the three periods. The first cluster in the first sample (1973-1982), indicates a strong correlation between inflation and the three commodities, gold, silver, and oil, supporting the strategy of using commodities as inflation hedges during the two oil crises. The inclusion of both short and long-term treasuries yields reflect that fact that fixed-income securities typically have an inverse relationship with inflation. The second cluster that includes together stocks and industrial production suggests that overall equity performance was more closely tied to real economic output during this decade. In the second sample, 1983-2008, commodities are still grouped together, but separated from CPI, which is now clustered with equities and industrial production, indicating that inflation rates were less directly related to commodities but more to economic growth. The last period 2009-2021 sees CPI clustering only with treasury rates, pointing to the positive correlation between inflation rates, which remained low in the aftermath of the Great financial crisis, and (decreasing) yields. Overall, this preliminary analysis highlighted the time varying co-dynamics between asset classes and economic variables. The shifts in the clustering of CPI from commodities to equities and then to treasuries suggests that the dynamics of asset classes did change over time, underlying the potential guidance of historical patterns for investment decisions.

[4] We exclude from this analysis the last two years of our sample (characterised by a high inflation regime).

Figure 2: Cluster Networks and Communities for Asset Classes



Notes: Periods are 1973-1982 (left panel), 1983-2008 (middle panel), 2009-2023 (right panel). Stock indices: S&P500 and NASDAQ, the short and long end of the US yield curve (S_Treas, L_Treas), corporate bonds (the ICE BofA US Corporate Index): 1-3 year (S_Corp), 15+year (L_corp), commodities (Oil, Gold, Silver), industrial production (IND) and inflation (CPI). All series are expressed as y-o-y growth rates. Sources: Datastream, FRED.

4.2 Industries Clusters

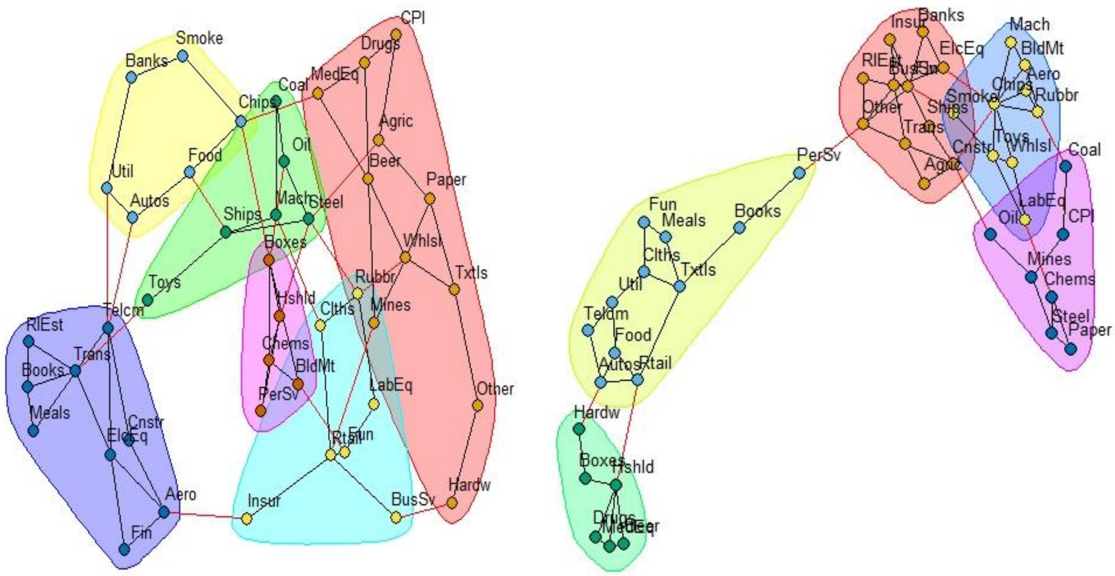
As in Bouaddi and Taamouti (2013), we now use the portfolios of industries provided by Kenneth French on his website[5]. The 49 industries portfolios are built from the NYSE, AMEX, and NASDAQ stocks each year based on the four-digit SIC codes and provide monthly returns from 1947 onwards. This is, to our knowledge, the longest historical financial dataset publicly available. Given the "high regime" inflation episodes found previously, we focus our analysis on two sample periods: 1947-1952, 1973-1982. We compute the year-over-year returns to reduce the amount of noise in the dataset. Moreover, given that we want to build portfolios, one also needs to consider the number of industries within each cluster, and more particularly in the CPI cluster. For the Louvain Community Detection, while several of the best-performing CVIs were used[6], no majority was achieved. Setting k =2, allowing for more granularity, yields a maximum of five clusters, and therefore an average of nine industries per cluster, which we deem reasonable for portfolio construction. As for Fuzzy partitions, we follow the

[5] Retrieved from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html.

[6] We used the Silhouette index, Elbow Index, Gap Statistic index Dunn index, Calinski-Harabasz index, COP index, Davies-Bouldin index.

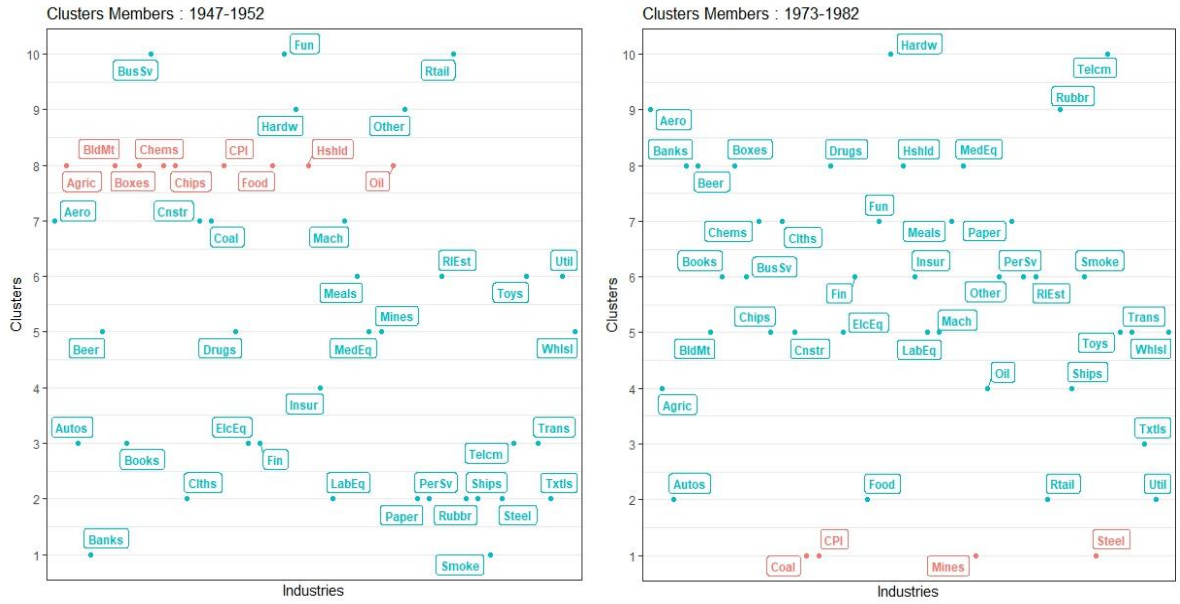
nomenclature in Wang and Zhang (2007) and use internal CVIs. However, given the constraint on the number of industries per cluster, we decided to set the maximum number of clusters to 10. Among the four internal CVIs used, three of them selected this maximum. Therefore, with 10 clusters for each period, we expect Fuzzy C-medoids clustering to provide a complementary perspective to the Louvain Community Detection algorithm.

Figure 3: Community Networks for the periods 1947-1952 and 1973-1982



Notes: 1947-1952 (left panel), 1973-1982 (right panel). The 49 industries are displayed following the names in Kenneth French's dataset. All industries returns are computed as y-o-y growth rates. *k*, the number of nearest neighbors is set equal to 2. Louvain communities are identified with identical colored nodes. Circles are drawn for illustration purposes.

Figure 4: Fuzzy network for the period 1947-1952 and 1973-1982



Notes: 1947-1952 (left panel), 1973-1982 (right panel). The 49 industries are displayed following the names in Kenneth French's dataset. All industries returns are computed as y-o-y growth rates. Fuzzy clusters are shown horizontally from 1 to 10. The fuzziness exponent is set to 1.5 The CPI cluster with its components is identified in red.

Figure 2 displays the network graphs with nodes and edges and clustered members optimized by the Louvain Community Detection algorithm, while Figure 3 displays the Fuzzy C-medoids clustering algorithm outputs, where the fuzzy partition is transformed into its equivalent sharp partition, and the list of industries for each cluster is then displayed horizontally. For the 1947-1952 period, the CPI cluster given by the Louvain method is tightly focused on consumer staples and essential goods industries (e.g., drugs, agriculture, beverages, paper, textiles) that consumers consistently demand, regardless of economic conditions. The network Fuzzy C-medoids CPIs cluster shows a more diverse picture, including not only consumer staples but also raw materials and industrial sectors like chemicals and oil, therefore reflecting a broader set of equity factors linked to consumer prices. For the 1973-1982 period, the results are less heterogenous. Both clustering methods show that the CPI is related to the raw materials and energy sectors. The CPI cluster in the Louvain Communities Detection graph highlights the strong correlation between CPI, oil, chemicals, steel, and paper, reflecting the economic challenges of the 1970s, with increases in oil prices leading to cost-push inflation that impacted industries reliant on other types of energy, such as chemicals and steel. The inclusion of coal and mines in the Fuzzy C-medoids CPI cluster further underscores the importance of energy and raw materials in driving economic conditions and equity performances during this decade. Overall, whilst the post-war period focus on reconstruction and consumer goods contrasts with the 1970's period emphasis on vulnerability to energy prices, the clustering analysis reveals how various sectors are interconnected and how some consistently correlate with inflationary pressures. Does this mean that the dynamics of stock industries during inflationary periods are similar enough and therefore imply that strategic portfolio construction can help capturing industry risk premia associated with inflation? We now investigate this question and assess if the co-dynamics highlighted in the 1950's and 1970's resulted in the outperformance of inflation clusters during the most recent inflation surge of 2021-2023.

5. Out-of-Sample Industries Portfolios

5.1 Portfolios Optimization

For each cluster computed from the previous analysis, we now compute several portfolios based on different methodologies. We refrain from using Markowitz portfolio optimization methods to allow for more diversification, and thus the following methods are used:

1) *Equal weights*

$$w_k^{EW} = \frac{1}{\sum_{i=1}^{N_{I_c}} I_i} \tag{12}$$

Where I_i represents the industries returns included within the same cluster, which include N_{I_c} industries.

2) *Distance-based weights*

The portfolios weights are based on the DTW distance as calculated in Equation (7) for each industry with regards to all other industries, reflecting the global distance of each industry to the average industry. The bigger the distance, the bigger the weight. This heuristic method allows to increase the differentiation towards other industries. Hence, the weights are given by:

$$D_i = \sum_{j \neq i} d_{ij} \tag{13}$$

$$w_k^{Dist} = \frac{D_i}{\sum_{i=1}^{N_{I_C}} D_i} \tag{14}$$

3) *Distance-based CPI weights*

The weights are based on the DTW distance for each industry with regards to CPI, reflecting the distance of each industry to the inflation rates dynamics. The lower the distance, the bigger the weight. This heuristic method allows to increase the weights to industries most connected with inflation. The weights are given by:

$$D_{i,CPI} = \frac{1}{d_{i,CPI}} \tag{15}$$

$$w_k^{D_{CPI}} = \frac{D_{k,CPI}}{\sum_{i=1}^{N_{I_C}} D_{i,CPI}} \tag{16}$$

4) *Genetic Algorithm weights*

Genetic Algorithm (GA) is well known for its ability to handle complex, multi-modal optimization problems and constraints typically present in portfolio optimization (Chang *et al.*, 2009). The genetic algorithm requires a fitness function to evaluate portfolios. We consider both the expected return and the risk of the portfolio with the use of the Sharpe ratio. The details of the algorithm are given in the Appendix. The next section discusses the results of the out-of-sample back-testing using the optimized weights (period 1947-1952 and 1973-1982) for the period April 2021 to May 2023.

5.2 Portfolios Performances

Table 1 illustrates the Compound Annual Growth Rates (CAGR), annualized volatility, and Sharpe ratio of portfolios for the period from May 2021 to May 2023, where the portfolios weights are computed based on clusters of industries and optimization methods using historical data from the 1947-1952 period. The key observation is that the CPI cluster (Cluster 4) from the Louvain method achieves the best performance for most weighting techniques (Distance, CPI Distance, Equally Weighted). Despite their higher volatilities, the CPI cluster portfolios also achieve the highest Sharpe ratio. The CPI cluster has the highest Sharpe ratio with the distance-based weighting method. Meanwhile, the wide range of CAGRs across different clusters underscores the diversity of portfolio performance, with some showing negative CAGRs.

The Fuzzy method's CPI cluster (Cluster 8) includes a broader mix of essential, cyclical, and technology sectors, and therefore shows higher diversification with lower volatility, but lower return and lower Sharpe ratio. The inclusion of oil and chemicals enhanced returns during the last inflationary episode, whereas other industries more sensitive to interest rate changes have faced headwinds. One should add that uncertainty around the fuzzy methodology was rather high, with no clear-cut probabilities attached to each cluster for many of them, including the CPI cluster. The sharp inflationary spikes followed by declines during the late 1940s is likely to have created an economic environment with different dynamics for stock performance. Industries that do well in inflationary times may not perform as strongly in deflationary periods, and vice versa, fuzzy clustering uncertainty being then the result of a volatile inflation regime. Noteworthy is that none of the Fuzzy CPI clusters achieve top performance since they do not include the top gainer, namely the Coal industry, with an outstanding CAGR of 87% during the last high inflation regime.

Table 1: Portfolios Performances for Louvain and Fuzzy Clusters for the period 2021/05-2023/05.

Algorithm	Louvain Clusters	CAGR	Volatility	Sharpe	Algorithm	Fuzzy Clusters	CAGR	Volatility	Sharpe
Dist	4	16.4%	25.5%	0.52	Dist	7	33.9%	28.5%	1.08
EW	4	10.6%	24.0%	0.31	GA	7	33.7%	27.6%	1.11
CPI_Dist	4	5.2%	22.8%	0.10	EW	7	29.6%	27.0%	0.99
GA	5	5.2%	21.4%	0.10	CPI_Dist	7	29.2%	27.2%	0.96
Dist	5	4.9%	22.7%	0.08	Dist	8	5.8%	18.9%	0.15
GA	4	4.1%	23.9%	0.05	EW	8	5.0%	18.5%	0.11
EW	5	3.9%	22.4%	0.04	GA	5	4.5%	16.6%	0.09
GA	6	3.5%	19.7%	0.03	CPI_Dist	8	4.0%	17.8%	0.06
CPI_Dist	5	3.0%	21.6%	0.00	CPI_Dist	9	4.0%	20.2%	0.05
Dist	6	1.0%	19.2%	-0.11	EW	9	3.9%	20.3%	0.05
CPI_Dist	6	1.0%	18.0%	-0.11	Dist	9	3.9%	20.4%	0.05
EW	6	0.5%	19.1%	-0.13	CPI_Dist	5	3.8%	17.4%	0.05
GA	2	-0.7%	14.5%	-0.25	GA	9	3.7%	23.2%	0.03
GA	1	-1.1%	16.4%	-0.25	EW	5	3.5%	16.9%	0.03
EW	2	-1.1%	17.1%	-0.24	Dist	5	2.9%	16.4%	0.00
Dist	2	-1.5%	17.9%	-0.25	GA	8	1.9%	18.7%	-0.06
CPI_Dist	2	-1.6%	15.4%	-0.30	GA	1	1.4%	20.5%	-0.08
CPI_Dist	1	-1.9%	16.7%	-0.30	CPI_Dist	1	-1.3%	19.5%	-0.22
EW	1	-2.4%	16.2%	-0.34	EW	1	-3.5%	19.3%	-0.34
Dist	1	-2.5%	16.2%	-0.34	GA	2	-4.1%	25.4%	-0.28
EW	7	-2.6%	20.1%	-0.28	Dist	1	-4.1%	19.3%	-0.37
Dist	7	-2.8%	20.2%	-0.29	EW	2	-5.8%	23.1%	-0.38
CPI_Dist	7	-3.2%	20.1%	-0.31	Dist	2	-5.9%	23.2%	-0.38
EW	3	-9.9%	21.2%	-0.61	CPI_Dist	2	-6.1%	22.6%	-0.40
CPI_Dist	3	-9.9%	20.7%	-0.62	CPI_Dist	6	-9.4%	19.2%	-0.65
Dist	3	-10.3%	21.8%	-0.61	Dist	3	-9.5%	24.9%	-0.50
GA	7	-11.8%	21.5%	-0.69	EW	6	-9.6%	19.8%	-0.64
GA	3	-19.9%	23.8%	-0.96	EW	3	-9.6%	24.3%	-0.52
					Dist	6	-9.9%	20.3%	-0.63
					CPI_Dist	3	-11.1%	22.6%	-0.62
					GA	3	-11.3%	22.2%	-0.64
					EW	10	-12.8%	24.9%	-0.63
					Dist	10	-12.8%	25.8%	-0.61
					CPI_Dist	10	-12.8%	23.6%	-0.67
					GA	10	-13.5%	31.5%	-0.52
					GA	6	-22.5%	23.8%	-1.08

Notes: Compound Annual Growth Rates (CAGR), annualized volatility, and Sharpe ratio of portfolios for the period from May 2021 to May 2023. Sharpe ratios are calculated with a risk-free rate of 3%. Portfolios weights are computed based on clusters of industries and algorithm methods using historical data from the 1947-1952 period. Cluster 4 and Cluster 8 represent the CPI cluster for Louvain and Fuzzy C-medoid respectively.

Table 2: Portfolios Performances for Louvain and Fuzzy Clusters for the period 2021/05-2023/05

Algorithm	Cluster	CAGR	Volatility	Sharpe	Algorithm	Cluster	CAGR	Volatility	Sharpe
GA	5	30.1%	35.0%	0.77	Dist	5	41.0%	34.9%	1.09
Dist	5	29.2%	31.0%	0.84	EW	5	37.6%	33.8%	1.02
EW	5	23.6%	29.3%	0.70	CPI_Dist	5	33.6%	33.4%	0.92
CPI_Dist	5	17.7%	28.2%	0.52	GA	5	21.3%	29.2%	0.63
GA	3	0.4%	14.2%	-0.18	Dist	10	-1.1%	19.5%	-0.21
Dist	3	-0.1%	15.3%	-0.20	EW	10	-1.5%	19.5%	-0.23
EW	3	-0.4%	15.4%	-0.22	CPI_Dist	10	-1.6%	19.3%	-0.24
CPI_Dist	4	-0.9%	18.9%	-0.20	GA	1	-2.0%	17.7%	-0.28
CPI_Dist	3	-1.0%	15.4%	-0.26	CPI_Dist	8	-2.5%	18.4%	-0.30
EW	4	-1.2%	19.4%	-0.22	GA	7	-2.7%	27.2%	-0.21
Dist	4	-1.4%	19.3%	-0.23	CPI_Dist	7	-2.7%	19.4%	-0.29
GA	1	-2.8%	19.6%	-0.30	GA	2	-3.2%	21.9%	-0.28
Dist	1	-3.1%	19.8%	-0.31	EW	2	-3.3%	21.9%	-0.29
EW	1	-3.5%	19.7%	-0.33	CPI_Dist	2	-3.4%	22.0%	-0.29
CPI_Dist	1	-3.6%	19.5%	-0.34	Dist	1	-3.4%	16.1%	-0.40
GA	4	-4.6%	19.9%	-0.38	EW	8	-3.4%	17.9%	-0.36
CPI_Dist	2	-7.6%	17.3%	-0.61	Dist	2	-3.5%	22.1%	-0.30
EW	2	-8.2%	19.4%	-0.58	EW	1	-3.6%	16.2%	-0.41
Dist	2	-8.3%	19.8%	-0.57	Dist	8	-3.9%	17.9%	-0.38
GA	2	-8.5%	20.4%	-0.56	EW	7	-4.1%	23.4%	-0.30
					CPI_Dist	1	-4.2%	16.0%	-0.45
					Dist	7	-4.3%	24.1%	-0.30
					GA	10	-4.7%	20.3%	-0.38
					GA	8	-6.8%	19.2%	-0.51
					CPI_Dist	3	-6.9%	21.1%	-0.47
					GA	9	-7.1%	17.3%	-0.59
					EW	6	-7.1%	24.6%	-0.41
					EW	9	-7.2%	17.3%	-0.59
					CPI_Dist	6	-7.3%	24.1%	-0.43
					Dist	3	-7.6%	20.8%	-0.51
					Dist	9	-7.6%	17.3%	-0.61
					Dist	6	-7.7%	25.0%	-0.43
					EW	3	-7.7%	21.0%	-0.51
					CPI_Dist	9	-8.2%	17.4%	-0.64
					GA	3	-10.6%	22.6%	-0.60
					GA	6	-11.7%	24.9%	-0.59

Notes: Compound Annual Growth Rates (CAGR), annualized volatility, and Sharpe ratio of portfolios for the period from May 2021 to May 2023. Sharpe ratios are calculated with a risk-free rate of 3%. Portfolios weights are computed based on clusters of industries and algorithm methods using historical data from the 1973-1982 period. Cluster 5 represents the CPI cluster for both Louvain and Fuzzy C-medoid.

Table 2 illustrates the Compound Annual Growth Rates (CAGR), annualized volatility, and Sharpe ratio of portfolios for the period from May 2021 to May 2023, where the portfolios weights are computed based on clusters of industries and optimization methods using historical data from the 1973-1982 period. The CPI cluster for both methods (Cluster 5) achieves the best performance across all optimization techniques (Distance, CPI Distance, Equally Weighted, Genetic Algorithm). Both clustering methods identify a high-performing CPI cluster, showing the highest CAGR and Sharpe ratios. The Fuzzy clustering method provides the highest returns and best risk-adjusted performances, albeit with slightly higher volatility, which may be the consequence of a focus on cyclical industries (coal, oil, steel, mines) that showed the strongest performances during the energy crisis. The mix of cyclical and more stable (chemicals, paper) industries given by the Louvain Method provides a more balanced portfolio that may be suitable for investors with lower risk appetite. These results may influence investment strategies where investors might need to balance the higher potential returns of CPI clusters by diversifying with lower-volatility investments, or by employing hedging strategies to manage volatility risk. Overall, both clustering methodologies succeed to leverage the co-dynamics between inflation and some selected industries, suggesting that one can use past inflationary episodes in order to build outperforming CPI-focused industries portfolios. Moreover, the results of our portfolios returns are significantly better when using the 1972-1983 period as benchmark, which may indicate that the most recent inflation period is more reminiscent of the 70's, with the energy crises as the main drivers of equity returns. In the next section, we provide some comparison and robustness analyses, where we assess first if CPI clusters industries have better hedging properties than commodities-based portfolios, and finally we extend our analysis during the very last part of the sample, where inflation has subdued and moved out of its high regime.

5.3 Industries vs. Commodities-based Portfolios

Table 3 illustrates the Compound Annual Growth Rates (CAGR), annualized volatility, and Sharpe ratio of portfolios for the period from May 2021 to May 2023, where the portfolios weights are computed from three commodities: gold, oil, and silver, optimized using historical data from the 1973-1982 period. The GA optimization technique achieves the highest CAGR with almost 8% per year and a Sharpe ratio of 0.26. Overall, the returns and Sharpe ratio are lower compared to the industry portfolios, albeit in line with their safe heaven properties, despite some heterogeneity. Events such as the Russia-Ukraine conflict, trade tensions between the US and China, and other regional conflicts spurred demand for gold (+5%) and oil (+9%).

Table 3: Commodities Portfolios Performances for the period 2021/05-2023/05

Algorithm	CAGR	Volatility	Sharpe
GA	7.9%	19.1%	0.26
CPI_Dist	7.6%	19.9%	0.23
EQ	6.0%	16.5%	0.18
Dist	5.5%	16.3%	0.15

Notes: Compound Annual Growth Rates (CAGR), annualized volatility, and Sharpe ratio of portfolios for the period from May 2021 to May 2023. Sharpe ratios are calculated with a risk-free rate of 3%. Portfolios weights are computed based on clusters of industries and algorithm methods using historical data from the 1973-1982 period.

We now focus on the second part of 2023, where inflation moved from its high to medium regime, below the 4% threshold. Table 4 displays the CAGR, annualized volatility and Sharpe ratio of the previous portfolios for the period May to December 2023. The CPI clusters show significantly high returns, with the Fuzzy method achieving up to 55.7% CAGR and exceptionally high Sharpe ratios, indicating excellent risk-adjusted returns. Whist all industries benefitted from extended favorable market conditions, CPI clustered industries provided significantly stronger returns and more favorable risk-adjusted performances, meaning that these industries succeeded in maintaining their profit margins and performance even past the acute inflationary environment. In contrast, all commodities-based portfolios resulted in negative returns for the last year of our sample as shown in Table 5. As economic conditions evolved, the factors driving demand for commodities shifted rapidly. Whilst the earlier part of the period benefitted from safe-haven demand and inflation concerns, the second part of 2023 saw the poor performance of commodity portfolios due to uncertainty in monetary policies among other economic, geopolitical, and structural factors. Only gold returned more than 5% per year during the broader period from May 2021 to December 2023.

Overall, the analysis underscores the added value of diversified industries portfolios over commodities-based investments for achieving superior investment outcomes. During the last commodities shocks, operational performance boosted overall profitability of energy and cyclical industries, translating into high equity returns. Moreover, our results also highlight the importance of looking beyond commodity prices to understand the full scope of factors influencing valuations in the energy sector.

Table 4: Portfolios Performances for Louvain and Fuzzy Clusters for the period 2023/05-2023/12

Algorithm	Cluster	CAGR	Volatility	Sharpe	Algorithm	Cluster	CAGR	Volatility	Sharpe
GA	5	47.3%	22.0%	2.02	Dist	5	55.7%	20.4%	2.59
Dist	5	46.4%	18.9%	2.30	EW	5	52.3%	19.6%	2.52
EW	5	41.7%	18.4%	2.11	CPI_Dist	5	49.4%	19.5%	2.39
CPI_Dist	5	37.5%	18.6%	1.86	GA	5	39.9%	18.3%	2.01
GA	1	30.5%	20.0%	1.37	Dist	3	31.9%	23.7%	1.22
Dist	1	29.7%	20.7%	1.29	CPI_Dist	3	31.7%	24.0%	1.20
EW	1	29.1%	20.4%	1.28	EW	3	31.3%	23.9%	1.19
CPI_Dist	1	28.7%	19.7%	1.30	Dist	10	27.9%	19.5%	1.28
EW	4	28.4%	20.7%	1.22	GA	10	27.8%	19.9%	1.24
Dist	4	28.1%	20.7%	1.22	CPI_Dist	6	27.5%	23.8%	1.03
CPI_Dist	4	28.0%	20.2%	1.23	EW	6	27.1%	23.3%	1.03
GA	4	25.7%	20.9%	1.09	EW	10	27.0%	19.3%	1.24
GA	2	17.4%	17.6%	0.82	Dist	6	26.5%	23.1%	1.02
CPI_Dist	3	16.7%	13.7%	1.00	CPI_Dist	10	25.5%	18.9%	1.19
EW	3	15.9%	13.5%	0.95	GA	6	25.2%	24.4%	0.91
Dist	2	15.5%	17.8%	0.70	CPI_Dist	1	23.9%	15.2%	1.38
EW	2	15.4%	17.8%	0.70	EW	1	23.0%	15.0%	1.34
Dist	3	15.3%	13.5%	0.91	Dist	1	22.7%	14.9%	1.32
CPI_Dist	2	14.5%	15.8%	0.73	GA	3	22.6%	24.0%	0.81
GA	3	12.4%	12.2%	0.77	GA	8	21.7%	15.4%	1.21
					GA	2	18.7%	24.4%	0.64
					EW	2	18.6%	24.4%	0.64
					CPI_Dist	2	18.4%	24.5%	0.63
					CPI_Dist	8	18.4%	13.7%	1.13
					GA	1	18.2%	15.7%	0.97
					Dist	2	18.2%	24.7%	0.61
					Dist	8	18.0%	13.8%	1.08
					EW	8	18.0%	13.7%	1.09
					GA	9	16.6%	11.7%	1.16
					EW	9	16.6%	11.7%	1.16
					Dist	9	16.5%	11.7%	1.15
					CPI_Dist	9	16.4%	11.7%	1.14
					Dist	7	10.1%	21.8%	0.32
					EW	7	9.8%	21.4%	0.32
					CPI_Dist	7	8.2%	18.7%	0.28
					GA	7	-2.5%	27.3%	-0.20

Notes: Compound Annual Growth Rates (CAGR), annualized volatility, and Sharpe ratio of portfolios for the period from May 2021 to May 2023. Sharpe ratios are calculated with a risk-free rate of 3%. Portfolios weights are computed based on clusters of industries and algorithm methods using historical data from the 1973-1982 period.

Table 5: Commodities Portfolios Performances for the period 2023/05-2023/12

Algorithm	CAGR	Volatility	Sharpe
Dist	-2.0%	4.3%	-0.33
EQ	-2.2%	4.1%	-0.36
GA	-2.9%	4.2%	-0.40
CPI_Dist	-3.9%	4.6%	-0.44

Notes: Compound Annual Growth Rates (CAGR), annualized volatility, and Sharpe ratio of portfolios for the period from May 2021 to May 2023. Sharpe ratios are calculated with a risk-free rate of 3%. Portfolios weights are computed based on clusters of industries and algorithm methods using historical data from the 1973-1982 period.

6. Conclusions

In the context of extreme geopolitical events and sudden shifts in economic environments, building an inflation resilient portfolio is a real challenge. We explored the inflation hedging performance of different equity portfolios by looking at more than 80 years of data with a focus on historical periods of high inflation. Our results suggest that it is possible to build inflation hedged equity only portfolios by studying the cluster dynamics of industries portfolios during « similar » past inflation regimes. This historical perspective can guide modern-day investors in identifying and constructing diversified portfolios, yielding significant gains for investors, even beyond traditional inflation hedges. Having said that, defining « similar » inflation regimes may be tricky as it implies to distinguish between different shocks (supply chain vs. exogenous oil/gas shocks). Relying solely on historical performance during non-recurring economic conditions can result in portfolios that do not align well with current market environments, leading to higher volatility and possibly lower returns. Therefore, investors should be cautious when extrapolating past relationships to future periods, as the factors driving asset performance can evolve, and one should consider sector-specific risks and opportunities. Investment strategies based on network clustering should be then adjusted towards more diversification and incorporate data from multiple historical periods and/or adjust more frequently to reflect changing economic conditions. Finally, future research on the topic of portfolio management and macroeconomic regimes should also incorporate contemporary economic indicators along with historical indicators into the investment decision-making process in order to better capture the economic momentum.

7. Appendix

The Genetic Algorithm for the portfolio optimization exercise in Section 5 is implemented as follows:

a) Initialization

Generate an initial population of portfolios. Each portfolio is represented as a chromosome with genes corresponding to the weights of assets in the portfolio. Each chromosome represents a potential portfolio with weights assigned to each asset. The chromosome structure is a vector of weights.

b) Selection

Tournament selection chooses parent portfolios for reproduction. This method selects the best portfolios from randomly chosen subsets of the population, ensuring a balance between exploration and exploitation.

c) Crossover and Mutations

Apply crossover and mutation operators to generate new portfolios. Crossover combines parts of two parent portfolios to produce offspring, while mutation introduces small random changes to the offspring to maintain genetic diversity.

$$\boldsymbol{w}_{child} = (\boldsymbol{w}_{parent1}[1:k], \boldsymbol{w}_{parent2}[1:k]) \tag{17}$$

Random changes are introduced to some portfolios to maintain genetic diversity. A typical mutation operation alters the weight of a randomly selected asset:

$$\boldsymbol{w}_k = \boldsymbol{w}_{child} + \delta \tag{18}$$

Where δ is a small random perturbation.

d) Replacement

Replace the least fit portfolios in the population with new offspring, ensuring that the population evolves towards better solutions over generations.

e) Convergence

Repeat the selection, crossover, mutation, and replacement steps until convergence criteria are met, such as a maximum number of generations or a threshold improvement in the best portfolio fitness.

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