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Abstract

This paper introduced a novel methodology for measuring nonlinear Granger causality in macroeconomic time series by combining Multivariate Singular Spectrum Analysis (MSSA) for data denoising with Artificial Neural Network (ANN) input occlusion for causal inference. We applied this framework to five countries, analyzing key macro-financial variables, including yield curve latent factors, equity indices, exchange rates, inflation, GDP, and policy rates. MSSA enhanced data quality by maximizing signal-to-noise ratios while preserving structural patterns, resulting in more stable ΔMSE values and reduced error variability. ANNs were trained on MSSA-denoised data to predict each target variable using lagged inputs, with input occlusion evaluating the marginal predictive contribution of each input to derive causality p-values. This approach outperformed traditional VAR-based Granger causality tests, identifying 38 significant causal relationships compared to 24 for VAR. Cross-country analysis of variables revealed differences in transmission mechanisms, monetary policy effectiveness, and growth-inflation dynamics. Notably, feature importance rankings showed that policy rates and stock market indices predominantly drove macroeconomic outcomes across countries, underscoring their critical role in economic dynamics. These findings demonstrated that combining MSSA and ANN input occlusion offered a robust framework for analyzing nonlinear causality in complex macroeconomic systems.

Keywords: *Nonlinear Granger causality, Input Occlusion,* Multiple Singular Spectrum Analysis, p-values

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1. Introduction

This study examined the complex interactions among key macroeconomic variables such as yield curve factors (LEVEL, SLOPE, CURVATURE), stock market indices (EQUITY), foreign exchange rates (FX), central bank policy rates (POLRATE), GDP growth rates (GDP), and inflation rates (INF), across five countries: United States (US), United Kingdom (UK), Egypt (EGP), Mexico (MEX), and South Africa (SAF). Macroeconomic systems are inherently nonlinear, with intricate relationships that linear models, such as traditional Granger causality, often fail to capture. These models struggle to account for the noisy nature of economic data, which can obscure underlying causal patterns and limit the accuracy of economic forecasts. To address these challenges, we proposed an innovative methodology that combined Multivariate Singular Spectrum Analysis (MSSA) for denoising with Artificial Neural Network (ANN)-based input occlusion to assess nonlinear Granger causality, providing a robust framework for economic dynamics.

MSSA decomposed time series into trend, seasonal, and noise components, enhancing signal clarity by filtering out irregularities. The denoised data was then analyzed using an ANN framework, where input occlusion systematically masked predictor variables to quantify their causal impact on target variables. This approach leveraged the flexibility of ANNs to model complex, nonlinear relationships and the interpretability of occlusion to isolate causal effects. By combining these techniques, our study filled a critical gap in the literature, to the best of our knowledge, no prior work has integrated MSSA denoising with ANN-based input occlusion for macroeconomic causality analysis. By applying this method across multiple countries, we demonstrated that our approach detected a richer and more economically meaningful set of causal structures than traditional linear methods, highlighting the critical role of denoising and model interpretability in modern macroeconomic analysis.

2. Literature Review

This literature review examined Granger causality testing, and input occlusion methods. We first surveyed linear and nonlinear Granger causality applications in macroeconomic forecasting, highlighting their strengths and limitations. Next, we discussed the critical need for denoising macroeconomic data. Finally, we explored input occlusion techniques, from computer vision, and their potential adaptation for nonlinear Granger causality in the context of economic analysis. By systematically evaluating these connected methodologies, we identified a significant gap in academic literature that was filled by our study.

Several studies demonstrated the application of linear Granger causality to macroeconomic linkages. Plihal (2016) identified the stock market as a predictor for industrial production and interest rates. Shareef & Shijin (2017) employed Granger causality alongside impulse response and variance decomposition to analyze Indian yield curve factors and macro variables. Coroneo et al. (2016) reported US economic growth Granger causing yield curve factors. Similarly, Jammazi et al. (2017) found bidirectional causality between the US 10-year Treasury yield and the stock market. Ahmed et al. (2017) applied the same techniques in Pakistan, concluding that interest rates Granger cause stock market movements. These studies relied on linear Granger causality, potentially overlooking complex nonlinear interactions inherent in economic systems. Recognizing the limitations of linear models in capturing complex dynamics, researchers increasingly moved towards nonlinear Granger causality methods.

The adoption, by academic scholars, of nonlinear causality methods addressed potential oversights of linear models. Papagiannopoulou et al. (2017) employed a kernel-based Granger causality framework to investigate climate vegetation interactions, uncovering feedback mechanisms that linear tests would have missed. Karagianni & Pempetzoglou (2009) applied Hiemstra-Jones nonlinear Granger causality to Turkish defense spending and economic growth, finding that defense spending only Granger caused growth in the nonlinear case, contradicting their linear results. Quaye et al. (2023) used wavelet based nonlinear Granger causality within an interconnectedness framework to analyze FDI and sustainable development, revealing bidirectional causality that linear tests failed to detect. Similarly, Hamid & Jena (2020) applied the Diks-Panchenko non-parametric test to India's FDI and growth relationship, finding no linear causality but significant nonlinear effects, suggesting that traditional methods underestimated these linkages. Rahimi et al. (2017) adopted a rolling-window nonlinear Granger causality approach to study short-term and long-term US interest rates, demonstrating that the relationship evolved over time, a behavior that static linear models cannot capture.

Macroeconomic data are inherently noisy, distorting causal inference and necessitating robust denoising techniques. Singular Spectrum Analysis (SSA) and its multivariate extension (MSSA) have proven effective for this purpose, as demonstrated by Hassani (2007), who extracted business cycle signals from noisy U.S. industrial production data using SSA to isolate trend, seasonal, and irregular components. Building on denoised data, input occlusion methods, originally developed for computer vision, have emerged as tools for interpreting complex models. Zeiler and Fergus (2014) pioneered occlusion by systematically masking image regions to identify critical features in CNNs, while Ancona et al. (2018) later formalized gradient-based attribution variants. Frequently applied to image data, the technique could also be extended to other types of inputs. Ismail et al. (2020) benchmarked occlusion in time series, revealing sensitivity to noise and lag specification. Though applied in image hierarchies (Khormuji & Rostami, 2022) and structured vision tasks like face parsing (Qiu et al., 2024), these methods remain largely untested in macroeconomics. From that standpoint, there is an academic literature gap on the integration of input occlusion with ANN-based nonlinear Granger causality on MSSA-denoised macroeconomic data to interpret causal p-values.

This literature review revealed that while nonlinear Granger causality and denoising methods have been separately applied to macroeconomic data, and while input occlusion has proven valuable in other domains, no existing study combined these approaches. This represented a critical methodological gap, as macroeconomic systems benefit from approaches that can simultaneously handle their noisy nature and nonlinear relationships. Our proposed integration of MSSA denoising, ANN-based nonlinear Granger causality, and adapted input occlusion method offered an innovative solution that would capture complex economic relationships.

3. Research Methodology

3.1. Data Sources

We conducted our analysis based on monthly data from 2006 until 2019. Our period of study captured different economic cycles, and the mortgage crisis in 2008-2009, as well as the European recession in 2012-2013. All observations that we have gathered were on a monthly basis, except for the GDP growth rates that were on a quarterly basis. Hence, we transformed the GDP frequency from monthly to quarterly using Cubic Splines, as they performed well in the GDP monthly transformation performed by Kaya (2013). The FX was modeled in terms of direct exchange rate, showing how much one unit of home currency was worth in foreign currency ($). The correlation matrix of standardized returns was used when computing the PCA on the different yield curves, and the first three latent factors were extracted for each studied country.

3.2. MSSA for Data Denoising

3.2.1. MSSA Algorithm

MSSA, an extension of Singular Spectrum Analysis (SSA) for multivariate time series, breaks down each variable into trend, seasonal, and noise components (Golyandina et al., 2001; Hassani, 2007). The process involved several steps: First, each time series was transformed into a matrix called a trajectory matrix, by selecting a window length, which determined how many data points were grouped together to form rows of the matrix. The trajectory matrix was then broken down using a Singular Value Decomposition (SVD), splitting the matrix into components that represented different patterns in the data, such as trends or seasonal cycles, ranked by their contributions. Afterwards, the components were categorized into three groups: trend, seasonal patterns, and noise. The number of components selected ensured that a sufficient portion of the data's structure was captured. Finally, the selected trend and seasonal components were combined to create a denoised version of the time series.

3.2.2. Parameter Optimization

We tested multiple window lengths (24, 36, 48, and 60 months), variance thresholds (80%, 85%, and 90% of the data's structure), and number of components (from 2 to 14). For each variable, we selected the combination of parameters that maximized a scoring metric balancing two measures: Signal-to-Noise Ratio (SNR) and Mean Absolute Deviation (MAD).

SNR measured how much of the denoised signal's strength (its variability) was preserved compared to the noise's strength (the variability of the residuals, i.e., the difference between the original and denoised series). A higher SNR, measured in decibels (dB), indicated better denoising. On the other hand, MAD measured the average absolute difference between the original and denoised series, reflecting the amount of noise removed. A lower MAD indicated better noise reduction. The scoring metric was defined as SNR minus 0.1 times scaled MAD, prioritizing high SNR while penalizing excessive residuals. The MSSA-denoised data was used as input for the ANN input occlusion Granger causality analysis to compute the p-values.

3.3. ANN Input Occlusion for Nonlinear Granger Causality P-Values

The proposed method extended traditional Granger causality by capturing nonlinear relationships through ANN modeling and assessing causality via input occlusion, following methodologies adapted from studies in machine learning interpretability (Zeiler & Fergus, 2014; Ancona et al., 2018). Based on the MSSA denoised data, all variables were standardized using the z-score method, apart from the yield curve factors that were already normalized.

3.3.1. Architecture and Training

For each target variable, a separate ANN model was constructed to predict its value based on lagged values of all other variables. The input data was structured to include 12 lagged time steps for each predictor variable. The ANN architecture consisted of an input layer, one hidden layer with 32 neurons using the hyperbolic tangent (tanh) activation function, and a linear output layer to predict the target variable. Layer normalization was applied after the hidden layer to stabilize training and improve convergence, and an L2 regularization with a strength of 0.01 was used. Weights were initialized using a random normal distribution with a standard deviation of 0.05 to ensure consistent starting conditions. Each model was trained for 300 epochs using the Adam optimizer with a learning rate of 0.001 and a gradient clipping norm of 1.0. The mean squared error (MSE) was used as the loss function. To ensure optimal model performance, the weights yielding the lowest MSE during training were saved and restored for subsequent occlusion analysis.

3.3.2. Causality Assessment

For each target variable, the trained ANN model was used to compute a baseline MSE using the full input data. Then, for each predictor variable, a random subset of its lagged values (between 1 and 12 lags) was occluded by setting the corresponding input values to zero. This occlusion was repeated 100 times with different random lag combinations to generate a distribution of MSE differences (ΔMSE) compared to the baseline (ΔMSE = Occluded MSE - Baseline MSE). The ΔMSE reflected the increase in prediction error when the predictor's information was removed, indicating its causal influence on the target variable. Unique occlusion patterns were enforced by tracking and excluding repeated lag combinations. The statistical significance of the ΔMSE was evaluated using a one-sided t-test, testing whether the mean ΔMSE was significantly greater than zero, indicating that the occluded predictor contributed to predicting the target variable. The resulting p-values represented the nonlinear Granger causality, with lower p-values suggesting stronger causal relationships. This methodology leveraged the flexibility of ANNs to model complex, nonlinear dynamics, while using occlusion to isolate the causal impact of individual predictors, providing a robust framework for Granger causality analysis in macroeconomic time series.

3.4. Feature Importance Analysis

To evaluate the relative importance of each predictor variable in the nonlinear Granger causality framework, a feature importance analysis was conducted based on the mean ΔMSE obtained from the ANN input occlusion process. This approach quantified the contribution of each predictor variable to the prediction of a target variable by assessing the increase in prediction error when the predictor's lagged values are occluded, building on methodologies for feature attribution in neural networks (Lundberg & Lee, 2017).

For each target variable and its corresponding predictor variables, the mean ΔMSE was calculated by averaging the ΔMSE values across all occlusion iterations. A higher mean ΔMSE indicated a greater increase in prediction error when the predictor was occluded, suggesting that the predictor has a stronger influence on the target variable's prediction. This approach was consistent with feature importance methods that measured the impact of altering input features on model performance

(Ribeiro et al., 2016). To facilitate the interpretation, the predictor variables were ranked within each target variable group based on their mean ΔMSE values, with the highest mean ΔMSE assigned the rank of 1, indicating the most important predictor, and so forth. This method offered a robust measure of feature importance that accounted for the variability introduced by random occlusion patterns, enhancing the interpretability of the ANN-based causality analysis (Tank et al., 2022).

4. Results

4.1. MSSA Denoised Data Results

4.1.1. Comparison between Raw Vs MSSA Data

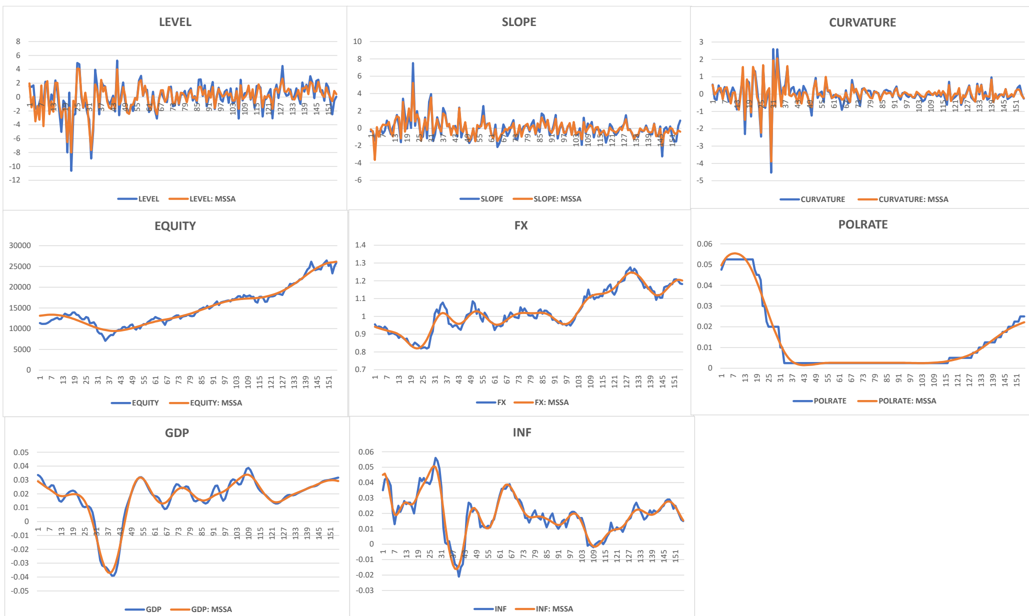

Figure 4.1 Raw Data vs MSSA Data

Figure 4.1 illustrated each variable raw data vs MSSA denoised data for the US country as an example. We concluded that the LEVEL raw data exhibited more erratic fluctuations and less structural form. Its MSSA revealed smoother long-term trends, suggesting clearer identification of business cycles. Additionally, the SLOPE and CURVATURE showed substantial short-term noise in raw form, especially during volatile financial periods (e.g., 2008 crisis). Their MSSA significantly reduced this high-frequency variation, enhancing trend–cycle decomposition. The raw EQUITY displayed high volatility with occasional spikes due to market shocks. Its MSSA preserved long-run growth trends while smoothing out short-run fluctuations, revealing cyclical patterns more effectively. The FX raw series included several sharp deviations, while its MSSA processed series showed smoother transitions, making underlying patterns and regime shifts more distinct. As a policy-driven variable, POLRATE is stepwise in nature with abrupt changes, its MSSA retained the core structure but allowed for better visualization of regime durations and transitions. Raw GDP and INF data were relatively smooth but still contained noise that may obscure nonlinear dependencies. Their MSSA series offered a clearer representation of economic cycles and inflation dynamics.

4.1.2. MSSA Data Impact on Input Occlusion ΔMSE

Table 4.1 ΔMSE Comparison: Raw Data vs MSSA Data

Metric	Raw Data	MSSA Denoised Data
Mean	0.13	0.070
Variance	0.25	0.10
Skewness	1.82	1.12
F-statistic	2.4	
p-value	0.00%	

We calculated in table 4.1 the descriptive statistics of the ΔMSE when the input occlusion was performed on raw data and MSSA denoised data for the US as an example. The mean was calculated by taking all ΔMSE values across all variables (from all occlusion experiments) and computed their arithmetic average. The mean of the ΔMSE values across all variables for the raw data was 0.13 and for the MSSA denoised data it was 0.07.

$$\text{Mean}_{\text{total}} = \frac{1}{N}\sum_{i=1}^{N}\Delta\text{MSE}_i$$

The variance of the ΔMSE values across all variables was also calculated in order to show how volatile or stable the ΔMSE responses were across repetitions and variables. The variance of the ΔMSE values across all variables for the raw data was 0.25 and for the MSSA denoised data it was 0.10.

$$\text{Var} = \frac{1}{N-1}\sum_{i=1}^{N}(\Delta\text{MSE}_i - \text{Mean})^2$$

The skewness was also calculated in order to measure the asymmetry in the distributions, or the presence of outliers or long tails. The MSSA denoised data was less skewed equal to 1.12, vs a skew of 1.82 for raw data.

$$\text{Skewness} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\Delta\text{MSE}_i - \mu}{\sigma}\right)^3$$

The MSSA-denoised data led to significantly more stable ΔMSE values with a lower mean (better average model performance), a lower variance, and a lower skewness (less distortion from extreme errors).

Additionally, we calculated the F-Test (equivalent to approx. 2.4) for variance comparison between both ΔMSEs, by dividing the variance on raw data by the variance of MSSA data, resulting in a p-value=0%. Since the p-value < 0.05, we rejected H0 that the variances were equal. Thus, the variance of the ΔMSE on the MSSA denoised data was significantly lower than it was on raw data.

$$F = \frac{s^2_{\mathrm{raw}}}{s^2_{\mathrm{mssa}}}$$

4.1.3. Combined MSSA Parameters Results

4.1.3.1. Variables Analysis

Table 4.2 MSSA Parameters per Variable

Variable	Most Frequent Window Length	Avg Explained Variance	Avg Components	Avg SNR
POLRATE	24	0.9618	2	16.5605
GDP	24	0.9412	3.4	15.4953
FX	24	0.9402	2.8	14.4035
EQUITY	24	0.9483	2.4	13.972
INF	24, 36	0.923	5.8	12.1246
CURVATURE	24	0.7881	14	7.5281
SLOPE	24	0.7658	14	6.2606
LEVEL	24	0.7539	14	6.0219

Table 4.2 illustrated the most frequent window length per variable, alongside average explained variance, components, and SNR, calculated across the five countries (US, UK, EGP, MEX, SAF). Variables were ordered by denoising quality (best to worst).

1. **POLRATE**:
   - **Denoising Quality**: Most Frequent Window Length = 24, Avg. Explained Variance = 0.9618, Avg. Components = 2.0, Avg. SNR = 16.5605. Best denoising, with the highest SNR, fewest components selected, and highest explained variance, indicating exceptional noise removal and signal preservation. MSSA effectively filtered noise while retaining nearly all signal.
   - **Smoothness and Behavior**: POLRATE MSSA curves were extremely smooth, capturing step-like policy rate changes (e.g., 2008–2009 rate cuts, post-2020 low rates) with minimal noise. Raw series were stable with discrete shifts, closely mirrored by MSSA, ensuring clear trend isolation.
2. **GDP**:
   - **Denoising Quality**: Most Frequent Window Length = 24, Avg. Explained Variance = 0.9412, Avg. Components = 3.4, Avg. SNR = 15.4953. Strong denoising, with high SNR,

few components selected, and high explained variance, indicating effective noise removal and robust signal retention. MSSA isolated growth trends efficiently.

- **Smoothness and Behavior**: GDP MSSA curves were smooth, capturing GDP growth trends and business cycles (e.g., pre-2008 growth, 2008–2009 recession dips, post-2020 recovery) while filtering minor fluctuations. Raw series showed periodic shocks, smoothed by MSSA.

3. **FX**:
    - **Denoising Quality**: Most Frequent Window Length = 24, Avg. Explained Variance = 0.9402, Avg. Components = 2.8, Avg. SNR = 14.4035. Strong denoising, with high SNR, few components selected, and high explained variance, indicating effective noise filtering and signal preservation. MSSA handled exchange rate complexity well.
    - **Smoothness and Behavior**: FX MSSA curves were very smooth, capturing exchange rate trends (e.g., pre-2008 stability, 2008–2009 crisis volatility, post-2020 fluctuations) with minimal short-term noise. Raw series showed moderate volatility, smoothed by MSSA.
4. **EQUITY**:
    - **Denoising Quality**: Most Frequent Window Length = 24, Avg. Explained Variance = 0.9483, Avg. Components = 2.4, Avg. SNR = 13.9720. Strong denoising, with high SNR, few components selected, and high explained variance, indicating effective noise removal and signal retention. MSSA isolated equity market trends robustly.
    - **Smoothness and Behavior**: EQUITY MSSA curves were highly smooth, capturing bull/bear market trends (e.g., pre-2008 growth, 2008–2009 crash, post-2020 recovery) while filtering monthly volatility. Raw series were highly volatile, with MSSA emphasizing major movements.
5. **INF**:
    - **Denoising Quality**: Most Frequent Window Length = 24, 36 (tie), Avg. Explained Variance = 0.9230, Avg. Components = 5.8, Avg. SNR = 12.1246. Good denoising, with moderate SNR and more components selected, balancing noise removal and signal retention. MSSA effectively handled inflation’s complex dynamics.
    - **Smoothness and Behavior**: INF MSSA curves were moderately smooth, capturing inflation trends (e.g., pre-2008 stability, post-2020 spikes) with some retained cyclicality. Raw series showed moderate fluctuations, smoothed by MSSA.
6. **CURVATURE**:
    - **Denoising Quality**: Most Frequent Window Length = 24, Avg. Explained Variance = 0.7881, Avg. Components = 14.0, Avg. SNR = 7.5281. Moderate denoising, with higher SNR than LEVEL/SLOPE but many components selected, balancing noise removal and

retention of yield curve dynamics. Lower explained variance suggested potential signal loss.

- **Smoothness and Behavior**: CURVATURE MSSA curves were moderately smooth, capturing yield curve curvature trends (e.g., humps or troughs) with reduced short-term volatility. Raw series showed frequent fluctuations, with MSSA emphasizing cyclical patterns.

7. **SLOPE**:
   - **Denoising Quality**: Most Frequent Window Length = 24, Avg. Explained Variance = 0.7658, Avg. Components = 14.0, Avg. SNR = 6.2606. Weak denoising, with lowest SNR, high components selected, and low explained variance, indicated noise retention or signal alteration. MSSA was able to moderately capture SLOPE's complex dynamics.
   - **Smoothness and Behavior**: SLOPE MSSA curves were less smooth, retaining cyclical yield curve shifts (e.g., steepening/flattening). Raw series were volatile, with MSSA smoothing minor fluctuations but preserving short-term cycles.

8. **LEVEL**:
   - **Denoising Quality**: Most Frequent Window Length = 24, Avg. Explained Variance = 0.7539, Avg. Components = 14.0, Avg. SNR = 6.0219. Weakest denoising, with low SNR and high component count, suggested retention of complex yield curve dynamics or residual noise. Low explained variance indicated potential signal loss.
   - **Smoothness and Behavior**: LEVEL MSSA curves were moderately smooth, capturing long-term yield curve trends (e.g., rate increases post-2008) but retaining cyclical fluctuations due to many components selected. Raw series showed volatile bond market shifts, with MSSA smoothing short-term noise.

4.1.3.2. MSSA Results Summary and Implications

MSSA denoising was most effective for POLRATE, GDP, FX, and EQUITY, with high SNR, few components, and high explained variance, producing smooth curves that captured trends and cycles (e.g., 2008–2009 crises, post-2020 recovery). INF showed good denoising with moderately smooth curves, though, its higher components count (5.8) reflected country-specific inflation complexity. LEVEL, SLOPE, and CURVATURE exhibited weaker denoising due to high components and lower SNR, with less smooth curves retaining cyclicality. UK excelled in denoising, followed by US, SAF, EGP, and MEX, reflecting differences in economic data stability. For nonlinear Granger causality analysis, MSSA-denoised POLRATE, GDP, FX, and EQUITY were highly suitable.

4.2. Stability of P-Values on MSSA-Denoised Data

Table 4.3 illustrated in the appendix p-values of nonlinear Granger causality tests for pairwise relationships among the eight macroeconomic variables derived from raw data across 100, 200, 300, 400, and 1000 iterations with those from denoised data using MSSA at 100 iterations. The objective was to evaluate the stability and convergence of p-values.

For raw data, p-values exhibited rapid convergence, typically stabilizing by 200–300 iterations. Across most variable pairs, p-values either remained consistently significant or non-significant after 200 iterations, with minimal changes observed at higher iterations (400 and 1000). This suggested that for raw data 200–300 iterations were generally sufficient for p-values to converge to stable values, whether significant or not. In contrast, p-values calculated on MSSA-denoised data at 100 iterations demonstrated remarkable stability. For most variable pairs, these p-values closely aligned with the converged p-values from raw data at 300–1000 iterations, indicating that MSSA denoising enabled faster convergence. The results highlighted the superior efficiency of MSSA-denoised data in nonlinear Granger causality analysis. While raw data p-values stabilized by 200–300 iterations, MSSA-denoised p-values achieved equivalent significance at 100 iterations. This stability was attributed to MSSA's ability to filter out noise, enabling the ANN to focus on underlying causal signals. The consistency between MSSA p-values and converged raw data p-values validated the denoising approach, as it did not change the causal relationships but enhanced their detection. The findings had implications for econometric modeling, suggesting that MSSA preprocessing can reduce computational demands without sacrificing accuracy.

4.3. Comparison between ANN Occlusion and VAR P-Values

Illustrated in table 4.4 in the appendix p-values from both, ANN-based tests on MSSA data, and VAR on the same MSSA data for the US. Based on a statistical significance at $p < 0.05$, we detected 38 significant relationships for the ANN p-values, compared to only 24 for the VAR p-values, which supported the argument that ANN was superior in this context, particularly for capturing nonlinear dynamics. Key potential reasons include the nonlinear sensitivity of the ANN, which VAR's framework often misses due to its reliance on linear assumptions. Additionally, another potential reason could be the MSSA denoising efficiency that enhanced ANN's ability to focus on underlying nonlinear signals, yielding highly significant p-values.

On the other hand, and unexpectedly, VAR detected 7 significant causalities that ANN did not, which could have been caused by the MSSA emphasizing linear components, making them detectable by VAR but not by ANN, or may be that the MSSA over-denoising could have suppressed nonlinear signals critical for ANN. Additionally, the VAR's lag structure could have also captured specific linear temporal dependencies missed by ANN.

Finally, ANN outperformed VAR in detecting causal relationships, identifying 38 significant pairs compared to VAR's 24 at a 5% significance level, due to its sensitivity to nonlinear dynamics and MSSA's denoising benefits. However, VAR's unique detection of 7 significant causalities that ANN did not, highlighted its relevance for linear relationships, suggesting that ANN was not universally superior.

4.4. ANN Granger Causality P-Values & Feature Importance Analysis

In this section, we evaluated both the p-values and feature importance rankings to identify general trends, cross-country patterns, and economic implications for all variables and all countries.

4.4.1. Causality for the LEVEL

Table 4.5 ANN P-Values & Feature Importance for the LEVEL

4.5.a ANN P-Values Y Variable: LEVEL

X Variable	US	UK	EGP	MEX	SAF
SLOPE	0.00%	0.00%	0.00%	0.00%	0.00%
CURVATURE	0.00%	0.00%	0.00%	0.00%	0.00%
EQUITY	0.00%	0.00%	0.00%	0.00%	0.00%
FX	0.00%	0.00%	0.00%	0.00%	0.00%
POLRATE	0.00%	0.00%	0.00%	0.00%	0.00%
GDP	0.00%	0.00%	0.00%	0.00%	0.00%
INF	0.00%	0.00%	0.00%	0.00%	0.00%

4.5.b Feature Importance Y Variable: LEVEL

US	UK	EGP	MEX	SAF
POLRATE	CURVATURE	SLOPE	INF	CURVATURE
INF	FX	POLRATE	GDP	EQUITY
CURVATURE	INF	GDP	POLRATE	GDP
EQUITY	SLOPE	FX	EQUITY	INF
GDP	POLRATE	CURVATURE	CURVATURE	SLOPE
FX	GDP	INF	FX	FX
SLOPE	EQUITY	EQUITY	SLOPE	POLRATE

As it is illustrated in table 4.5.a all variables had statistically significant nonlinear predictive effects on the LEVEL in each country, implying that the LEVEL was a highly endogenous variable. The LEVEL seemed to be strongly affected by its yield curve own factors, SLOPE and CURVATURE for all countries, similar to Sowmya & Prasanna (2018) findings, each highly ranked in the UK, EGP, and SAF, as illustrated in table 4.5.b. The EQUITY had a significant impact in SAF (ranking 2 in SAF), and moderate in the US and MEX (4 in US, 4 in MEX). As one would economically expect, a rally in the EQUITY would cause an increase in wealth, which would cause a rise in spending and inflation. Thus, higher inflationary expectations eventually cause a rise in the LEVEL (Rudebusch & Wu, 2004; Ang and Piazzesi, 2003; Diebold et al., 2006). The FX had a significant impact in the UK (ranking 2 in UK), and moderate in EGP (ranking 4 in EGP). In fact, an appreciation of the FX is due to a higher demand in the country's currency, signaling higher investments inflows and a growing economy, which will lead to a rise in the LEVEL. The POLRATE had a significant impact in the US, EGP and MEX (ranking 1 in US, 2 in EGP, 3 in MEX). According to academic literature, the monetary policy could affect the whole yield curve, not just the short rate, which is evidence of a strong monetary policy transmission mechanism, and conform to the Expectation Hypothesis (Rhodes & Aazim, 2011; Sowmya & Prasanna, 2018). Thus, the US, EGP, and

MEX had an efficient transmission mechanism. Consistent with academic literature, economic growth led to higher inflationary pressures that triggered a rise in the Level, prompting the central bank to hike its policy rate, the INF had a significant impact on the LEVEL in MEX, US, and the UK (ranking 1 in MEX, 2 in US, 3 in UK), compared to the GDP's significant impact in MEX, EGP and SAF (ranking 2 in MEX, 3 in SAF, 3 in EGP). Thus, countries like the US and the UK were more focused on taming inflation, while others like EGP and SAF were more focused on growth, compared to MEX who had a balanced approach towards inflation and growth.

4.4.2. Causality for the SLOPE

Table 4.6 ANN P-Values & Feature Importance for the SLOPE

4.6.a ANN P-Values Y Variable: SLOPE

X Variable	US	UK	EGP	MEX	SAF
LEVEL	100.00%	99.98%	100.00%	100.00%	100.00%
CURVATURE	0.00%	0.00%	0.00%	0.00%	0.00%
EQUITY	0.00%	0.00%	0.00%	0.00%	0.00%
FX	0.00%	0.00%	0.00%	0.00%	0.00%
POLRATE	0.00%	0.00%	0.00%	0.00%	0.00%
GDP	0.00%	0.00%	0.00%	0.00%	0.00%
INF	0.00%	0.00%	0.00%	0.00%	0.00%

4.6.b Feature Importance Y Variable: SLOPE

US	UK	EGP	MEX	SAF
POLRATE	GDP	POLRATE	GDP	EQUITY
EQUITY	EQUITY	EQUITY	INF	GDP
GDP	POLRATE	INF	EQUITY	INF
CURVATURE	INF	GDP	FX	FX
INF	FX	FX	CURVATURE	CURVATURE
FX	CURVATURE	CURVATURE	POLRATE	POLRATE
LEVEL	LEVEL	LEVEL	LEVEL	LEVEL

With the exception of the LEVEL, all variables Granger caused the SLOPE, as it is illustrated in table 4.6.a. The CURVATURE had a moderate to low impact on the LEVEL in most countries suggesting that it did not strongly drive changes in yield curve steepness. As it is illustrated in table 4.6.b the EQUITY had a high importance for the SLOPE for all countries (ranking 2 in US, 2 in UK, 2 in EGP, 3 in MEX, 1 in SAF), suggesting that the stock market performance consistently influenced yield curve steepness. Since the stock market was considered a leading indicator for economic growth, it caused the SLOPE to change, announcing an upcoming growth or recession. The FX had a moderate to low impact on the SLOPE, as the monetary policy relationship with foreign exchange rates differed based on the country's currency system (Dilmaghani & Tehranchian, 2015). Moreover, the POLRATE had a high impact on the SLOPE in the US, EGP, and UK (ranking 1 in US, 1 in EGP, 3 in UK), highlighting the ability of these countries' central banks to change the yield curve slope. Chirinos-Leañez & Pagliacci (2015) found out that the short end of the yield curve responded promptly to the monetary policy. In fact, during unstable economic conditions, the monetary policy impact was significant towards the short end of the yield curve (Aazim, 2011). In addition, INF ranked highly in MEX and EGP (2 in MEX, 3 in EGP), reflecting their sensitivity to inflationary pressures, which steepened the yield curve. Indicating that economic growth influenced the SLOPE through expectations of future economic activity, the GDP had high importance in the US, UK, MEX and SAF (ranking 3 in US, 1 in UK, 4 in EGP, 1 in MEX, 2 in SAF).

4.4.3. Causality for the CURVATURE

Table 4.7 ANN P-Values & Feature Importance for the CURVATURE

4.7.a ANN P-Values Y Variable: CURVATURE

X Variable	US	UK	EGP	MEX	SAF
LEVEL	100.00%	100.00%	100.00%	100.00%	100.00%
CURVATURE	100.00%	100.00%	100.00%	100.00%	100.00%
EQUITY	0.00%	0.00%	0.00%	0.00%	0.00%
FX	0.00%	0.00%	0.00%	0.00%	0.00%
POLRATE	0.00%	0.00%	0.00%	0.00%	0.00%
GDP	0.00%	0.00%	0.00%	0.00%	0.00%
INF	0.00%	0.00%	0.00%	0.00%	0.00%

4.7.b Feature Importance Y Variable: CURVATURE

US	UK	EGP	MEX	SAF
EQUITY	FX	POLRATE	EQUITY	FX
GDP	POLRATE	FX	FX	EQUITY
POLRATE	EQUITY	EQUITY	GDP	POLRATE
FX	GDP	INF	POLRATE	GDP
INF	INF	GDP	INF	INF
SLOPE	SLOPE	SLOPE	SLOPE	SLOPE
LEVEL	LEVEL	LEVEL	LEVEL	LEVEL

As it is illustrated in table 4.7.a the CURVATURE was Granger caused by most variables, except the LEVEL and SLOPE. The EQUITY had a high importance for the CURVATURE in all countries (ranking 1 in US, 3 in UK, 3 in EGP, 1 in MEX, 2 in SAF), underscoring its role in shaping yield curve curvatures and twists. In addition, the FX had also a significant impact on the CURVATURE in most countries (ranking 1 in UK, 2 in EGP, 2 in MEX, 1 in SAF). Furthermore, the POLRATE had a significant role and ranked highly in four countries (3 in US, 2 in UK, 1 in EGP, 3 in SAF), reflecting monetary policy's influence on yield curve curvature through short-term rate adjustments, with EGP's POLRATE showing the strongest effect on the CURVATURE due to its managed monetary framework, while MEX's moderate effect suggested that other factors like EQUITY or FX dominated. On the other hand, the GDP ranked highly in only the US and MEX (2 in US, 3 in MEX), reflecting a strong role in these countries, suggesting that economic growth influenced yield curve twists in these countries, making these markets vulnerable to growth shocks. Finally, the INF had a low impact on the CURVATURE in most countries.

4.4.4. Causality for the EQUITY

Table 4.8 ANN P-Values & Feature Importance for the EQUITY

4.8.a ANN P-Values Y Variable: EQUITY

X Variable	US	UK	EGP	MEX	SAF
LEVEL	100.00%	100.00%	100.00%	100.00%	100.00%
CURVATURE	100.00%	100.00%	100.00%	100.00%	100.00%
EQUITY	100.00%	100.00%	100.00%	100.00%	100.00%
FX	0.00%	0.00%	0.00%	0.00%	100.00%
POLRATE	0.00%	0.00%	0.00%	100.00%	100.00%
GDP	0.00%	0.00%	11.45%	100.00%	100.00%
INF	0.00%	0.00%	0.00%	100.00%	100.00%

4.8.b Feature Importance Y Variable: EQUITY

US	UK	EGP	MEX	SAF
POLRATE	POLRATE	INF	FX	FX
GDP	INF	POLRATE	POLRATE	POLRATE
INF	GDP	FX	GDP	GDP
FX	FX	GDP	INF	INF
CURVATURE	CURVATURE	CURVATURE	CURVATURE	CURVATURE
SLOPE	SLOPE	SLOPE	SLOPE	SLOPE
LEVEL	LEVEL	LEVEL	LEVEL	LEVEL

As it is illustrated in table 4.8.a the FX Granger caused the EQUITY in the US, UK, EGP, and MEX, with a significant importance in MEX and EGP (ranking 3 in EGP, 1 in MEX), and moderate in the US and UK (4 in US, 4 in UK). It is worth mentioning that the FX was the only significant variable in MEX, reflecting its sensitivity to exchange rate volatility, which suggested that currency stability was important for equity market performance, in open or managed economies. Ahmed et al. (2017) found a Causality relationship from the exchange rate to the stock market. The POLRATE Granger caused the EQUITY in three countries, the US, UK, and EGP, with a very high importance in these countries (ranking 1 in US, 1 in UK, 2 in EGP), suggesting that the monetary policy had a strong impact on stock markets, likely through interest rate expectations affecting equity valuations. Laopodis (2013) suggested that the relationship between the monetary policy and the stock market was dynamic and not consistent. In MEX and SAF, the POLRATE did not Granger cause the EQUITY because their monetary policy was not transmitted effectively to the stock market. The GDP Granger caused the EQUITY in the US and UK only, with high importance in few countries (ranking 2 in US, 3 in UK). Thus, stock markets were sensitive to economic growth. In EGP, GDP's moderate role suggested it was secondary to other drivers like the POLRATE. The INF Granger caused the EQUITY in three countries, the US, UK and EGP, with a high importance in these countries (ranking 3 in US, 2 in UK, 1 in EGP), reflecting inflation's impact on equity valuations through cost pressures and investor expectations. In EGP, US, and UK, controlling inflation was crucial for stabilizing equity markets, as inflation expectations influence stock valuations.

4.4.5. Causality for the FX

Table 4.9 ANN P-Values & Feature Importance for the FX

4.9.a ANN P-Values Y Variable: FX

X Variable	US	UK	EGP	MEX	SAF
LEVEL	100.00%	100.00%	100.00%	100.00%	100.00%
SLOPE	100.00%	100.00%	100.00%	100.00%	100.00%
CURVATURE	100.00%	100.00%	100.00%	100.00%	100.00%
EQUITY	0.00%	0.00%	100.00%	0.00%	0.00%
POLRATE	0.00%	0.00%	0.00%	100.00%	100.00%
GDP	0.00%	0.00%	100.00%	100.00%	100.00%
INF	0.00%	0.00%	0.00%	100.00%	100.00%

4.9.b Feature Importance Y Variable: FX

US	UK	EGP	MEX	SAF
EQUITY	INF	INF	EQUITY	EQUITY
INF	GDP	POLRATE	POLRATE	POLRATE
GDP	POLRATE	EQUITY	GDP	GDP
POLRATE	EQUITY	GDP	INF	INF
CURVATURE	CURVATURE	CURVATURE	CURVATURE	CURVATURE
SLOPE	SLOPE	SLOPE	SLOPE	SLOPE
LEVEL	LEVEL	LEVEL	LEVEL	LEVEL

As illustrated in table 4.9.a the EQUITY Granger caused the FX in the US, UK, MEX, and SAF, ranking highly in the US, MEX and SAF (1 in US, 1 in MEX, 1 in SAF), probably due to global capital flows. As we have previously mentioned that the EQUITY was a leading indicator of economic growth, thus, positive sentiment led to the appreciation of the country's currency and vice versa. As one would expect, the POLRATE Granger caused the FX in the US, UK, and EGP, with a high importance in the UK and EGP (ranking 3 in UK, 2 in EGP and moderate ranking of 4 in US), suggesting that the monetary policy had a strong practical impact on exchange rates, likely through interest rate differentials affecting capital flows. According to Ahmed et al. (2017) interest rates caused a slight appreciation in the country's exchange rate. Dilmaghani & Tehranchian (2015) stated that the country's exchange rate was also affected by other macro variables such as the inflation and GDP. Though, the GDP Granger caused the FX in only the US and UK, with a high importance in these two countries, reflecting economic growth's role in driving exchange rate movements, particularly in these two developed countries. Additionally, INF Granger caused the FX in the US, UK, and EGP, with a very high importance on their currency exchange rates. The impact of growth and inflation on the exchange rate of developed economies, like the US and UK, reflected effective transmission mechanisms. However, for the rest of the countries, stabilizing the exchange rate could be linked to either inflation or growth, depending on the country.

4.4.6. Causality for the POLRATE

Table 4.10 ANN P-Values & Feature Importance for the POLRATE

4.10.a ANN P-Values Y Variable: POLRATE

X Variable	US	UK	EGP	MEX	SAF
LEVEL	100.00%	100.00%	100.00%	100.00%	100.00%
SLOPE	100.00%	100.00%	100.00%	100.00%	100.00%
CURVATURE	100.00%	100.00%	100.00%	100.00%	100.00%
EQUITY	0.00%	100.00%	100.00%	0.00%	0.00%
FX	0.00%	100.00%	0.00%	0.00%	0.00%
GDP	0.00%	100.00%	100.00%	0.00%	0.00%
INF	0.00%	100.00%	100.00%	0.00%	0.00%

4.10.b Feature Importance Y Variable: POLRATE

US	UK	EGP	MEX	SAF
INF	FX	FX	EQUITY	INF
GDP	GDP	EQUITY	FX	GDP
EQUITY	EQUITY	INF	GDP	FX
FX	INF	GDP	INF	EQUITY
CURVATURE	CURVATURE	CURVATURE	CURVATURE	CURVATURE
SLOPE	SLOPE	SLOPE	SLOPE	SLOPE
LEVEL	LEVEL	LEVEL	LEVEL	LEVEL

As illustrated in table 4.10.a the EQUITY Granger caused the POLRATE in the US, MEX, and SAF, with a high impact in the US and MEX (ranking 3 in US, 1 in MEX, 4 in SAF), suggesting that the stock market performance influenced central banks decisions, reflecting economic confidence and market sentiment. Suhaibu et al. (2017) stated that stock markets were affected by their respective monetary policies through interest rates, and in the long term this relation is bidirectional. The FX Granger caused the POLRATE in US, EGP, MEX, and SAF, ranking highly in these countries (1 in EGP, 2 in MEX, 3 in SAF), suggesting that exchange rate movements significantly influenced policy rates, reflecting currency stability's role in monetary policy (Olamide & Maredza, 2019). Conform to academic literature, the GDP and INF Granger caused the POLRATE in three countries, the US, MEX and SAF, ranking highly in these countries, which reflected inflation and economic growth role in driving monetary policy decisions.

4.4.7. Causality for the GDP

Table 4.11 ANN P-Values & Feature Importance for the GDP

4.11.a ANN P-Values Y Variable: GDP

X Variable	US	UK	EGP	MEX	SAF
LEVEL	100.00%	100.00%	100.00%	100.00%	100.00%
SLOPE	100.00%	100.00%	100.00%	100.00%	100.00%
CURVATURE	100.00%	100.00%	100.00%	100.00%	100.00%
EQUITY	0.00%	0.00%	0.00%	0.00%	0.00%
FX	0.00%	0.00%	0.00%	0.00%	0.00%
POLRATE	0.00%	0.00%	0.00%	0.00%	0.00%
INF	0.00%	0.00%	0.00%	100.00%	0.00%

4.11.b Feature Importance Y Variable: GDP

US	UK	EGP	MEX	SAF
EQUITY	INF	INF	EQUITY	INF
POLRATE	POLRATE	FX	POLRATE	POLRATE
FX	FX	POLRATE	FX	EQUITY
INF	EQUITY	EQUITY	INF	FX
CURVATURE	CURVATURE	CURVATURE	CURVATURE	CURVATURE
SLOPE	SLOPE	SLOPE	SLOPE	SLOPE
LEVEL	LEVEL	LEVEL	LEVEL	LEVEL

As illustrated in table 4.11.a the EQUITY Granger caused GDP across all countries, ranking highly in the US, MEX, and SAF, and moderately in others, which was likely due to economic confidence, wealth effects and the stock market leading indicator role for economic growth (Plíhal, 2016). The FX Granger caused GDP across all countries, ranking highly in the US, UK, EGP, and MEX. Khandare (2017) stated that the correlation between the currency exchange rate and the GDP growth was positive and equivalent to +0.16, and different results between countries were affected by their respective exchange rate regime. Although, Pramanik (2021) found out that currency exchange rates depreciations were accompanied by economic growth in several studied countries, this relationship was not apparent for Mexico, and could differ between countries. As it is economically expected, the POLRATE Granger caused the GDP in all countries, being second in importance in the US, UK, MEX and SAF, highlighting monetary policy's strong role in shaping economic growth, with consistent influence in both developed (US, UK) and developing countries (EGP, MEX, SAF), influencing investment and consumption through interest rate channels. Amaral et al. (2022) demonstrated that the monetary policy did have a positive impact on economic growth. Lee & Werner (2018) concluded that interest rates followed the GDP growth and were positively correlated. Contrarily, Hameed (2011) argued that the interest rate had a minor impact on the GDP, and Ryan-Collins et al. (2016) found out that short and long-term interest rates did not affect the GDP. With the exception of MEX, INF Granger caused GDP in all countries, being the most influential variable in the UK, EGP, and SAF, emphasizing the need for price stability to support growth. A higher inflation would prompt the central bank to hike its rates, which will negatively affect economic growth.

4.4.8. Causality for the INF

Table 4.12 ANN P-Values & Feature Importance for the INF

4.12.a ANN P-Values Y Variable: INF

X Variable	US	UK	EGP	MEX	SAF
LEVEL	100.00%	100.00%	100.00%	100.00%	100.00%
SLOPE	100.00%	100.00%	100.00%	99.95%	100.00%
CURVATURE	99.99%	0.21%	100.00%	30.78%	41.09%
EQUITY	0.00%	0.00%	0.00%	0.00%	0.00%
FX	0.00%	0.00%	0.00%	0.00%	0.00%
POLRATE	0.00%	0.00%	0.00%	0.00%	0.00%
GDP	0.00%	0.00%	0.00%	0.00%	0.00%

4.12.b Feature Importance Y Variable: INF

US	UK	EGP	MEX	SAF
GDP	GDP	EQUITY	GDP	GDP
EQUITY	EQUITY	FX	EQUITY	POLRATE
POLRATE	POLRATE	POLRATE	FX	EQUITY
FX	FX	GDP	POLRATE	FX
CURVATURE	CURVATURE	CURVATURE	CURVATURE	CURVATURE
SLOPE	SLOPE	SLOPE	SLOPE	SLOPE
LEVEL	LEVEL	LEVEL	LEVEL	LEVEL

As illustrated in table 4.12.a the CURVATURE did not Granger cause INF in most countries, except for the UK, indicating it generally did not lead INF. The EQUITY Granger caused INF in all countries, ranking highly in several countries (2 in US, 2 in UK, 1 in EGP, 2 in MEX, 3 in SAF). EQUITY's high importance in all countries, particularly in EGP, reflected the stock market role in driving inflation, likely through wealth effects and demand pressures. Pradhan et al. (2015) found causality from both, economic growth, and the stock market, to the inflation; and Chiang (2022) found evidence of negative correlation between the stock market and inflation, although, Plihal (2016) did not find evidence of the stock market effect on the inflation rate. The FX Granger caused INF in all countries, with a high importance in EGP and MEX (ranking 2 in EGP, 3 in MEX), and moderate in the US, UK and SAF (4 in US, 4 in UK, 4 in SAF). FX's high importance in EGP and MEX reflected their sensitivity to exchange rate volatility, likely due to import-driven inflation in these developing countries. Its influence on the US, UK, and SAF indicated that exchange rate movements impacted inflation universally, affecting both developed and developing countries through trade, capital flows, and price dynamics. The POLRATE Granger caused INF in all countries, ranking highly in several countries (3 in US, 3 in UK, 3 in EGP, 2 in SAF), highlighting the monetary policy's critical role in shaping inflation. Its consistent ranking across all countries reflected its universal impact. As it is economically expected, with economic growth comes inflation, the GDP Granger caused INF in all countries, having the highest impact in the US, UK, MEX and SAF (ranking 1 in US, 1 in UK 1 in MEX, 1 in SAF), with the exception of EGP (ranking 4 in EGP) where other factors such as EQUITY and FX dominated INF.

4.4.9. General Trends and Economic Implications for all Variables

- **Dominance of Macroeconomic and Financial Variables**: Across all target variables, macroeconomic and financial factors (EQUITY, FX, POLRATE, GDP, INF) consistently exhibited strong Granger causality and high feature importance rankings, underscoring their critical role in driving economic and financial outcomes. EQUITY was a leading indicator for GDP and INF, reflecting wealth effects and economic confidence. FX significantly influenced INF and POLRATE, particularly in developing countries like EGP and MEX, due to trade and capital flow dynamics. POLRATE shaped multiple variables (LEVEL, SLOPE, CURVATURE, EQUITY, FX, INF), highlighting its persistent influence. GDP drove INF and EQUITY in developed markets (US, UK) and select developing markets (MEX, SAF), while INF impacted EQUITY, FX, and POLRATE, especially in EGP, US, and UK.

- **Cross-Country Consistency and Variation**: Macroeconomic variables (EQUITY, FX, POLRATE, GDP, INF) showed consistent influence across countries, but their relative importance varied. Developed markets (US, UK) emphasized GDP and POLRATE for EQUITY and INF, reflecting robust economic and monetary policy transmission. Developing markets (EGP, MEX, SAF) highlighted FX and EQUITY for INF and POLRATE, driven by currency volatility and market sentiment. SAF's commodity-driven economy amplified FX and EQUITY's roles, while EGP's managed monetary framework emphasized POLRATE and FX.

- **Global Integration Effects**: FX and EQUITY's high importance across all countries reflected global capital flows and market sentiment's role in shaping economic variables. FX's influence on INF and POLRATE was universal, driven by trade and currency dynamics, while EQUITY's impact on GDP and INF underscored global investor confidence. This global integration was particularly pronounced in emerging markets, where external shocks via FX and EQUITY significantly affected domestic outcomes.
- **Bidirectional Relationships**: Bidirectional causality was evident in several relationships, such as EQUITY and GDP, POLRATE and INF, and FX and INF, indicating feedback loops where variables mutually reinforced each other. For example, the GDP drove EQUITY through economic growth, while EQUITY influenced the GDP via wealth effects, particularly in the US and MEX.
- **Monetary Policy**: POLRATE's consistent Granger causality and high importance across variables (LEVEL, SLOPE, CURVATURE, EQUITY, FX, INF) made it a critical tool for managing economic outcomes. Central banks influenced INF, FX, and GDP through interest rate adjustments, particularly in EGP and SAF for INF, and US and UK for GDP. However, the effectiveness of monetary policy varied, with MEX and SAF showing weaker transmission to EQUITY, suggesting the need for complementary policies to enhance impact.
- **Inflation Management**: INF's strong influence on EQUITY, FX, and POLRATE, especially in EGP, US, UK, and SAF, underscored the importance of price stability. Central banks must prioritize inflation control to stabilize equity markets and exchange rates, particularly in EGP, where INF is a top driver of EQUITY. In MEX, where INF's causality is weaker for some variables, other factors like FX and EQUITY dominated, requiring targeted currency and market policies.
- **Currency Stability**: FX's robust causality and high importance for INF and POLRATE, particularly in EGP and MEX, highlighted the need for currency stability to manage inflation and monetary policy. Developing markets, sensitive to import-driven inflation and global capital flows, should implement policies to mitigate exchange rate volatility, such as foreign exchange interventions or capital controls, to support economic stability.
- **Economic Growth Sensitivity**: GDP's strong causality and high importance for INF, EQUITY, and FX in US, UK, MEX, and SAF indicated that economic growth drove multiple economic outcomes. Policymakers should adopt sustainable growth to support equity markets and stabilize exchange rates, while monitoring growth shocks that could exacerbate inflation, particularly in developed markets.
- **Equity Market Monitoring**: EQUITY's high importance for GDP, INF, and FX, especially in US, MEX, and EGP, suggested that stock market performance was a critical indicator of economic conditions. Policymakers and investors should monitor equity markets to anticipate growth and inflation trends, leveraging positive market sentiment to boost economic confidence.

4.4.10. Bidirectional Causality

Table 4.13 Bidirectional Causality per Country

Country	Causality FX ↔ INF	Causality POLRATE ↔ GDP	Causality EQUITY ↔ GDP	Causality EQUITY ↔ INF
US	Yes	Yes	Yes	Yes
UK	Yes	Yes	Yes	Yes
EGP	Yes	X	Yes	X
MEX	Yes	Yes	Yes	X
SAF	Yes	Yes	Yes	X

As illustrated in table 4.13 the bidirectional causality between FX and INF across all countries reflected the critical interplay of exchange rates and inflation. In open economies, like the US and UK, exchange rate fluctuations drove inflation through import prices, while inflation impacted currency valuation due to purchasing power effects. In other countries like EGP, MEX, and SAF this relationship was amplified by import reliance (EGP, MEX) and commodity-driven export dynamics (SAF), where currency volatility directly affected inflation, and inflation influenced currency stability. This dynamic interdependence underscored the need for policymakers to monitor exchange rate movements to manage inflation, particularly in developing economies sensitive to global trade and capital flows.

The bidirectional causality between the POLRATE and GDP in the US, UK, MEX, and SAF highlighted monetary policy's role in shaping economic growth and GDP's effect on policy rate decisions as well. In developed economies (US and UK) central banks adjusted policy rates to stabilize growth, while strong GDP performance prompted tighter monetary policy to control inflation. In developing countries, like MEX and SAF, this two-way interaction was critical due to sensitivity to global economic conditions and commodity markets, respectively. Thus, policymakers must balance rate adjustments with growth objectives, as GDP dynamics directly influence monetary policy responses.

The bidirectional causality between the EQUITY and GDP, across all countries, underscored stock markets as both drivers and indicators of economic growth. In the US and UK, robust stock market performance signaled investor confidence, boosting economic activity through wealth effects, while GDP growth enhanced equity valuations. In developing countries, EGP, MEX and SAF, stock markets played a growing role in signaling and supporting economic expansion, particularly in resource driven (SAF) or trade-dependent (MEX) economies. This two-way interaction highlighted the importance of financial market stability for fostering economic growth across diverse economic contexts.

The bidirectional causality between the EQUITY and INF bidirectional causality in the US and UK reflected the interaction between stock markets and inflation. Equity market performance influenced inflation expectations through wealth and consumption effects, while inflation impacted stock valuations by altering cost structures and investor sentiment. This relationship was pronounced in developed financial markets like the US and UK where stock market dynamics were closely tied to monetary policy and inflation expectations, emphasizing the need for central banks to monitor equity trends to manage inflationary pressures.

4.4.11. Country Analysis

The US exhibited strong monetary policy transmission, with POLRATE driving LEVEL, SLOPE, CURVATURE, EQUITY, FX, and INF. GDP and EQUITY were critical for INF and FX, reflecting the US's developed market status and sensitivity to economic growth and market sentiment. INF's influence on EQUITY and FX underscored the importance of price stability. Yield curve factors (LEVEL, SLOPE, CURVATURE) were endogenous but had minimal impact on other variables, allowing focus on macroeconomic drivers. EQUITY and INF mutually influenced each other via wealth effects, as did FX and INF through trade dynamics, POLRATE and GDP through policy feedback, and EQUITY and GDP via market signals, highlighting reciprocal dynamics between financial markets, currency, monetary policy, and economic growth in the US's robust economy.

Similar to the US, the UK showed strong POLRATE influence on LEVEL, SLOPE, CURVATURE, EQUITY, and FX, with GDP and INF driving EQUITY and FX. FX and EQUITY's moderate roles on INF highlighted global integration, while CURVATURE's weak causality for INF suggested a unique sensitivity to yield curve twists. The UK's developed market status emphasized GDP and POLRATE, with inflation control critical for equity and currency stability. EQUITY and INF, as well as FX and INF, mutually affected each other through market and trade dynamics, POLRATE and GDP through policy feedback, and EQUITY and GDP via growth signals, reflecting the UK's interconnected financial and economic systems.

EGP's managed monetary framework amplified POLRATE and FX's roles in INF and EQUITY, with EQUITY as the top driver of INF, reflecting market-driven inflation pressures. FX's high importance for INF and POLRATE underscored currency volatility's impact in this country. GDP had a secondary role, suggesting a focus on currency and market stability over growth for inflation control. FX and INF mutually influenced each other via import prices, and EQUITY and GDP reciprocally affected each other through financial growth, emphasizing EGP's sensitivity to currency fluctuations and the growing role of financial markets.

MEX showed strong EQUITY and FX influence on GDP, INF, and POLRATE, reflecting its emerging market sensitivity to global capital flows. POLRATE and GDP drove growth, but POLRATE's weak causality for EQUITY suggested limited monetary policy transmission to stock markets. INF's weaker role for some variables indicated that currency and equity dynamics dominated inflation management. FX and INF, POLRATE and GDP, and EQUITY and GDP mutually influenced each other via trade, policy, and growth dynamics, highlighting MEX's trade-driven economy and financial-growth linkages.

SAF's commodity-driven economy amplified FX and EQUITY roles in INF and GDP, with the POLRATE being a key driver for both. INF's high importance for GDP and POLRATE reflected sensitivity to price pressures, while GDP drove multiple outcomes. Yield curve factors were irrelevant for non-yield curve variables, emphasizing macroeconomic and financial drivers for this country. FX and INF, POLRATE and GDP, and EQUITY and GDP mutually affected each other via commodity prices, policy feedback, and growth signals, underscoring the interplay of currency, policy, and markets in SAF's resource-based economy.

5. Conclusion

This study established an effective framework for analyzing nonlinear Granger causality in macroeconomic systems by integrating MSSA denoising with ANN-based input occlusion. By examining macroeconomic variables across several countries, we demonstrated the superiority of this approach over VAR Granger causality, identifying 38 significant causal relationships compared to 24 for VAR. The findings highlighted the critical roles of equity markets, exchange rates, and policy rates in driving yield curve factors, GDP, and inflation, with cross-country variations reflecting unique economic structures. For instance, developed markets like the US and UK showed strong monetary policy transmission, while developing markets like Egypt and Mexico emphasized currency and equity dynamics. MSSA's ability to reduce noise enhanced the stability and convergence of causality p-values, enabling the ANN to focus on underlying signals and capture complex, nonlinear interactions effectively.

The implications of this research are noteworthy for policymakers and economists seeking to understand and manage dynamic economic nonlinear systems. The consistent influence of policy rates across variables underscored the importance of monetary policy in shaping economic outcomes, particularly in stabilizing inflation and supporting growth. Similarly, the strong causality from equity markets and exchange rates highlighted the need for vigilant monitoring of financial markets and currency stability, especially in developing economies sensitive to global capital flows. While our methodology exceled in detecting nonlinear dynamics, the detection of some linear relationships by VAR suggested a complementary role for both approaches. A limitation of this study is that the MSSA denoising step may over-smooth the data: an aggressively chosen noise-reduction threshold risks discarding causal signals and, consequently, some economically meaningful relationships. Future research could expand this framework to an LSTM network to further enhance temporal dependencies.

Additionally, we could benchmark the occlusion-based ANN against a bootstrap-driven alternative, where block-bootstrapped resamples of the denoised series are fed into the same network to estimate empirical distributions of nonlinear Granger statistics. Finally, this study provided a robust, adaptable tool for unraveling the complexities of macroeconomic nonlinear interactions, offering actionable insights for policy formulation.

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Appendix

Table 4.3 Raw vs MSSA p-values

	Iterations	100	200	300	400	1000	MSSA 100
Y Variable	X Variable	P-Value	P-Value	P-Value	P-Value	P-Value	P-Values
LEVEL	SLOPE	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
LEVEL	CURVATURE	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
LEVEL	EQUITY	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
LEVEL	FX	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
LEVEL	POLRATE	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
LEVEL	GDP	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
LEVEL	INF	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
SLOPE	LEVEL	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%
SLOPE	CURVATURE	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
SLOPE	EQUITY	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
SLOPE	FX	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
SLOPE	POLRATE	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
SLOPE	GDP	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
SLOPE	INF	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
CURVATURE	LEVEL	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%
CURVATURE	SLOPE	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%
CURVATURE	EQUITY	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
CURVATURE	FX	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
CURVATURE	POLRATE	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
CURVATURE	GDP	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
CURVATURE	INF	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
EQUITY	LEVEL	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%
EQUITY	SLOPE	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%
EQUITY	CURVATURE	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%
EQUITY	FX	26.03013%	0.00071%	0.45634%	3.74679%	0.00599%	0.00002%
EQUITY	POLRATE	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
EQUITY	GDP	99.98957%	99.99993%	100.00000%	99.99999%	100.00000%	0.00000%
EQUITY	INF	0.03383%	1.11385%	0.00482%	0.01415%	0.00000%	0.00116%
FX	LEVEL	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%
FX	SLOPE	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%
FX	CURVATURE	99.99967%	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%
FX	EQUITY	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
FX	POLRATE	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
FX	GDP	0.00001%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
FX	INF	0.00006%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
POLRATE	LEVEL	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%
POLRATE	SLOPE	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%
POLRATE	CURVATURE	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%

	Iterations	100	200	300	400	1000	MSSA 100
Y Variable	X Variable	P-Value	P-Value	P-Value	P-Value	P-Value	P-Values
POLRATE	EQUITY	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
POLRATE	FX	0.00001%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
POLRATE	GDP	0.00004%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
POLRATE	INF	0.27318%	0.00052%	0.00000%	0.00000%	0.00000%	0.00000%
GDP	LEVEL	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%
GDP	SLOPE	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%
GDP	CURVATURE	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%
GDP	EQUITY	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
GDP	FX	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
GDP	POLRATE	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
GDP	INF	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%	0.00007%
INF	LEVEL	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%
INF	SLOPE	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%
INF	CURVATURE	100.00000%	100.00000%	100.00000%	100.00000%	100.00000%	99.98727%
INF	EQUITY	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
INF	FX	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
INF	POLRATE	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%
INF	GDP	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%	0.00000%

Table 4.4 MSSA p-values vs VAR MSSA p-values

		MSSA 100	VAR MSSA
Y Variable	X Variable	P-Values	P-Values
LEVEL	SLOPE	0.00000%	4.12706%
LEVEL	CURVATURE	0.00000%	26.32160%
LEVEL	EQUITY	0.00000%	9.83244%
LEVEL	FX	0.00000%	18.68650%
LEVEL	POLRATE	0.00000%	0.26714%
LEVEL	GDP	0.00000%	14.80841%
LEVEL	INF	0.00000%	0.05575%
SLOPE	LEVEL	100.00000%	94.10353%
SLOPE	CURVATURE	0.00000%	91.42867%
SLOPE	EQUITY	0.00000%	97.91004%
SLOPE	FX	0.00000%	68.82886%
SLOPE	POLRATE	0.00000%	2.51553%
SLOPE	GDP	0.00000%	83.24277%
SLOPE	INF	0.00000%	0.94950%
CURVATURE	LEVEL	100.00000%	0.00000%
CURVATURE	SLOPE	100.00000%	0.00073%
CURVATURE	EQUITY	0.00000%	3.78274%
CURVATURE	FX	0.00000%	0.00383%

Y Variable	X Variable	MSSA 100 P-Values	VAR MSSA P-Values
CURVATURE	POLRATE	0.00000%	0.00003%
CURVATURE	GDP	0.00000%	0.00000%
CURVATURE	INF	0.00000%	0.00009%
EQUITY	LEVEL	100.00000%	58.80360%
EQUITY	SLOPE	100.00000%	66.86698%
EQUITY	CURVATURE	100.00000%	38.54675%
EQUITY	FX	0.00002%	2.71256%
EQUITY	POLRATE	0.00000%	16.47825%
EQUITY	GDP	0.00000%	17.32381%
EQUITY	INF	0.00116%	9.39006%
FX	LEVEL	100.00000%	59.69996%
FX	SLOPE	100.00000%	77.10969%
FX	CURVATURE	100.00000%	98.09645%
FX	EQUITY	0.00000%	15.55821%
FX	POLRATE	0.00000%	70.26149%
FX	GDP	0.00000%	43.25522%
FX	INF	0.00000%	3.85058%
POLRATE	LEVEL	100.00000%	0.00015%
POLRATE	SLOPE	100.00000%	0.00000%
POLRATE	CURVATURE	100.00000%	0.00016%
POLRATE	EQUITY	0.00000%	0.71807%
POLRATE	FX	0.00000%	0.00014%
POLRATE	GDP	0.00000%	0.03313%
POLRATE	INF	0.00000%	0.00484%
GDP	LEVEL	100.00000%	0.10855%
GDP	SLOPE	100.00000%	17.96824%
GDP	CURVATURE	100.00000%	61.19914%
GDP	EQUITY	0.00000%	92.56364%
GDP	FX	0.00000%	20.88933%
GDP	POLRATE	0.00000%	0.56234%
GDP	INF	0.00007%	21.31093%
INF	LEVEL	100.00000%	56.93867%
INF	SLOPE	100.00000%	17.49975%
INF	CURVATURE	99.98727%	1.19947%
INF	EQUITY	0.00000%	22.15520%
INF	FX	0.00000%	18.66607%
INF	POLRATE	0.00000%	10.50828%
INF	GDP	0.00000%	23.99003%