Deep Impulse Response Functions for Macroeconomic Dynamics: A Hybrid LSTM-Wavelet Approach Compared to an ANN-Wavelet and VECM Models

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Abstract

This study presents a novel hybrid framework that integrated Long Short-Term Memory (LSTM) networks with Daubechies wavelet transforms to estimate Deep Impulse Response Functions (DIRF) for monthly macroeconomic time series, across five economies: Brazil, Egypt, Indonesia, United States, and the United Kingdom. Eight key variables, yield curve latent factors (LEVEL, SLOPE, CURVATURE), foreign exchange rates, equity indices, central bank policy rates, GDP growth rates, and inflation rates, were modeled using the proposed LSTM-Wavelet approach, and were compared against an ANN-Wavelet hybrid, and a traditional Vector Error Correction Model (VECM). The LSTM-Wavelet model achieved a superior overall median R2, outperforming the ANN-Wavelet and VECM. The approach excelled in capturing nonlinear dynamics and temporal dependencies for variables such as equity indices, policy rates, GDP, and inflation. Db4 was superior for capturing short and medium-term patterns in macroeconomic variables like GDP, EQUITY, and FX, cause its shorter filter and moderate smoothing excelled at isolating cyclical patterns in noisy, volatile data. Cumulative DIRFs revealed consistent cross variable dynamics e.g., yield curve shocks propagated to equity, FX, policy rates, GDP, and inflation, in line with economic theory. These findings underscored the hybrid model's ability to capture non-linearity, multiscale interactions in macroeconomic data, offering valuable insights for forecasting and policy analysis.

Keywords: Deep Impulse Response Function, Long Short-Term Memory, Daubechies Wavelet transform, Macroeconomics, nonlinearity, Forecasting

Deep Impulse Response Functions for Macroeconomic Dynamics: A Hybrid LSTM-Wavelet Approach Compared to an ANN-Wavelet and VECM Models

1. Introduction

This study introduced a novel approach to deep impulse response functions based on a hybrid framework that integrated Long Short-Term Memory (LSTM) networks with wavelet transforms to estimate Deep Impulse Response Functions (DIRF) for monthly macroeconomic time series. The framework was applied to key variables, across five countries: Brazil (BRA), Egypt (EGP), Indonesia (IND), UK (UK), and the US (US). These variables include yield curves first three latent factors (LEVEL, SLOPE and CURVATURE), foreign exchange rates (FX), stock market indices (EQUITY), central bank policy rates (POLRATE), GDP growth rates (GDP), and inflation rates in percentage (INF). The proposed model was compared against Impulse Response Functions (IRF) generated from: a hybrid Artificial Neural Network (ANN)-Wavelet model, and a traditional Vector Error Correction Model (VECM). By leveraging the nonlinear modeling capacity and temporal dependencies of LSTM, in addition to the denoising properties of wavelet, this approach aimed to enhance the accuracy and interpretability of IRFs, while addressing the limitations of linear econometric models.

IRFs are one of the structural analysis tools derived from VAR or VECM that have long been used in the analysis of economic time series such as GDP growth rates, inflation rates, foreign exchange rates, stock market indices, and yield curves. They allow researchers to examine how a change in one variable propagates through a system to other variables, thereby illustrating the dynamic relationship between macro variables. While these models have provided valuable contributions to understanding the interactions between variables, their limitations such as linearity, low explanatory power (R2), and sensitivity to model specification, have paved the way for more advanced techniques capable of capturing complex nonlinear dynamics inherent in economic data.

Recent advancements in deep learning, particularly LSTM networks and ANNs, offer an alternative framework for capturing the complex, nonlinear dynamics inherent in macroeconomic data (Fischer & Krauss, 2018). In fact, LSTM excel at capturing complex nonlinear dynamics, and temporal dependencies, making them ideal for modeling economic time series (Hochreiter & Schmidhuber, 1997). Moreover, Wavelet transforms enable multiscale analysis by decomposing signals into frequency components, isolating short-term fluctuations and long-term trends while reducing noise (Mallat, 1989). Hybrid models combining these methodologies have shown superior performance in forecasting tasks like predicting GDP growth (Zhang et al., 2023) and foreign exchange rates (Arslan et al., 2024).

This study contributed to academic literature in four ways: we addressed the gap in empirical studies of the DIRF application on macro variables by introducing a hybrid LSTM-Wavelet framework for estimating DIRFs; we evaluated the performance of DIRFs against both machine learning (ANN-Wavelet) and traditional (VECM) methods; we analyzed the behavior of Daubechies wavelet when applied onto our framework and macro variables; and we applied the methodology to diverse economies, offering comparative perspectives on macroeconomic dynamics. Ultimately, our findings may provide valuable insights for policymakers, researchers, and financial analysts seeking to better understand the transmission mechanisms of macroeconomic shocks and improve forecasting accuracy.

2. Literature Review

IRF is one of the structural analysis VAR/VECM reports that have long been used in the analysis of economic time series. It allows researchers to examine how a change in one variable propagates, through an interconnected system, to other variables, thereby illustrating the dynamic relationship between macro variables. Derived primarily from VAR or VECM, IRFs have historically offered valuable insights into how variables interact. However, the restrictive assumptions of these linear frameworks, limited explanatory power, and dependence on specific model choices, have necessitated the exploration of more advanced methods capable of modeling the nonlinear behavior of economic variables. Stock & Watson (2001) highlight how traditional VAR models often fail to account for heteroskedasticity and structural shifts. This literature review explored traditional IRF methodologies for economic time series analysis such as VAR/VECM, advancements in neural networks, the use of specialized neural network methods like LSTM, the benefits of wavelet transform methods, and the emerging use of DIRF frameworks. This review concluded with suggestions on gaps in academic research and the introduction of a novel hybrid approach combining LSTM and wavelets to address these gaps.

IRFs based on VAR and VECM have primarily been used by academic scholars for macroeconomic research in recent decades, providing foundational insights into the interactions between key macro variables. Sims (1980) initiated the use of VAR models to analyze monetary policy shocks, while **J**ohansen (1991) extended this framework to cointegrated analysis using VECM. These methods have been widely adopted to study fiscal multipliers (Blanchard & Perotti, 2002), inflation dynamics (Stock & Watson, 2001), and FX rate adjustments (Clarida & Galí, 1994). Rudebusch and Wu (2004) examined the connection between the US yield curve and macroeconomic variables by employing IRF and variance decomposition. Ang and Piazzesi (2003), similarly, utilized IRF and variance decomposition to analyze the interplay between the US yield curve and macroeconomic factors. Djuranovik (2014) applied IRF and variance decomposition to investigate the relationship between the country's yield curve and macroeconomic indicators. More recently, Sowmya and Prasanna (2018) explored the dynamics between yield curves and macroeconomic variables in Asian markets through IRF analysis. Despite their utility, these models suffered from linearity, hence failing to capture the complexity of economic relationships. Moreover, the R2 values generated by VAR and VECM models were frequently low and statistically insignificant, suggesting limited predictive accuracy (Stock & Watson, 2001). A study by Hamilton (1994) highlighted how these models struggled with regime-switching behaviors, particularly during crises, where nonlinear dynamics dominated. Critics argued that these models struggled to account for structural breaks, regime shifts, and non-stationary behaviors commonly observed in macroeconomic data (Stock & Watson, 2001). Furthermore, a potential drawback of IRF is its reliance on a specific order of variables. When variables exhibit strong correlations, the variables' ordering can influence the results, potentially leading to inconsistencies or variations in outcomes. Conversely, if variables are weakly correlated, the choice of order has a minimal impact on the analysis (Tsay, 2010; Brooks, 2014; Enders, 2015). Unlike VAR/VECM, LSTMs learn complex, nonlinear, relationships between variables through backpropagation and optimization, rather than imposing a fixed recursive structure. The model does not rely on the Cholesky decomposition, meaning there's no strict causality assumption based on variable order. Unlike traditional models with fixed autoregressive structures, LSTMs rely on learned weights, meaning their responses to shocks are derived directly from the data rather than predefined by an arbitrary ordering. However, the arrangement of input data can still shape the model's learning if variables are sequenced in a way that prioritizes certain features over others, this may indirectly influence how the LSTM captures temporal dependencies, as the model could disproportionately focus on variables presented earlier in the sequence (Paliath, 2011; Kitson & Constantinou, 2024).

Recent advancements in technology resources have paved the way for alternative methodologies better suited for capturing the complex relationships between variables. Neural networks are able to tackle the limitations of traditional econometric techniques with their flexible designs and capability of capturing nonlinearity. Scholars such as Zhang et al. (2001) demonstrated the potential of ANNs in modeling stock market volatility, highlighting their superior performance compared to ARIMA-based benchmarks. Similarly, Tkacz (2001) applied neural networks to predict Canadian GDP growth rates, achieving higher accuracy than conventional models. Recent advancements by Fischer & Krauss (2018) integrated deep learning architectures with ANNs to analyze financial market data, achieving outstanding results in predicting stock market movements. One of the key strengths of ANNs is their ability to learn elaborate relationships without relying on strict functional structures, making them highly effective for examining highly unpredictable systems, such as financial markets (Kaastra & Boyd, 1996). Furthermore, advances in regularization techniques have mitigated concerns about overfitting, enhancing their robustness across diverse datasets (Hornik et al., 1989). A study by Yu et al. (2008) combined ensemble learning with wavelet decomposition to model crude oil price dynamics, demonstrating improved interpretability and predictive accuracy over traditional VECM approaches.

LSTM models, a specialized class of Recurrent Neural Network (RNN), have emerged as powerful tools for forecasting economic time series, outperforming both traditional econometric models and standard ANNs. Hochreiter and Schmidhuber (1997) introduced LSTMs to address the vanishing gradient problem associated with conventional RNNs, allowing them to retain information over extended periods, which is crucial for handling sequential dependencies in macroeconomic data. Recent studies underscore the efficiency of LSTMs in predicting inflation trends (Zahara et al., 2020; Mirza at al., 2024), and stock market movements (Fischer & Krauss, 2018; Kasture & Shirsath, 2024). In fact, LSTM models showed significant advantages over traditional methods, such as ARIMA, in terms of prediction accuracy (Chen, Han, Shen, & Ye, 2021). Unlike traditional models constrained by linearity, LSTM models exceled at identifying patterns and adapting to changing regimes, improving prediction accuracy. Additionally, hybrid architectures incorporating wavelet decomposition have shown promise in isolating short and long-term components of economic signals, facilitating the denoising of data while preserving essential information (Yu et al., 2008).

Wavelet transforms offer a novel approach to analyzing and forecasting economic time series by breaking down signals into various frequency components, enabling multiscale analysis. Since its introduction by Mallat (1989), wavelet theory has helped researchers identify temporary characteristics and periodic patterns in noisy data, thereby improving interpretability and prediction accuracy. Wavelet applications are widespread across multiple fields, including foreign exchange rate modeling (Gençay et al., 2001), and yield spread forecasting (Shah & Debnath, 2017). Mitra (2006) explored the econometric relationship between money, output, and price for the Indian economy using a wavelet filtering approach, unlike traditional analyses at the original series level, this study used wavelet decomposition to analyze variables. Hybrid approaches, integrating wavelets with machine learning techniques, have proven highly effective, highlighting enhanced resilience to noise and structural variations, while reducing the number of features needed for forecasting while improving accuracy (Yu et al., 2008; Ospina et al., 2019). Recent research by Parvini at al. (2022) integrated Wavelet Transform with LSTM to predict cryptocurrency, highlighting their ability to decompose the input time series into details components (high-frequency components) and trends (low-frequency components), by which reducing the noise and isolating patterns, in order to enhance the data quality before feeding it into the forecasting model.

The integration of LSTM models with wavelet transforms has emerged as a particularly promising approach for analyzing economic time series, leveraging the strengths of both methodologies. Wavelet decomposition allows for the separation of signals into different frequency components, capturing both short-term fluctuations and long-term trends, while LSTMs excel at modeling sequential dependencies and nonlinear dynamics. This combination has been successfully applied in several domains, such as predicting electricity prices (Shejul et al., 2024), predicting GDP (Zhang et al., 2023), and predicting foreign exchange rates (Arslan et al., 2024). In fact, LSTM-Wavelet hybrid models have proven to be more effective than standalone LSTM models in capturing asymmetric responses to economic shocks, especially during periods of heightened uncertainty (Yenokyan, 2018). By preprocessing data with wavelet transforms, LSTMs can focus on relevant time-frequency components. Moreover, attention mechanisms integrated into LSTM-Wavelet frameworks have shown potential for identifying key drivers of economic fluctuations, providing policymakers with actionable insights (Qiu et al., 2020).

Deep Impulse Response Functions, leveraging advancements in deep learning, have attracted the attention of academic scholars seeking to enhance the precision and interpretability of IRFs. Richard et al. (2022) developed a DIRF methodology for macroeconomic applications, emphasizing its ability to capture nonlinear interactions and asymmetric responses. Recent work by Yu and Kleijn (2020) introduced a deep learning framework for IRFs in room acoustics, ensuring adherence to theoretical principles while improving predictive accuracy. Jia and Wong (2024) applied deep impulse control to interest rate interventions, demonstrating its utility in predicting and stress-testing potential losses from central bank interventions. These efforts highlight the growing recognition of deep learning's potential to revolutionize IRF analysis by overcoming longstanding limitations of VAR and VECM. However, there is a notable lack of academic papers on DIRF for macro variables.

In conclusion, this literature review highlighted the use of IRFs in economic time series analysis while critiquing the shortcomings of traditional VAR and VECM approaches. Advances in neural networks, particularly LSTM, and wavelet transforms have increased the synergy of deep learning and economic theory. Nevertheless, there is a gap in academic literature regarding the development and application of deep learning methodologies tailored specifically for IRFs. Hence, our study proposed a new hybrid framework that combined LSTM models with wavelet transforms to generate a DIRF for macro variables, and we compared its performance with IRFs derived from a hybrid ANN-Wavelet and a

VECM. By bridging this gap, we aimed to contribute to a deeper understanding of macroeconomic dynamics. Finally, our findings may provide valuable insights for policymakers, researchers, and financial analysts seeking to better understand the transmission mechanisms of macroeconomic shocks.

3. Research Methodology

3.1. Data Sources

This study was based on macro variables from several countries: Brazil (BRA), Egypt (EGP), Indonesia (IND), the US (US), and the UK (UK). These variables include yield curves first three latent factors: LEVEL (yield curve first latent factor, parallel shift), SLOPE (second latent factor, change in slope), CURVATURE (third latent factor); in addition to foreign exchange rates (FX), stock market indices (EQUITY), central bank policy rates (POLRATE), GDP growth rates (GDP), and inflation rates as a percentage (INF). The FX was modeled in terms of direct exchange rate, showing how much one unit of home currency was worth in foreign currency ($). We have conducted our analysis based on monthly data from 2006 till 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 monthly basis, except for the GDP growth rates that were on quarterly basis. Hence, we have 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 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. Deep Impulse Response Methodology

This study introduced a hybrid modeling framework that combined LSTM with wavelet transforms, Daubechies wavelet, to examine the dynamic interactions among key macroeconomic variables. For a comparative analysis, we compared the IRF forecasting accuracy R2 of the hybrid LSTM-Wavelet model with both a hybrid ANN-Wavelet model (using the same hyperparameters) and the VECM. The VECM, a traditional econometric approach, models cointegrated time series to capture long-run relationships and short-run dynamics among variables, serving as a benchmark for assessing the performance of the neural network-based hybrid models. All three models were trained or estimated on 70% of the data, with prediction accuracies measured by R2 on the test or validation data (30% of the data), serving as the primary risk metrics for comparing their effectiveness.

Due to the complex nature of the proposed LSTM architecture, the training required extensive processing time and resource allocation. Hence, this methodology was implemented in two distinct phases (similar steps were followed for the ANN model), each coded as a separate script: (1) a training script that built and optimized the hybrid LSTM-Wavelet model, saving the best weights, performance metrics, and wavelet parameters; and (2) a deep impulse response generation script that used the pre-trained models to compute DIRF and cumulative DIRF.

3.2.1. Model Training and Optimization

The first phase developed a hybrid LSTM-Wavelet model tailored to each macroeconomic variable, optimizing its performance across various wavelet configurations and preserving the results for later use.

3.2.1.1. Data Preparation and Processing

The data was split into a training set (70% of observations) and a test set (30%) to enable out-of-sample validation. Variables were normalized by the z-score method, fitted on the training data and applied to both sets. The standardization ensured that the training process was smooth and the cost function was not caught in local minimums.

3.2.1.2. Wavelet Transformation with Parameter Exploration

A discrete wavelet transform (DWT) was applied to each variable to capture both temporal and frequency-domain characteristics. To determine the optimal transformation for each series, we systematically cycled through several configurations, including variations in selected wavelet types (specifically Daubechies wavelets: db4, db5, and db6), decomposition levels (levels 1 and 2), and boundary modes (Symmetric and Periodic). In each configuration, the DWT decomposed the original time series into approximation (cA) and detail coefficients (cD), and the signal was then reconstructed using only the approximation coefficients for level 1 decomp, and approximation and details coefficients for level 2 decomp. This approach emphasized smoothed trends while filtering out high-frequency noise.

Our wavelets selection was based on the evidence provided from academic literature demonstrating the effectiveness of these specific Daubechies wavelets, db4, db5, and db6, for analyzing economic and financial data. For example, Schleicher (2002) argued that the db4 wavelet was particularly effective in capturing mid-range fluctuations and long-term trends attributes that were essential when analyzing data, such as GDP and inflation. Similarly, Gencay, Selcuk & Whitcher (2002) highlighted that the db4 wavelet was adequate for revealing hidden cyclical patterns in financial time series, such as those seen in stock market indices and foreign exchange rates. On the other hand, Badiei and Mohammadi (2011) explored the application of db5 in analyzing cyclical trends in stock markets, and demonstrated that it provided optimal results in identifying cyclical patterns, such as weekly, monthly, quarterly, and yearly trends. On the forecasting front, Mitra (2006) reported that db5 clarified the signal in noisy macroeconomic indicators, thereby facilitating trend extraction. In the context of exchange rate forecasting, Al-deen Wazzer and Hameed (2022) employed db6 wavelet within the Wavelet-ARIMA model to enhance prediction accuracy and the authors noted db6 superiority over other wavelet functions. Finally, Shah & Debnath (2017) showed that embedding features extracted via the db6 into neural network architectures improved yield spread forecasting by separating the underlying signal from the noise.

We looped through a decomposition level of 1 and 2 only, because we found out that higher decomposition levels sometimes led to a loss in the prediction R2, where the model captured noise in the data instead of the underlying patterns due to the inherent volatility and noise in macroeconomic data (Crowley & Hallett, 2018). Only Symmetric and Periodic boundary modes were used as these yielded higher and smoother prediction accuracies R2. The effectiveness of Symmetric and Periodic boundary modes for our economic time series data could be attributed to their ability to handle the characteristics of macro variable data. Symmetric boundary mode reflects the data at the edges, which helps maintain smoothness and continuity, useful for non-periodic economic indicators. On the other hand, Periodic boundary mode assumes the data repeats itself, which is ideal for capturing cyclic patterns often found in economic data.

3.2.1.3. Time Series Sequence Generation

The wavelet-transformed training and test data were converted into sequences with a lag length of 12 timesteps, equivalent to 12 months. This process generated overlapping sequences of inputs and targets, enabling the LSTM to learn temporal dependencies and cyclical patterns over a year-long horizon. The choice of 12 timesteps was deliberate, designed to capture seasonal fluctuations, policy response lags, or macroeconomic interdependencies, enhancing the model's ability to model recurring dynamics inherent in monthly economic data (Hyndman & Athanasopoulos, 2018). In addition, Chirinos-Leañez & Pagliacci (2015) stated that the relationship between inflation and long-term yields takes around six months to be formed. Moreover, Boeck & Feldkircher (2021) suggested that it takes within a year until news was fully absorbed by macro variables.

3.2.1.4. LSTM Model Architecture and Training

There is no universally established scientific method for determining the optimal number of hidden layers and hidden neurons in neural network architectures, including LSTM models. As widely acknowledged in the academic literature, these hyperparameters are typically selected through empirical experimentation and trial-and-error approaches, rather than a formal theoretical framework. In table 3.1, we have presented the number of hidden neurons/layers per country that were used in our LSTM, and ANN models.

Table 3.1 Number of Hidden Neurons/Layers per country

Country	US	UK	BRA	EG	IND
Hidden Neurons	150	50	150	150	50
Hidden Layers	2	1	2	2	1

To ensure reproducibility, the random seed was fixed to control all stochastic processes such as weight initialization and data shuffling. We applied the default activation functions of an LSTM network, a Sigmoid activation for the input, forget, and output gates to regulate information flow, and a Hyperbolic Tangent (Tanh) activation for the cell state and hidden state updates to introduce non-linearity. The TanH activation function was used for the ANN network. We experimented with two activation functions in the ANN hidden layers: Sigmoid and Tanh. Our findings indicated that the Tanh activation yielded a higher overall median R2, with notable improvements for the yield curve latent factors (LEVEL, SLOPE, CURVATURE) across all countries. However, the Sigmoid activation performed better, in some countries, for certain macro variables, specifically EQUITY, FX, POLRATE. Given the superior overall performance of Tanh, we adopted it for the final ANN implementation, acknowledging that future research could explore variable-specific activation functions to further enhance performance for macro variables. Each hidden layer's activation function (Tanh for the ANN, Sigmoid and Tanh for the LSTM) was followed by a Layer Normalization to stabilize the training process and improve generalization (for both LSTM and ANN). In the Output layer, we applied a dense layer with 8 units (one per variable) based on a linear activation function, suitable for regression tasks. All variables were trained simultaneously within a single multivariate model to capture their interdependencies, allowing the LSTM and ANN to learn the complex, cross-variable, relationships that characterize macroeconomic systems. In terms of regularization, only an L2 regularization with a strength of 0.01 was used to prevent overfitting, since, the addition of a dropout of inputs (standard and recurrent) caused a deterioration in the results. Additionally, we tested an LSTM Autoencoder architecture, and the incorporation of a Gaussian Noise layer into our LSTM model, as strategies to address the high level of noise present in the data, however, neither of the two approaches resulted in any performance improvements. We experimented as well by applying an LSTM with Exogenous Breakpoints (Regime Shift), for Egypt, to account for the structural break in the data, however, the results did not improve. We attributed that to the fact that the LSTM had partially captured the regime shift in the time series even without explicitly engineered regime shift features.

Weight initialization in LSTM models for economic time series was crucial for stable learning. Poor initialization can lead to vanishing or exploding gradients, hindering the model's ability to capture long-term dependencies in economic data. Hence, weight initialization improves convergence and enhances generalization. We have comparatively tested several weight initialization methods, including Orthogonal, Xavier Uniform, and Xavier Normal, yielding inconclusive performance improvements. For both LSTM and ANN, we ultimately opted for the Random Normal initialization method (with a mean 0, standard deviation 0.05 and a fixed seed) based on its more favorable outcomes observed during the experimentation. Random normal weight initialization has shown successful outcomes in neural networks by improving convergence stability, especially in LSTM and CNN-LSTM architectures for tasks like time series modeling and handwriting classification (Ghazi, et al., 2019; Skorski, Temperoni, & Theobald, 2021; Masood, et al., 2023). For each wavelet configuration (combination of wavelet type, decomposition level, and boundary mode), the model was trained for 300 epochs using the Adam optimizer (initial learning rate 0.001, clipnorm 1.0 to improve the stability and convergence by limiting the magnitude of the gradient updates) and a Learning Rate Scheduler that reduced the learning rate by a factor of 0.5 if the validation loss did not improve for 10 epochs. The mean squared error (MSE) loss was minimized, and the performance was assessed using R2 scores and MSE for each variable on both training and test sets. All 300 epochs were simulated for each configuration, and after each epoch, the test R2 was compared to the best prior value for each variable (for both LSTM and ANN). If the test R2 improved, the model's weights, wavelet type, decomposition level, boundary mode, epoch number, training R2, test R2, and corresponding MSE values were updated as the best result for that variable. This thorough process ensured that the best performing model per variable, defined by the highest test R2 across all 300 epochs and wavelet configurations, was selected.

3.2.1.5. Residuals Analysis and Results Storage

For each variable, the best wavelet parameters (type, level, mode) and weights were retrieved, and the corresponding wavelet transform were reapplied to the data. Sequences of lagged values and their corresponding target values were then prepared from the transformed data to train the prediction model. These prepared sequences were used to generate predictions using the best weights. Residuals (actual minus predicted values) were calculated for both training and test sets, concatenated, and their standard deviations were computed to measure forecast error volatility. These standard deviations were used as the shock magnitude in the IRF analysis. Results, including wavelet parameters, best epoch, training R2, test R2, MSE values, and residuals' standard deviations, were saved for each variable.

3.2.2. Deep Impulse Response Function Generation

The second phase utilized the pre-trained models to simulate the dynamic responses of macroeconomic variables to shocks, producing DIRFs and cumulative DIRFs.

3.2.2.1. Model Reconstruction

The best wavelet parameters, training R2, test R2, and residuals' standard deviations were loaded (from the previous step), and the corresponding weights for each variable which ensured that the interpretation phase directly utilized the optimized models from Phase 1, maintaining consistency in parameters and architecture for both LSTM and ANN. For each variable, both LSTM and ANN models were reconstructed with the same architecture as in the training.

3.2.2.2. DIRF Computation

The DIRFs and cumulative DIRFs were computed by simulating the model's response to a one-time shock in each variable, based on its residuals' standard deviation, generated in Phase 1. The simulation begun with an input sequence of shape initialized with zeros, in order to establish a neutral baseline, representing a state with no prior shocks or activity, ensuring that subsequent responses were attributable to the introduced shock, and the model's learned dynamics. At the last timestep (t=12), a shock equal to the variable's residual standard deviation was applied to the variable, while others remain zero. The model predicted the next period's values for all 8 variables, capturing their immediate responses. These predictions are fed back into the sequence by shifting it left (discarding the oldest timestep) and inserting the prediction at the last timestep. This autoregressive process iterated for 12 periods, simulating the shock's propagation over time. For each period, responses were recorded for all variables, and cumulative responses were calculated by summing the period by period, reflecting the total impact over the horizon. This procedure was repeated for each variable.

3.2.3. Comparative Benchmark: VECM Implementation

To provide a traditional econometric benchmark, a Vector Error Correction Model (VECM) was implemented for the eight macroeconomic variables using the raw data (without z-score normalization or wavelet transformation, unlike the LSTM and ANN models, which applied z-score normalization prior to wavelet decomposition). The data was split into a 70% training set and a 30% test set as well. The optimal lag order was determined using the Akaike Information Criterion (AIC) with a heuristic cap on maximum lags (maxlags= min(12, len(train_data)/(len(endog_vars)×2)), resulting in a maximum of 6 lags to ensure at least 2 observations per variable per lag, and the selected lag order was adjusted as k_ar_diff= max (1, AIC−1). The cointegration rank was estimated using the Johansen test at a 5% significance level, with a fallback to a rank of 1 if the test failed due to numerical issues. The VECM was fitted on the undifferenced training data (as VECM handles differencing internally) with the selected lag order and cointegration rank, including a constant inside the cointegration relation (deterministic="ci").

Forecasts were generated for the test period directly in the original scale, and R2 scores were computed for each variable by comparing the forecasted values to the actual test data values.

4. Results

4.1. Models Prediction Results

The table below summarized the median R2 per country for each model across the eight macroeconomic variables (LEVEL, SLOPE, CURVATURE, EQUITY, FX, POLRATE, GDP, INF), with an overall median R2 per model at the bottom.

Table 4.1 Prediction Accuracy R2 per Country

Median R2	LSTM	ANN	VECM
BRA	38.57%	22.14%	-140.67%
EGP	19.06%	7.83%	-35.17%
IND	70.74%	43.90%	-112.26%
UK	43.34%	38.52%	-270.87%
US	44.58%	37.00%	-139.91%
Median R2 Per Model	**43.34%**	**37.00%**	**-139.91%**

In terms of country specific performance, the highest median prediction accuracy R2 was recorded by Indonesia (IND) LSTM equivalent to 70.74%, suggesting that Indonesia's macroeconomic data has patterns highly compatible with the LSTM model, likely due to strong trends in macro variables. The US had the second highest prediction accuracy R2 (LSTM), with consistent performance across most variables. The UK had the third highest prediction accuracy R2, with balanced overall results. Generally, the LSTM's overall median R2 of 43.34% underscored its ability to capture long-term dependencies in macroeconomic data, outperforming both the ANN and VECM. The ANN's overall median R2 of 37% was lower than the LSTM's 43.34% but represents a significant improvement over the VECM, which was probably due to its architecture and capability to capture the non-linear behavior of macro variables. The VECM model performed poorly across all countries, highlighting its limitations in capturing the non-linear dynamics of the data, especially without wavelet transformation.

4.2. Variables Prediction Results

Table 4.2 examined the prediction accuracy of the LSTM model across the eight macroeconomic variables by analyzing their median R2 values over the five countries. The table below includes the R2 for each variable in each country, the median R2 per variable, and the maximum R2 for the LSTM model to highlight the best performance.

Table 4.2 LSTM Prediction Accuracy Per Variable R2

Variables	BRA	EGP	IND	UK	US	Median R2	Max R2
LEVEL	-2.4%	19.0%	13.0%	26.5%	35.1%	**19.0%**	**35.1%**
SLOPE	49.4%	29.2%	26.8%	17.3%	35.9%	**29.2%**	**49.4%**
CURVATURE	8.6%	12.8%	5.6%	25.2%	5.3%	**8.6%**	**25.2%**
EQUITY	63.9%	30.6%	79.6%	64.5%	53.8%	**63.9%**	**79.6%**
FX	28.4%	13.9%	74.2%	43.6%	56.7%	**43.6%**	**74.2%**
POLRATE	60.5%	6.6%	67.3%	74.8%	53.3%	**60.5%**	**74.8%**
GDP	27.9%	48.4%	87.8%	43.1%	88.5%	**48.4%**	**88.5%**
INF	48.7%	19.1%	75.4%	51.5%	22.8%	**48.7%**	**75.4%**
Median R2	**38.57%**	**19.06%**	**70.74%**	**43.34%**	**44.58%**		

The LSTM model demonstrated a strong predictive performance across most variables, with median R2 values reflecting its ability to capture both yield curve dynamics and macro variable trends. The EQUITY had the highest median prediction accuracy R2 of 63.9%, with a maximum of 79.6% in IND, which Indicated the LSTM's effectiveness in capturing equity market trends, likely due to their cyclical nature and sensitivity to macroeconomic conditions. The POLRATE had the second highest median prediction accuracy of 60.5%, with a maximum of 74.8% in the UK, reflecting the LSTM's ability to model the cyclical patterns of policy rates, which are often influenced by central banks responses to economic conditions. The LSTM exceled at capturing GDP trends, with a maximum R2 of 88.5% in the US, and a median R2 of 48.4%, which are central to macroeconomic analysis and often exhibit long-term dependencies that the LSTM's memory mechanisms can model effectively. INF's predictability, with a maximum R2 of 75.4% in IND and a median R2 of 48.7%, aligned with its association with the GDP, as noted by academic scholars, where economic growth often drives inflationary pressures. With a median R2 of 43.6% and a maximum R2 of 74.2%, the LSTM reflected the ability to model foreign exchange rate dynamics (FX), which are influenced by both domestic and global economic factors. Finally, the three yield curve latent factors had the lowest median R2, showing more variability, possibly due to noise in the data.

IND had the highest median R2 equivalent to 70.74%, with a strong performance across almost all macro variables. We attributed this to IND's efficient market dynamics, with clear macroeconomic trends, making it highly compatible with the LSTM's ability to capture long-term dependencies. The US had the second highest median R2 of 44.58%, with an exceptional performance for the GDP and FX, reaching 88.5% and 56.7% respectively. In fact, the US, as a developed and efficient market, benefited from high-quality data and predictable economic patterns, leading to strong LSTM performance. The UK had a balanced performance with a median R2 of 43.34%, and a notable R2 accuracy for the POLRATE at

74.8% and the EQUITY at 64.5%. The UK's developed market characteristics supported consistent predictions, though yield curve factors like SLOPE at 17.3% were less predictable. BRA emerging market dynamics introduced more noise, affecting the LSTM's performance on some variables, reaching a median R2 of 38.57%. EGP had the lowest median R2 of 19.06%. Clearly, EGP has less predictable economic dynamics, or data quality issues, which likely contributed to the LSTM's challenges in this market.

4.3. Daubechies Wavelet Transform Analysis

Illustrated in table 4.3 the Daubechies wavelet (db4, db5, db6) types that were selected by our LSTM model that maximized each variable R2 per country. We have illustrated the frequency of Daubechies wavelet type: per variable in table 4.3 a), and per country in table 4.3 b). For example, from table 4.3 a), when the LEVEL was optimized, db4 & db5 were used once, and db6 was used three times to achieve the highest prediction accuracy R2.

Table 4.3 Frequency of Daubechies Wavelet type per Variable per Country

a) Frequency of Wavelets Type per Variable

Variable	db4	db5	db6
LEVEL	1	1	3
SLOPE	2	3	0
CURVATURE	2	2	1
EQUITY	3	1	1
FX	3	2	0
POLRATE	1	2	2
GDP	4	1	0
INF	2	2	1
Total	**18**	**14**	**8**

b) Frequency of Wavelets Type per Country

Country	db4	db5	db6
BRA	5	2	1
EGP	4	4	0
IND	4	3	1
UK	3	2	3
US	2	3	3

From table 4.3, db4 is the most frequently selected wavelet type, used 18 times in total. This suggested that db4, with its moderate smoothing and ability to capture both short and medium-term patterns, was well-suited for a wide range of macroeconomic variables.

Db4 was selected in 4 out of 5 countries when optimizing the GDP, indicating that GDP's long-term trends were best captured by db4's balanced frequency resolution. Db6 was favored, in 3 out of 5 countries, when optimizing the LEVEL, which often exhibited smoother, longer-term trends, benefiting from db6's higher vanishing moments, which exceled at capturing low-frequency components. The SLOPE and FX showed a mix of db4 and db5, indicating that these variables may have more medium-frequency patterns that db4 and db5 were better at capturing. In addition, db4 was also selected, in 3 out of 5 countries, when optimizing the EQUITY, reflecting its suitability for capturing the cyclical patterns in equity markets. The POLRATE, CURVATURE, and INF showed a more balanced distribution across wavelet types, suggesting that their dynamics vary across countries, requiring different frequency resolutions.

BRA and IND both heavily favored db4, indicating that their macroeconomic variables likely exhibited patterns best captured by db4's balanced smoothing, possibly due to similar emerging market dynamics, with a mix of short- and medium-term fluctuations. In addition to db4 that was selected 4 times for EGP, db5 was also selected more times than in BRA and IND, suggesting a focus on shorter to medium-term patterns, possibly due to noisier or less predictable economic data. Finally, the UK and US showed a more balanced distribution and use of wavelets. This balance probably reflected the developed nature of these economies, where variables may exhibit a wider range of frequency components (short-term noise to long-term trends), requiring different wavelet types.

Key Insights:

- **GDP:** Selected 4 times with db4, likely because GDP exhibited medium-term cyclical trends (e.g., business cycles of 2–5 years) and short-term fluctuations (e.g., quarterly variations).
- **EQUITY:** Selected 3 times with db4, reflecting its ability to capture cyclical patterns in stock markets (e.g., weekly, monthly, or yearly trends). Equity markets often show short- to medium-term volatility driven by economic news or policy changes.
- **FX:** Selected 3 times with db4, aligning with its ability to model medium-frequency patterns in exchange rates, which are influenced by both short-term market sentiment and medium-term economic fundamentals.
- **POLRATE and INF:** These variables showed a balanced distribution of wavelet types (e.g., POLRATE: 1 db4, 2 db5, 2 db6; INF: 2 db4, 2 db5, 1 db6). Central bank policy rates and inflation exhibit both medium-term cycles (e.g., policy adjustments over 1–2 years) and long-term trends (e.g., persistent inflation regimes), making db5 and db6 suitable in some contexts, especially in developed markets with stable policy frameworks.
- **GDP, EQUITY, FX:** These variables were dominated by db4, suggesting that their dynamics are primarily short- to medium-term (e.g., business cycles, market volatility).
- **LEVEL and db6:** Selected with db6 in 3 out of 5 countries. The LEVEL often captures long-term trends driven by persistent factors like inflation expectations or monetary policy outlooks. The higher R2 for the LEVEL in the US (35.1%) and UK (26.5%) aligned with

db6’s use in these developed markets, where long-term trends may be more pronounced due to efficient market dynamics.

- **Decomposition Levels**: Level 1 captured shorter-term patterns (e.g., monthly fluctuations), while level 2 captured medium-term patterns (e.g., quarterly to yearly trends). The dominance of db4 at these levels suggested it effectively balanced short- and medium-term pattern extraction without over-smoothing.
- **Developed Markets (US, UK):** These markets showed a balanced use of db4, db5, and db6 (e.g., US: 2 db4, 3 db5, 3 db6; UK: 3 db4, 2 db5, 3 db6). This suggested that some variables in developed economies exhibited longer-term patterns (e.g., stable yield curve trends or policy-driven cycles), which db5 and db6 are better at capturing due to their smoother filters.
- **Developing Markets (BRA, IND, EGP):** These markets heavily favored db4 (e.g., BRA: 5 db4, IND: 4 db4, EGP: 4 db4), with less use of db5 and db6. Emerging markets often exhibit volatile, short- to medium-term fluctuations due to economic instability or external shocks, making db4 more suitable. The lower selection of db5 and db6 suggested that long-term trends are less dominant or harder to isolate in these datasets.

4.4. Cumulative Deep Impulse Response Functions Analysis

In this section, we have analyzed the Cumulative Deep Impulse Response Functions for yield curves and macro variables for all the studied countries. We have focused on identifying similar trends, discrepancies, and potential causes, drawing on the economic context of each country and the variables’ dynamics.

4.4.1. The LEVEL Impulse

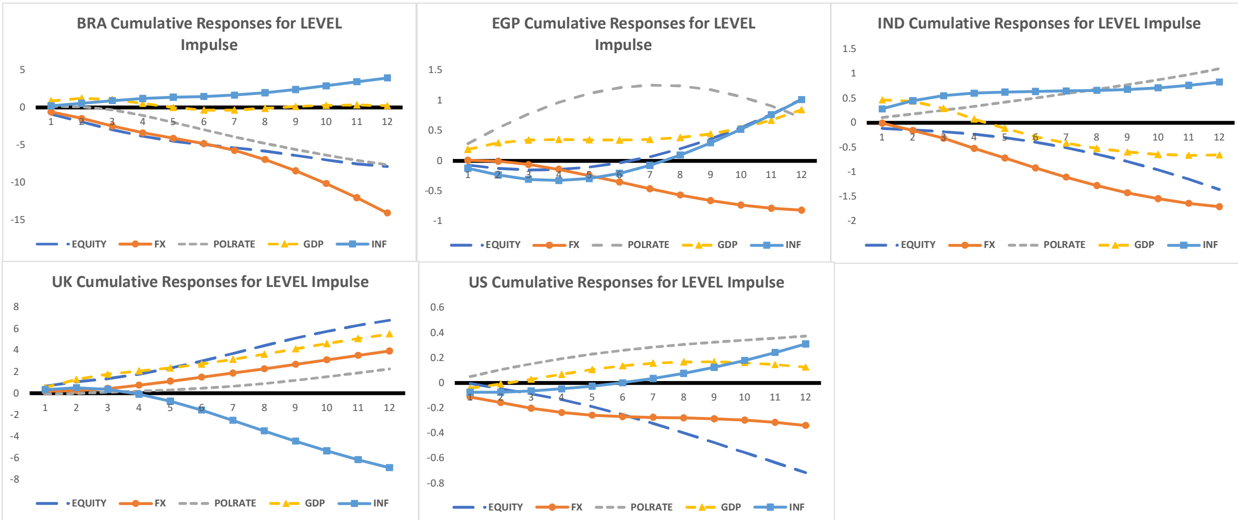

Figure 4.1 LEVEL Impulses and Cumulative Responses Per Country

We have illustrated in figure 4.1 the LEVEL (the yield curve parallel shift) impulses and cumulative responses (EQUITY, FX, POLRATE, GDP, and INF) across our five studied countries (BRA, EGP, IND, UK and US) over 12 periods (months).

With the exception of the UK, most countries exhibited an immediate negative EQUITY response to the LEVEL impulse, attributed to an increase in borrowing costs, reducing the present value of future cash flows and dampening equity markets, a typical response to higher interest rate and inflation expectations, as the LEVEL reacts according to higher future inflation expectations. According to Ahmed et al. (2017) interest rates Granger Caused the stock market. EGP's response turned positive by period 7 which could reflect a quicker recovery or foreign investment inflows. We believe that emerging markets like BRA are more sensitive to the LEVEL due to higher economic volatility, which explained the particularly pronounced EQUITY response observed, as indicated by higher residual volatility. Moreover, a shock to the LEVEL caused a negative response in most countries exchange rates (FX), as it is an indication of future inflationary pressures. Higher interest rates typically attract capital inflows, strengthening the currency, but risk aversion and inflationary risks override the interest rate effect. Egilsson (2020) proved that higher interest rates can cause inflation and currency depreciation. BRA's FX response to the LEVEL was again more severe, similar to its EQUITY response, reflecting its economic volatility and sensitivity to shocks. It is worth noting that the UK showed a positive FX and EQUITY response to LEVEL impulses, attributed to the country's market stability and capital inflows, outweighing inflation expectations. Furthermore, the POLRATE responded positively to an impulse in the LEVEL, in most countries. An impulse in the LEVEL is an indication of inflationary pressures, prompting central banks to raise rates to manage inflation. These findings are consistent with academic literature, since a growth in the economy leads to higher inflationary pressures that will trigger a rise in the yield curve in the form of a parallel shift (the LEVEL), prompting the central bank to hike its policy rate (Ang & Piazzesi, 2003; Rudebusch & Wu, 2004; Diebold, Rudebusch, & Aruoba, 2006; Djuranovik, 2014; Coroneo, Giannone, & Modugno, 2016; Shareef & Shijin, 2017). BRA showed a negative POLRATE response, unlike the positive trends in other countries, suggesting a countercyclical policy to counteract economic contraction (e.g., declines in EQUITY and FX), typical in emerging markets facing growth challenges. A countercyclical policy is when a central bank acts against the prevailing economic trend to stabilize the economy. In BRA's case, despite rising inflation expectations, the central bank lowered rates to support economic growth (Barroso et al., 2020; Araujo, Araujo, & Ferrari-Filho, 2022). This approach is often used in emerging markets facing economic contraction, such as falling equity prices and currency depreciation, where the priority shifts from fighting inflation to stimulating growth and preventing a further contraction of economic activities. By lowering the policy rate, the central bank aims to counteract economic weakness and encourage investment and consumption, despite of inflationary risks. As we have previously mentioned, and is supported by findings in academic literature, the LEVEL, INF, POLRATE and GDP are associated, thus, an impulse in the LEVEL caused a positive GDP response in most countries. IND's GDP response to the LEVEL impulse was mixed, it rose till period 4, then fell afterwards till period 12. The association between the LEVEL and the GDP explained the initial GDP boost (periods 1–4), but higher rates eventually curbed borrowing and investment, leading to a downturn (periods 5–12) amid weak credit and exchange-rate channels and global "risk-off" reversals (Cepni et al., 2021; Deléchat, Rawat, & Stepanyan, 2024). In BRA, changes in long-term bond yields barely affect growth because banks keep large gaps between their funding costs and loan rates, and many yield moves reflect debt-risk worries (de Mello & Pisu, 2009), which might be the reason for BRA's GDP minor response to the LEVEL impulse. As expected, INF responses to LEVEL impulses were positive in the long-term for most countries, with the exception of the UK. The INF negative response in the UK could be attributed to an effective demand suppression, possibly due to tighter monetary policy (POLRATE increase), in other words, a combination of effective monetary policy, well defined inflation expectations, and efficient market dynamics. EGP's INF response to the LEVEL impulse was negative till period 7, turning positive afterwards. In fact, higher borrowing costs, initially reduced demand and lowered inflation in Egypt, which explained the negative INF response from periods 1 to 7. EGP's FX response showed a gradual depreciation. In emerging markets, currency depreciation raises the cost of imported goods, leading to imported inflation with a lag (Gagnon & Ihrig, 2004). However, this effect is not immediate. From period 8 onward, these pressures began to dominate, turning the INF response positive.

4.4.2. The SLOPE Impulse

We have illustrated in figure 4.2 the SLOPE (the yield curve slope) impulses and cumulative responses (EQUITY, FX, POLRATE, GDP, and INF) across our five studied countries (BRA, EGP, IND, UK and US) over 12 periods (months).

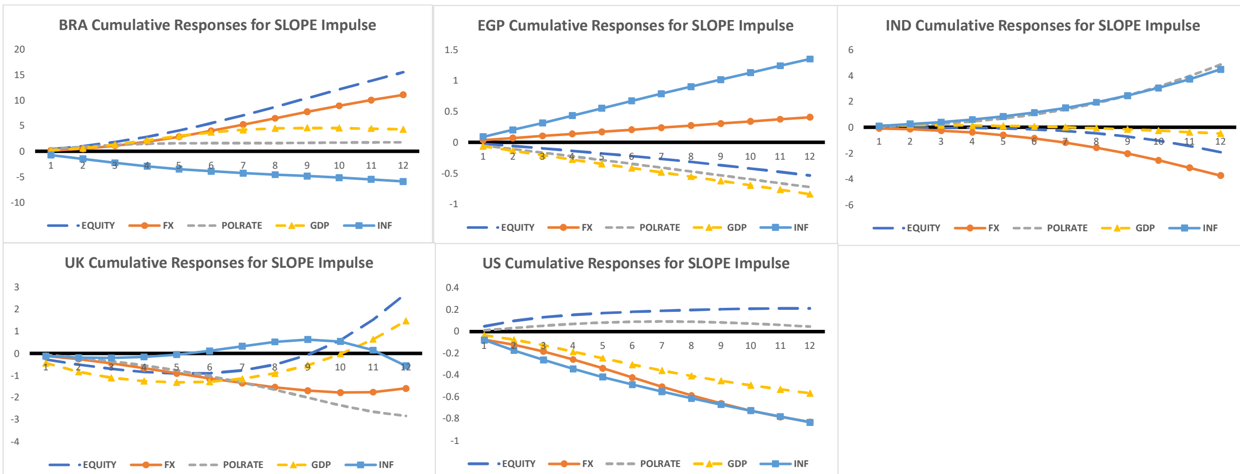

Figure 4.2 SLOPE Impulses and Cumulative Responses Per Country

The EQUITY responses to impulses in the SLOPE were mixed, with BRA, and the US exhibiting positive responses, and EGP and the IND exhibiting negative ones. In fact, shocks to the LEVEL and SLOPE react according to higher inflation expectations, hence, causing the EQUITY to fall. Thus, the UK response was negative as well, similar to EGP and IND, until period 9 where the response turned positive, meaning inflationary fears are less persistent in the UK since it has a more developed market. According to Ahmed et al. (2017) interest rates Granger Caused the stock market. In addition, higher US interest rates cause emerging markets' equity markets to decline due to their sensitivity to the global risk sentiment and capital outflows (Frankel & Okongwu, 1996). For BRA and US, a steepening yield curve could be signaling expectations of future economic growth, thus, their EQUITY responses rose. It's clear that the EQUITY responses to the SLOPE were different from a country to another, relative to the economic maturity, inflation levels, and sector exposures, highlighting its specific nature. Furthermore, FX responses to SLOPE impulses were mainly negative (currency depreciation) for three countries: IND, UK, and the US. In fact, the FX seemed strongly influenced by information coming from the yield curve, the LEVEL (in the previous section), and the SLOPE as well, as they are an indication of inflationary pressures. Noting that a positive shock, or impulse, to the SLOPE could be caused by a decrease in the policy rate that were rapidly transmitted into the foreign exchange rate (Kearns & Manners, 2005). FX responses of BRA and EGP were positive (currency appreciation), thus, a steepening yield curve in these countries attracted capital inflows due to perceived growth prospects, highlighting their reliance on capital inflows. In response to an impulse in the SLOPE, BRA, IND, and the US increased their POLRATE to tighten monetary policy in response to inflation signals from the steepening yield curve. On the other hand, EGP and the UK POLRATE decreased, suggesting a focus on stimulating growth, rather than taming inflation. As a steepening yield curve predicts future growth in academic literature, following an impulse in the SLOPE (steepening yield curve), the GDP of BRA grew (positive response), while IND's GDP response was immediately positive then turned negative, and the UK's GDP response was negative then turned positive. In fact, the predictive power of the SLOPE over the GDP was extensively studied in academic literature (Jamriska, 2008; Abdymomunov, 2013; Hannikaeinin, 2017). On the other hand, the US and EGP exhibited a negative response in the GDP. Academic scholars like Kaya (2013) found no evidence of such a relationship, and Chinn and Kucko (2010) argued that the prediction power of the yield curve has deteriorated over time. As we have previously mentioned, a steepening yield curve leads to growth, and with growth comes inflation, as a result, with the exception of BRA and the US, INF rose in EGP, IND and the UK (delayed response) following an impulse in the SLOPE.

4.4.3. The CURVATURE Impulse

We have illustrated in figure 4.3 the CURVATURE (the yield curve curvature) impulses and cumulative responses (EQUITY, FX, POLRATE, GDP, and INF) across our five studied countries (BRA, EGP, IND, UK and US) over 12 periods (months).

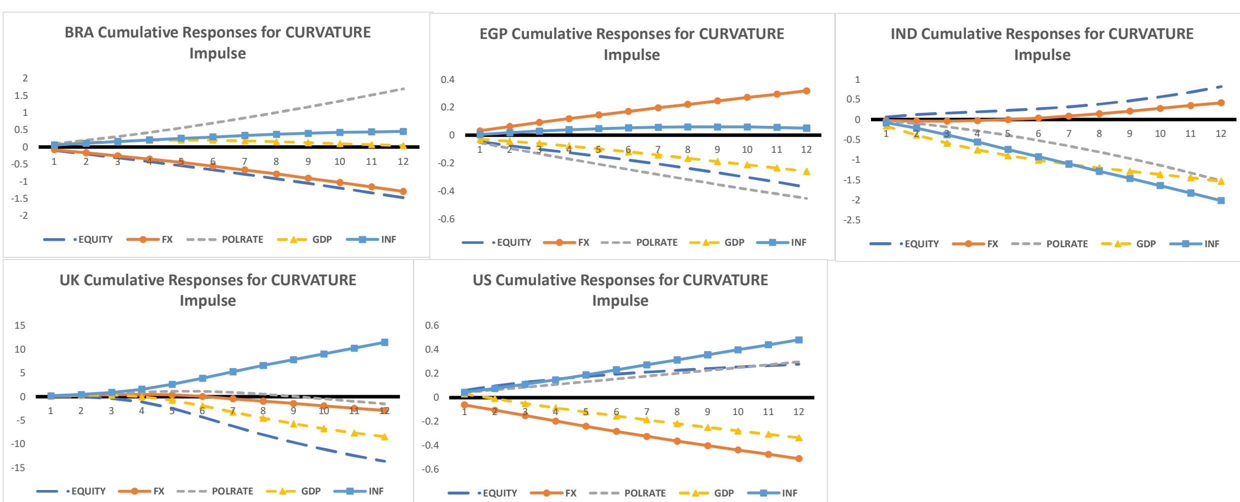

Figure 4.3 CURVATURE Impulses and Cumulative Responses Per Country

The CURVATURE is defined by a yield curve changing in a humped way, which is an unusual movement for yield curves, even less likely than the SLOPE. Generally, yield curves take the form of a humped shape when the market is not sure about the future outcome of the economy, or when the economy is about to turn its direction. EQUITY responses to the CURVATURE were mainly negative in BRA, EGP and the UK. While the US and IND exhibited positive responses. Academic scholars proved that the stock market is a leading indicator for economic growth (Plíhal, 2016). Furthermore, FX responses were negative, in three countries, BRA, UK and the US, probably due to yield curve volatility and uncertainty about the economy leading to capital outflows. For IND and EGP, FX responses were positive. The responses of POLRATE to CURVATURE shocks were mixed, with some countries showing an increase and others a decrease. BRA, UK, and the US all showed a general positive cumulative POLRATE response, suggesting that their central banks raised policy rates in response to CURVATURE shocks, to address potential inflationary pressures or stabilize financial markets. EGP and IND negative responses suggested a focus on stimulating growth. GDP responses to CURVATURE shocks were mostly negative, signaling expectations of economic contraction. INF responses to CURVATURE shocks were mostly positive. The rise in inflation might have been driven by their currency depreciation. We have noted the negative association between the GDP and INF responses for CURVATURE impulses, implying a stagflation.

4.4.4. The EQUITY Impulse

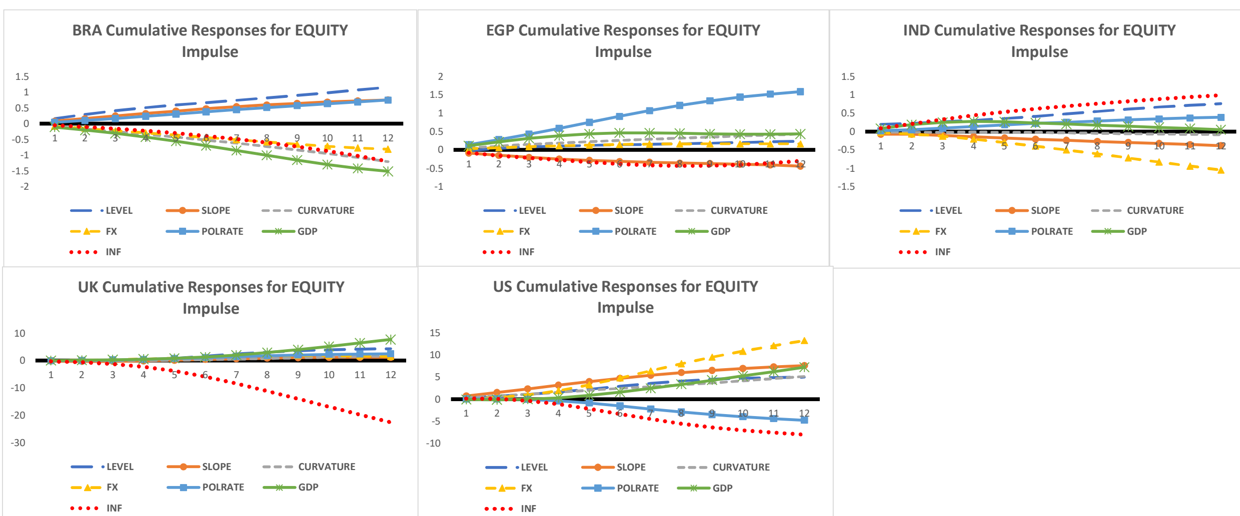

Figure 4.3 EQUITY Impulses and Cumulative Responses Per Country

The LEVEL responses to the EQUITY were mainly positive, as we have mentioned in the previous section that the stock market is a leading indicator of economic performance, thus, a rise in EQUITY signals an upcoming economic expansion that would be accompanied by inflationary pressures, leading eventually to an increase in the LEVEL. Most countries showed positive SLOPE responses to the EQUITY, in BRA, UK and US. As the EQUITY is a leading indicator of economic growth, in response to an EQUITY shock, the yield curve steepened. In EGP and IND, SLOPE responses were negative indicating a flattening yield curve. Academic scholars found evidence of a relationship between the stock market and inflation, hence, a shock to the EQUITY led to a negative response in the Slope, caused by the reaction of the short rate to higher inflation expectations (Pradhan, Arvin, & Bahmani, 2015; Chiang, 2022). CURVATURE responses were mixed, with some countries showing positive, or negative, or negligible, responses. FX responses were mixed to EQUITY impulses. In BRA and IND, these responses were negative implying a depreciation of the currency, which could be attributed to international investors rebalancing their portfolios or investors taking profits. Ojea-Ferreiro & Reboredo, (2022) found out that in emerging markets like Brazil, positive shocks in local equity prices caused a depreciation of the country's currency because foreign investors "take profits". Additionally, EGP, UK, and US FX responses were positive. Ahmadian-Yazdi et al. (2025) found that causality runs from the stock market to the FX, with the currency strengthening following an equity rise (Bems & Moussa, 2023). POLRATE responses to EQUITY impulses were mainly positive, meaning that these countries could be prioritizing inflation control over growth. Rising equity prices increases wealth, thus, could lead to an increase in future spending, and cause inflationary pressures. Suhaibu, Harvey, & Amidu (2017) found out that the stock markets are affected by their respective monetary policies through interest rates, and in the long term this relation is bidirectional. In academic literature, the stock market is a leading indicator of economic growth, meaning an impulse in the EQUITY should lead to a positive response in the GDP. Thus, GDP responses in four countries were positive. EQUITY impulses caused mainly negative responses in the INF. The negative inflation responses in BRA, EGP, UK, and the US following EQUITY impulses were likely driven by monetary tightening or currency appreciation.

4.4.5. The FX Impulse

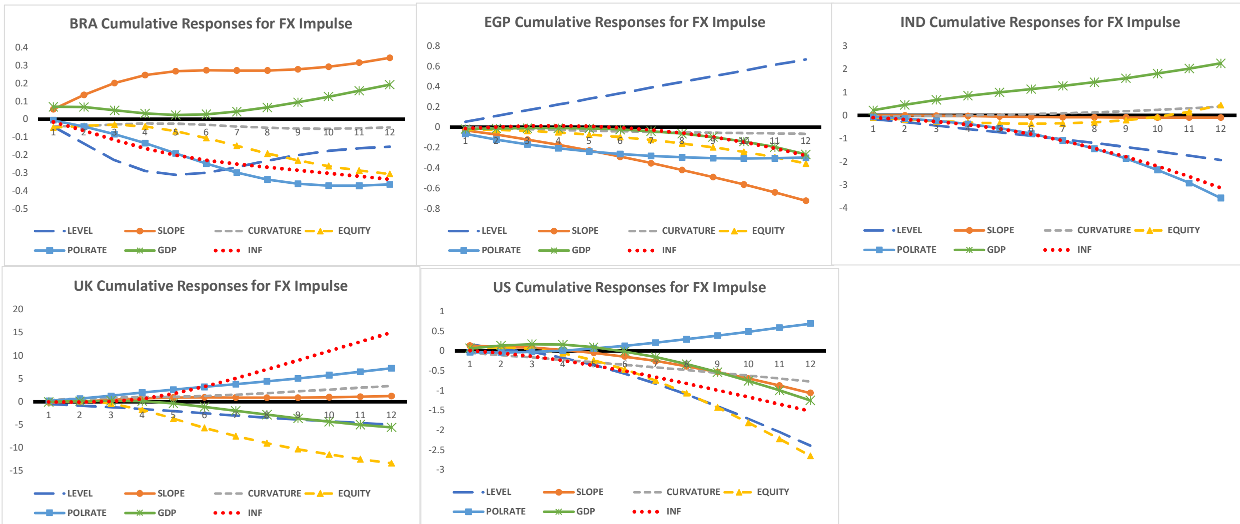

Figure 4.4 FX Impulses and Cumulative Responses Per Country

The FX was modeled in terms of direct exchange rate, showing how much one unit of home currency was worth in foreign currency ($). FX impulses (currency appreciations) caused mainly negative LEVEL responses. Declining LEVEL responses in most countries may reflect lower inflation expectations or economic slowdown following a currency depreciation. Ang and Piazzesi (2003) argued that the relationship between the Level and the foreign exchange was debated with controversy in academic literature. SLOPE responses to FX impulses were mixed, and CURVATURE responses were minimal. EQUITY responses to FX impulses were mainly negative. Equity markets tend to respond unfavorably to foreign exchange shocks, when investors anticipate inflationary pressures, rising interest rates, or deteriorating terms of trade (Hausmann & Panizza, 2010). POLRATE responses were negative in three countries, BRA, EGP and IND. Negative POLRATE responses suggested lower inflationary pressures following a currency appreciation, or monetary easing to support growth. When the domestic currency appreciates, exports become more expensive and less competitive, potentially slowing economic growth. Monetary easing helps stimulate the economy by offsetting these effects, supporting growth in these emerging markets where export competitiveness is often a priority. FX shocks caused positive POLRATE responses in the UK and US. In these countries a currency appreciation might lead to cheaper imports, which could fuel inflationary pressures, or signal strong capital inflows that need stabilization. GDP responses were different for the five studied countries, meaning that the relationship between the FX and the economy was not straightforward. For BRA and IND, GDP responses were positive. In BRA and IND, stronger currencies reduced import costs, eased inflationary pressure, led to a boost in output. Emerging markets often rely heavily on imported raw materials, and when their currencies appreciate, these imports become cheaper, reducing production costs. Lower costs benefit industrial production, encourage investment, and ultimately boost GDP. This is consistent with strong exchange-rate pass-through. In contrast, developed markets typically have more domestic supply chains, so they don't feel this cost-reduction effect as strongly, currency appreciation reduces net exports and slows growth. Thus, in the UK and US, GDP responses started positive then turned negative. The initial positive GDP responses might be explained by short-term confidence or capital inflow effects that temporarily boosted output before export losses dominated. Finally, in EGP the GDP response was negligible, meaning a non-responsive economy to FX impulses, likely due to structural rigidities or limited pass-through effects in Egypt's economy, which may not heavily rely on exchange rate-driven cost reductions for growth. Following FX impulses (currency appreciation), the INF responses were mainly negative, reflecting a strong exchange pass through, by lowering import prices.

4.4.6. The POLRATE Impulse

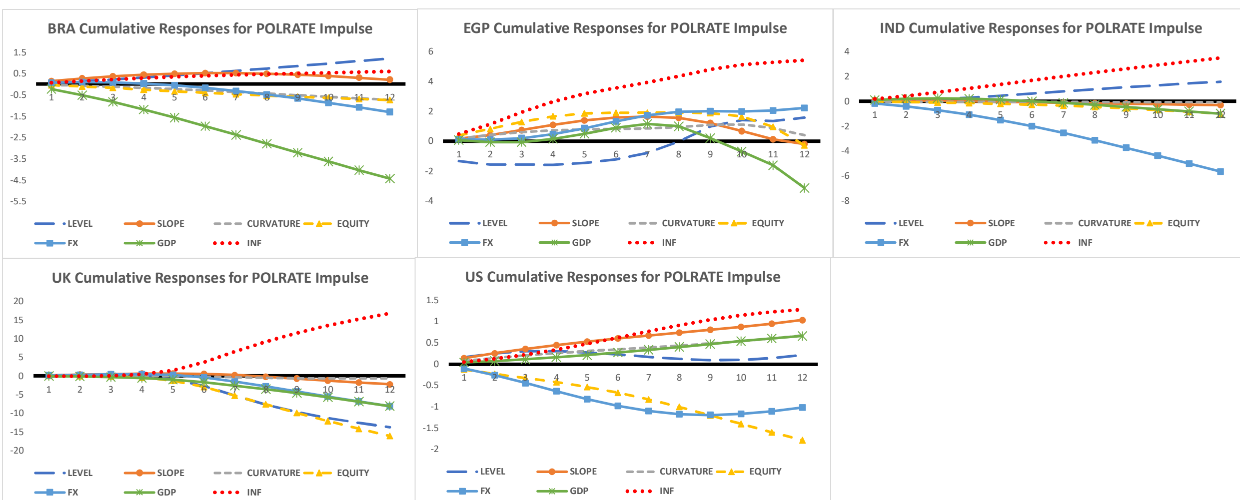

Figure 4.5 POLRATE Impulses and Cumulative Responses Per Country

Following POLRATE impulses (monetary tightening), the LEVEL responses were mainly positive in three countries: BRA, IND and the US, probably due to inflationary pressures, suggesting an effective transmission mechanism in these countries. As it has been highlighted in academic literature and as we have previously mentioned, there is an economic association between the LEVEL, POLRATE, INF and the GDP. A growth in the economy leads to higher inflationary pressures that will trigger a rise in the yield curve in the form of a parallel shift (the Level), prompting the central bank to hike its policy rate (Rudebusch & Wu, 2003; Ang and Piazzesi, 2003; Diebold et al., 2006; Djuranovik, 2014; Coroneo et al., 2016; Shareef and Shijin, 2017). EGP's LEVEL response to the POLRATE impulse was negative and turned to positive starting period 8, suggesting a delayed transmission of monetary policy to the yield curve, reflecting Egypt's volatile economic structure and weaker policy pass-through. In contrary, UK's LEVEL response was positive till period 4 turning negative afterwards, indicating a short-term alignment with expected inflationary pressures from tightening, raising the yield curve (positive LEVEL). The subsequent negative response could reflect market expectations of slower growth or controlled inflation. The SLOPE responses to an impulse of the POLRATE were mainly positive, showing steepening yield curves. Accordingly, the short end of the yield curve responds promptly to the monetary policy, reflecting the ability of the central bank to control the whole yield curve (Chirinos-Leañez & Pagliacci, 2015). This positive SLOPE response to the POLRATE was also confirmed in the short term in IND and the UK. CURVATURE responses to the POLRATE were all mixed. As one would expect, the responses of the EQUITY to the POLRATE were negative, with the exception of EGP. Higher POLRATE is a sign of higher inflation expectations. According to Ahmed et al. (2017) interest rates Granger Caused the stock market. The FX responses to the POLRATE were mainly negative, with the exception of EGP, suggesting that markets may perceive the policy rate increase as insufficient to offset concerns about economic weakness or inflation, potentially driving capital outflows. While EGP's FX response to the POLRATE was positive, aligning with conventional economic theory, where higher interest rates attract capital inflows. An impulse in the POLRATE led to mainly negative GDP responses with different delays or response times between countries, aligning with contractionary monetary policy impacts, suggesting an effective transmission mechanism. The INF responses to the POLRATE impulse were positive in all countries, highlighting what we have previously mentioned, the association between the POLRATE and INF.

4.4.7. The GDP Impulse

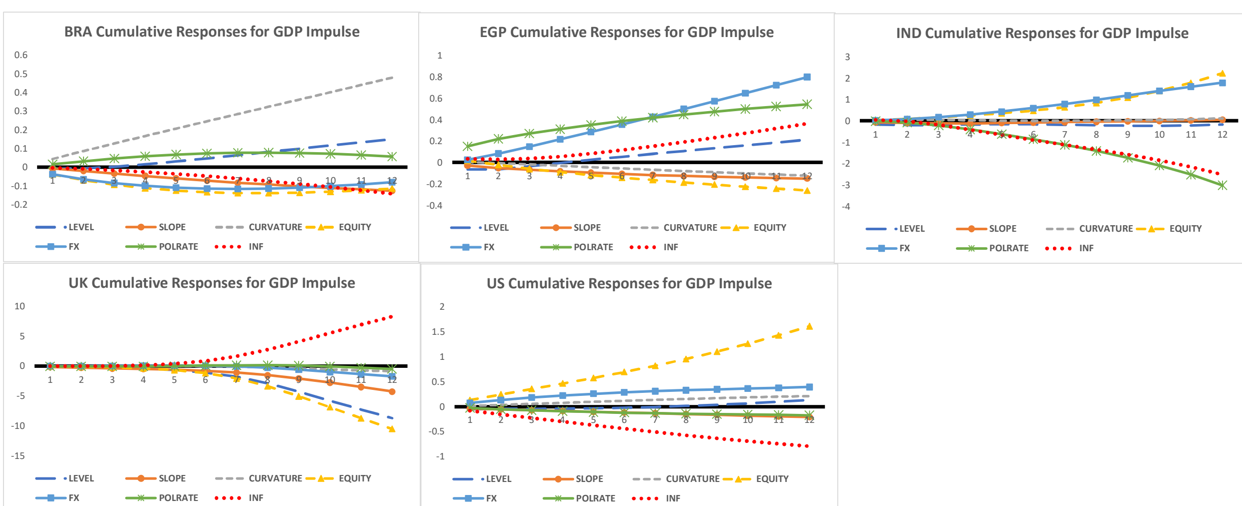

Figure 4.6 GDP Impulses and Cumulative Responses Per Country

GDP impulses caused positive LEVEL responses in BRA and EGP. Additionally, the US LEVEL positive response came with a delay starting period 8. A rise in the GDP would be accompanied by inflationary pressures, leading eventually to an increase in the LEVEL. Hence, shocks to the GDP mainly caused positive responses in the LEVEL (Diebold et al., 2006; Djuranovik, 2014; Coroneo et al., 2016; Shareef and Shijin, 2017). Contrary to the typical expectation of inflationary pressures raising yields, IND and UK LEVEL responses were negative, which could be caused by a muted inflationary pass-through or an effective monetary policy reducing inflation expectations. As we have previously mentioned that economic growth is accompanied by higher inflation, leading to a positive response in the LEVEL and POLRATE, thus, a shock to the GDP led to negative responses in the SLOPE, as the short rate rises. The CURVATURE responses to the GDP were mixed and muted. EQUITY responses to impulses in GDP were mainly negative in three countries, BRA, EGP and UK, meaning economic growth did not translate into equity market gains, possibly due to market expectations of monetary tightening to control inflation. On the other hand, EQUITY responses were positive in IND and the US, indicating that GDP growth boosted investor confidence. FX responses were mainly positive (currency appreciation) following GDP impulses in three countries, IND, EGP, and the US. While the response was negative in BRA and muted in the UK. A positive GDP shock boosts investor confidence, and attracts capital inflows that strengthen the domestic currency, which leads to a positive FX response. Following GDP impulses, BRA and EGP exhibited positive POLRATE responses (raising policy rates), likely reflecting concerns about inflationary pressures from economic growth, prompting their central banks to tighten monetary policy to maintain price stability amid inflation volatility. In contrast, IND and the US showed negative POLRATE responses (lowering policy rates), possibly to sustain growth momentum or because GDP shocks were driven by non-inflationary factors like productivity gains. The UK displayed a muted POLRATE response, suggesting a balanced approach where GDP growth did not significantly alter inflation expectations or necessitate immediate policy adjustments, consistent with its stable monetary framework and diversified economy. Finally, GDP impulses caused negative INF responses in three countries, BRA, IND and the US; while the INF responses were positive in EGP and the UK. The negative INF responses in BRA, IND, and the US suggested that economic growth in these countries could be driven by supply-side improvements, such as productivity gains or lower input costs, which reduced inflationary pressures. On the contrary, the positive INF responses in EGP and the UK indicated that GDP growth caused demand-side pressures, increasing inflation. In EGP, structural vulnerabilities like reliance on imports may amplify price pressures, while in the UK, a demand-driven growth surge in a developed economy could push inflation higher, reflecting tighter capacity constraints.

4.4.8. The INF Impulse

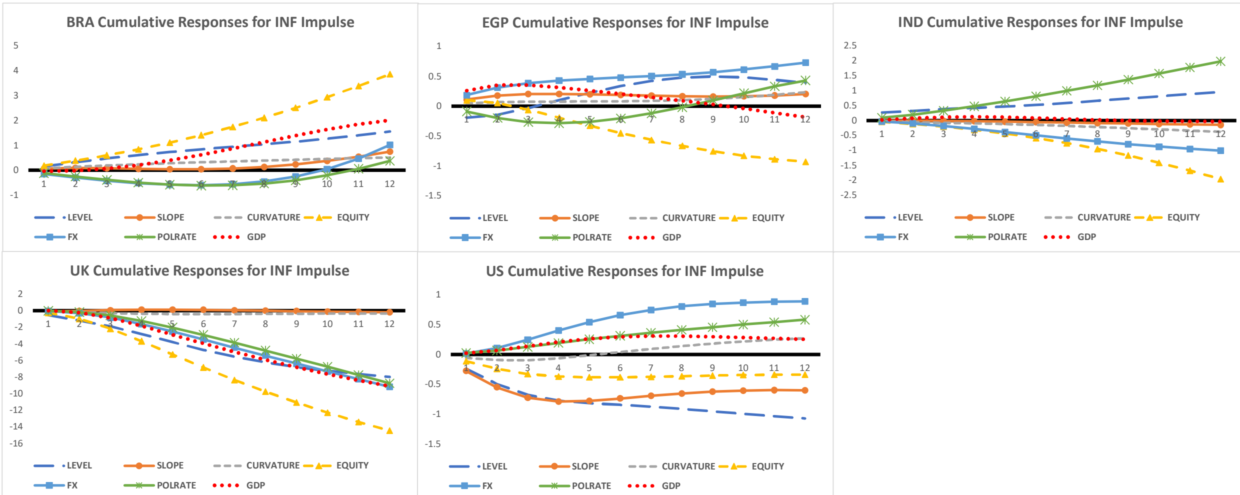

Figure 4.7 INF Impulses and Cumulative Responses Per Country

As we have previously mentioned, the INF is associated with the LEVEL, INF impulses caused positive LEVEL responses in three countries, BRA, EGP, and IND; while LEVEL responses were negative in the UK and US. INF impulses leading to positive LEVEL responses in BRA, EGP, and IND, aligned with the expectation that higher inflation increases nominal yields across maturities, reflecting higher inflationary expectations in these countries, that has a strong pass-through effect to the yield curve (Diebold et al., 2006). Contrarily, the negative LEVEL responses in the UK and US suggested that inflation shocks may be perceived as transitory or effectively managed by credible monetary policies, reducing long-term yield expectations. The impact of the surge in INF on the SLOPE and CURVATURE was mixed across countries. Additionally, the EQUITY reacted negatively to impulses in INF in most countries, suggesting that rising inflation negatively affected investor confidence, likely due to expectations of monetary tightening, which would increase borrowing costs and reduce corporate profitability. Impulses in the INF caused negative FX responses (currency depreciation) in three countries, BRA, IND and the UK; while the FX responses were positive (currency appreciation) in EGP, and the US. Negative FX responses in BRA, IND, and UK, likely reflected investors' concerns about eroding purchasing power and economic stability, prompting capital outflows that weakened these currencies. On the other hand, positive FX responses in EGP and the US suggested that inflation shocks attracted capital inflows, possibly due to expectations of robust monetary tightening or, in the US, the dollar's safe-haven status, while EGP's appreciation may stem from specific policy measures or external support stabilizing the currency despite inflation. Following INF impulses, POLRATE responses were mainly negative in three countries, BRA, EGP, and the UK; while being positive in IND and the US. The negative POLRATE responses to INF impulses suggested that central banks in these countries prioritized economic growth or perceived the inflation shock as transitory, opting for monetary easing to mitigate potential output losses rather than tightening to control inflation. The positive POLRATE responses indicated proactive monetary tightening to address inflationary pressures, aligning with inflation-targeting regimes. Aligning with economic theory, with growth comes inflation due to increased demand or cost pressures, INF impulses caused positive GDP responses in most countries.

4.5. Summary of Results

4.5.1. Forecasting Accuracy

The hybrid LSTM-Wavelet model demonstrated superior predictive performance, achieving an overall median R2 of 43.34% across all countries, significantly outperforming the ANN-Wavelet model and the VECM. The highest median predictions R2 were observed in IND (70.74%), followed by the US (44.58%) and the UK (43.34%), reflecting the model's strength in capturing complex, nonlinear dynamics in economies with clear cyclical patterns and high-quality data. BRA (38.57%) and EGP (19.06%) showed lower performance, likely due to emerging market volatility and data quality issues, respectively. The VECM's negative R2 values highlight its limitations in modeling nonlinear dynamics without wavelet preprocessing, underscoring the advantages of hybrid deep learning approaches.

4.5.2. Daubechies Wavelet Transform Analysis

The LSTM-Wavelet model exceled in forecasting variables with strong cyclical patterns and long-term dependencies. EQUITY achieved the highest median prediction R2 (63.9%, max 79.6% in IND), reflecting the model's ability to capture equity market trends driven by macroeconomic conditions. POLRATE followed closely (median R2 60.5%, max 74.8% in the UK), leveraging the model's capacity to model central bank responses to economic cycles. GDP (median R2 48.4%, max 88.5% in the US) and INF (median R2 48.7%, max 75.4% in IND) also exhibited strong performances, aligning with their economic interdependencies, meaning economic growth drives inflationary pressures, which in turn influence central bank policy rates, a relationship well-documented by academic scholars. In contrast, yield curve factors: the LEVEL (median R2 19.0%), SLOPE (29.2%), and CURVATURE (8.6%); exhibited lower predictions R2, likely due to noise and complex interactions, making them harder to predict accurately.

The db4 wavelet was the most frequently selected type (18 times), particularly for macro variables like GDP (4 times out of 5), EQUITY (3 times), and FX (3 times), aligning with the LSTM's strong prediction performance R2 for these variables, indicating its effectiveness in capturing short- and medium-term patterns for these variables. The preference for db6 in the LEVEL, and its use in developed markets like the US and UK, may explain the LSTM's better performance for the LEVEL in these countries (e.g., US: 35.1%, UK: 26.5%), as db6 has the ability to capture smoother, low-frequency trends that match the dynamics of yield curve factors in efficient markets. SLOPE and FX showed a mix of db4 and db5, reflecting medium-frequency dynamics, while CURVATURE, POLRATE, and INF displayed balanced wavelet type usage, suggesting diverse frequency components across countries. Countries like, BRA, IND, and EGP, favored db4, likely due to their volatile patterns, whereas more developed markets, like US, and UK, used a balanced mix of db4, db5, and db6, reflecting varied economic dynamics.

4.5.3. Deep Impulse Response Function

Key insights:

- In most countries, a LEVEL shock led to negative EQUITY and FX responses, reflecting higher borrowing costs and inflationary pressures. POLRATE typically rose to counter inflation, except in BRA, where the policy rate decreased to support growth. GDP responses were generally positive following LEVEL impulses. INF responses were positive in the long-term, except in the UK, where effective monetary policy suppressed demand.
- A SLOPE shock (steepening yield curve) caused mixed EQUITY responses, positive in BRA and the US (signaling growth) but negative in EGP and IND (reflecting inflation fears). FX responses were mostly negative, except in BRA and EGP, where capital inflows strengthened currencies. POLRATE rose in BRA, IND, and the US to address inflation, but fell in EGP and the UK to stimulate growth. GDP and INF responses varied, with growth-inflation linkages evident in some countries.
- CURVATURE shocks (humped yield curve) generally depressed EQUITY and FX, signaling economic uncertainty. POLRATE responses were mixed, with increases in BRA, UK, and the US to stabilize markets. GDP responses were mostly negative, indicating contraction fears, while INF rises, suggested stagflation.
- EQUITY shocks drove positive LEVEL and SLOPE responses in most countries, reflecting growth expectations. FX responses were mixed, with depreciation in BRA and IND due to profit-taking. POLRATE rose to curb inflation, and GDP responses were positive, except in EGP.
- FX shocks (currency appreciation) lowered the LEVEL, reflecting reduced inflation expectations. EQUITY and POLRATE responses varied, with negative GDP responses in developed markets due to export losses. INF fell due to cheaper imports.

- POLRATE shocks raised the LEVEL in most countries, steepening the SLOPE, and depressing the EQUITY and FX, aligning with contractionary policy effects. GDP declined, and INF rose, confirming policy-inflation connections.
- GDP shocks raised the LEVEL in BRA and EGP, but responses varied elsewhere. EQUITY and FX responses were mixed, with the POLRATE rising in BRA and EGP to control inflation. INF responses reflected demand versus supply-driven growth.
- INF shocks raised the LEVEL in emerging markets, depressed EQUITY, and weakened FX in most countries. POLRATE responses varied, with GDP rising due to demand pressures.

5. Conclusion

This research demonstrated that a hybrid LSTM-Wavelet methodology significantly enhanced the modeling of impulse response functions for macroeconomic time series, outperforming both ANN-Wavelet and traditional VECM benchmarks. By combining wavelet-based denoising with the temporal memory of LSTMs, the approach captured complex nonlinear and multiscale interactions across key macro variables and diverse economies. The superiority of db4 wavelets for macro variables and the different selection of wavelet types across markets emphasize how frequency-domain preprocessing can be tailored to specific data characteristics.

The deep impulse response analysis uncovered rich dynamics: yield curve shifts propagated to equity, exchange rates, policy rates, GDP, and inflation in patterns that vary by country maturity and market structure. These insights provide policymakers and analysts with a more nuanced understanding of shock transmission and can inform more effective monetary and fiscal interventions.

Limitations include the fixed 12-month horizon, potential overfitting in smaller samples, and reliance on a single wavelet family. Future research should explore alternative wavelet bases, longer forecast horizons, regime-switching architectures, and real-time policy applications to further validate and extend the deep IRF framework.

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