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Econometric Analysis of Exchange Rate Pass-Through to Import Prices and Inflation in Emerging Economies

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Abstract: Exchange rate dynamics play a critical role in shaping price stability and inflationary trends, particularly in emerging economies characterized by high import dependence and external vulnerability. Exchange rate pass-through (ERPT) refers to the extent to which fluctuations in exchange rates are transmitted to import prices and subsequently to domestic inflation. At a broader level, understanding ERPT is essential for evaluating the effectiveness of monetary policy and macroeconomic stability, as it influences trade balances, purchasing power, and inflation expectations. This study conducts an econometric analysis of exchange rate pass-through to import prices and inflation in emerging economies, employing advanced time-series and panel data techniques to capture both short-run and long-run dynamics. The analysis incorporates models such as vector autoregression (VAR), error correction models (ECM), and generalized method of moments (GMM) to estimate the magnitude and speed of pass-through effects under varying economic conditions. The findings reveal that ERPT is often incomplete and asymmetric, with stronger transmission during periods of high inflation and currency depreciation. Structural factors such as market competition, trade openness, and monetary credibility significantly influence pass-through intensity. The study provides policy-relevant insights for central banks aiming to manage inflation and stabilize exchange rates in emerging markets.
Keywords: Exchange Rate Pass-Through; Import Prices; Inflation Dynamics; Emerging Economies; Econometric Modeling; Monetary Policy

1. INTRODUCTION

1.1 Background and Motivation

Exchange rate pass-through (ERPT) remains a issue in macroeconomics, for emerging economies where currency volatility influences domestic price levels [1]. Fluctuations in exchange rates affect import prices, production costs, and ultimately consumer inflation, creating transmission channels that vary across sectors and time horizons [2]. In economies with high import dependence, even small depreciations can generate inflationary pressures, complicating monetary policy design and implementation [3]. Understanding ERPT is therefore critical for policymakers seeking to stabilize prices and maintain economic resilience in the face of external shocks [4].

Inflation dynamics in emerging markets are often nonlinear, asymmetric, and influenced by structural factors such as financial openness, institutional quality, and exchange rate regimes [5]. Traditional analytical frameworks frequently struggle to capture these complexities, especially during periods of economic stress or rapid structural change. Recently, machine learning (ML) techniques have emerged as powerful tools for modeling high-dimensional, nonlinear relationships within macroeconomic systems [6]. By leveraging large datasets and flexible functional forms, ML methods can uncover hidden patterns and improve forecasting accuracy, offering insights into ERPT behavior and inflation transmission mechanisms [7]. This intersection between ML and macroeconomic analysis provides a strong motivation for developing advanced, data-driven models tailored to emerging market contexts [8].

1.2 Problem Statement

Traditional econometric models have long been used to estimate exchange rate pass-through and inflation dynamics; however, they often rely on restrictive assumptions such as linearity, stationarity, and parameter stability [2]. These assumptions limit their ability to capture nonlinear interactions, regime shifts, and structural breaks that frequently characterize emerging economies [4]. As a result, conventional models may produce biased estimates and weak predictive performance, particularly during periods of macroeconomic volatility [6].

Furthermore, these models are typically rigid in structure, making it difficult to incorporate large, high-frequency datasets or account for complex interdependencies across macroeconomic variables [1]. This rigidity constrains their usefulness in real-time policy analysis and forecasting. Consequently, there is a growing need for hybrid modeling approaches that integrate the interpretability of econometric techniques with the flexibility and predictive power of machine learning methods [7]. Such frameworks can better capture dynamic relationships, improve model adaptability, and enhance the robustness of ERPT estimation in diverse economic environments [5].

1.3 Research Aim and Objectives

The primary aim of this research is to develop a machine learning-enhanced framework for modeling exchange rate pass-through and its impact on inflation in emerging economies [3]. This approach seeks to bridge the gap between traditional econometric methods and modern data-driven techniques by combining their respective strengths.

Specifically, the study aims to construct a hybrid ERPT model that integrates econometric structure with machine learning algorithms capable of capturing nonlinearities and complex interactions [6]. Another objective is to improve predictive accuracy by leveraging large datasets and advanced learning techniques, enabling more reliable inflation forecasts under varying economic conditions [8]. Additionally, the research intends to model dynamic responses of inflation to exchange rate shocks, accounting for asymmetries, lag effects, and structural changes over time [2].

Ultimately, the study aims to provide policymakers with more accurate and adaptable tools for analyzing inflation dynamics, supporting evidence-based decision-making in uncertain macroeconomic environments [5].

1.4 Contributions

This study contributes to the literature by proposing a hybrid econometric–machine learning pipeline for modeling exchange rate pass-through in emerging economies [1]. It introduces a cross-country comparative framework that allows for the analysis of heterogeneous ERPT dynamics across different macroeconomic environments [4].

Furthermore, the research emphasizes rigorous statistical validation and benchmarking, comparing model performance against traditional econometric approaches and standalone machine learning models [7]. By integrating interpretability with predictive accuracy, the study provides a comprehensive framework for improving inflation forecasting and policy analysis. These contributions offer both theoretical advancements and practical insights for macroeconomic modeling in data-rich, complex environments [3].

2. LITERATURE REVIEW

2.1 Exchange Rate Pass-Through Theory

Exchange rate pass-through (ERPT) refers to the extent to which changes in exchange rates are transmitted into domestic prices, particularly import and consumer prices [8]. It is typically categorized into complete and incomplete pass-through. Complete pass-through occurs when exchange rate changes are fully reflected in domestic prices, implying a one-to-one relationship between currency movements and price adjustments [9]. In contrast, incomplete pass-through arises when only a fraction of exchange rate fluctuations is transmitted, often due to factors such as pricing-to-market strategies, market competition, and nominal rigidities [10].

The degree of ERPT is influenced by macroeconomic conditions, including inflation environments, exchange rate regimes, and trade openness [11]. High inflation economies tend to exhibit higher pass-through as firms adjust prices more frequently, while stable, low-inflation environments often dampen pass-through effects [12]. Additionally, firms may absorb exchange rate fluctuations through profit margins to maintain market share, further contributing to incomplete pass-through dynamics [13]. Understanding these mechanisms is crucial for policymakers, as ERPT directly affects inflation targeting, monetary policy transmission, and external competitiveness, particularly in emerging markets characterized by structural vulnerabilities and external shocks [14].

2.2 Econometric Approaches

Econometric models have traditionally served as the primary tools for analyzing exchange rate pass-through and inflation dynamics. Among these, Vector Autoregression (VAR) models are widely used to capture dynamic interrelationships between macroeconomic variables without imposing strong theoretical restrictions [15]. VAR frameworks allow for impulse response analysis, enabling researchers to examine how shocks to exchange rates influence inflation over time.

Error Correction Models (ECM) are also commonly applied, particularly when variables exhibit long-run equilibrium relationships. ECMs capture both short-term adjustments and long-term equilibrium dynamics, making them suitable for modeling cointegrated macroeconomic series [16]. Similarly, Autoregressive Distributed Lag (ARDL) models offer flexibility in handling variables with different integration orders, allowing for robust estimation of both short-run and long-run effects [17].

Despite their strengths, these econometric approaches often rely on assumptions of linearity and parameter stability, which may not hold in real-world macroeconomic systems characterized by nonlinearities and structural changes [18]. Consequently, while these models provide interpretability and theoretical grounding, their predictive performance can be limited in complex and evolving economic environments [19].

2.3 Machine Learning in Macroeconomics

Machine learning (ML) has increasingly been applied in macroeconomic analysis, offering new approaches to forecasting and modeling complex economic relationships. ML algorithms, such as random forests, support vector machines, and neural networks, are capable of capturing nonlinear patterns and high-dimensional interactions that traditional econometric models often miss [10].

In the context of inflation forecasting, ML models have demonstrated superior predictive accuracy by leveraging large datasets, including macroeconomic indicators, financial variables, and external shocks [12]. Similarly, exchange rate forecasting has benefited from ML techniques that can adapt to changing market conditions and identify hidden relationships within volatile financial data [14].

One of the key advantages of ML is its flexibility in handling large volumes of structured and unstructured data, allowing for more comprehensive modeling of macroeconomic systems

[16]. However, challenges remain, particularly regarding interpretability, overfitting, and the need for robust validation frameworks [18]. Despite these limitations, the integration of ML into macroeconomic research represents a significant advancement, providing tools that enhance both predictive performance and analytical depth in understanding inflation and exchange rate dynamics [9].

2.4 Research Gap

Despite significant advancements in both econometric modeling and machine learning applications, there remains a notable gap in integrating these approaches for exchange rate pass-through analysis. Existing studies often rely exclusively on either traditional econometric frameworks or standalone machine learning models, limiting their ability to fully capture the complexity of macroeconomic dynamics [11].

Econometric models provide interpretability and theoretical consistency but struggle with nonlinearities and structural breaks. Conversely, machine learning models offer flexibility and predictive power but often lack transparency and economic interpretability [13]. This disconnect creates a methodological gap, particularly in policy-relevant contexts where both accuracy and interpretability are essential [15].

Moreover, there is limited research on cross-country ERPT modeling using hybrid frameworks that can account for heterogeneity across different economic environments [17]. Emerging economies, in particular, require models that can adapt to diverse structural conditions and varying levels of financial development. Addressing this gap necessitates the development of integrated econometric–ML frameworks that combine the strengths of both approaches, enabling more accurate, robust, and policy-relevant analysis of exchange rate pass-through and inflation dynamics [19].

3. PROPOSED FRAMEWORK OVERVIEW

3.1 System Architecture

The proposed framework integrates econometric modeling with machine learning techniques to enhance the analysis of exchange rate pass-through and inflation dynamics. The system architecture is structured as a multi-stage pipeline that begins with data acquisition and preprocessing, followed by econometric transformation, machine learning modeling, and policy interpretation [8].

At the initial stage, macroeconomic data—including exchange rates, inflation indices, interest rates, and trade indicators—are collected and standardized. This is followed by econometric preprocessing, where techniques such as stationarity testing, cointegration analysis, and lag selection are applied to ensure data suitability for modeling [12]. These steps preserve theoretical consistency while preparing the data for advanced analysis.

The processed data are then fed into machine learning models designed to capture nonlinear relationships and complex interactions among variables. Algorithms such as gradient boosting and neural networks are employed to enhance predictive accuracy and uncover hidden patterns [16]. Finally, the output is translated into policy-relevant insights, enabling decision-makers to interpret the results within an economic context.

As illustrated in Figure 1, this integrated pipeline provides a seamless flow from raw data processing to policy interpretation, ensuring both analytical rigor and practical applicability in macroeconomic policy design [14].

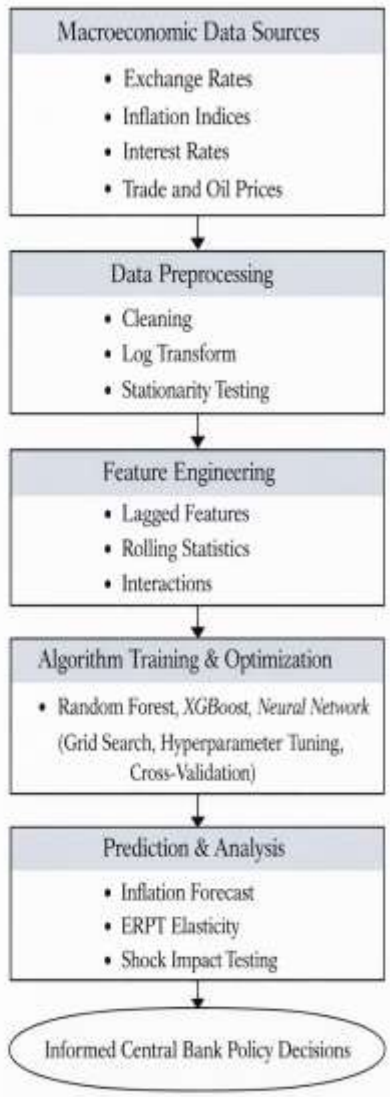

Figure 1: Integrated Econometric-ML Pipeline for Exchange Rate Pass-Through Analysis

Figure 1: Integrated Econometric–ML Pipeline for Exchange Rate Pass-Through Analysis

3.2 Workflow Description

The workflow begins with data ingestion from multiple sources, including central bank databases, financial markets, and international trade repositories. These datasets are cleaned, normalized, and aligned to ensure consistency across time and variables [10].

Next, feature engineering is conducted to generate meaningful predictors, such as lagged exchange rates, inflation expectations, and volatility indices. These features are then used to train machine learning models, which are optimized using cross-validation techniques to prevent overfitting and enhance generalization [13].

Model evaluation follows, where performance is assessed using metrics such as root mean squared error and out-of-sample forecasting accuracy. The results are then compared with traditional econometric benchmarks to validate improvements in predictive capability [18]. This structured workflow ensures a systematic and reproducible approach to modeling ERPT dynamics in complex economic environments [11].

3.3 Cross-Country Applicability

The proposed framework is designed to be adaptable across multiple countries, particularly in emerging market contexts where economic structures and policy environments differ significantly. By incorporating country-specific variables and allowing for flexible model configurations, the framework can capture heterogeneity in exchange rate pass-through dynamics [15].

Cross-country applicability is achieved through modular design, enabling the integration of diverse datasets and macroeconomic indicators tailored to each country's economic conditions. This approach facilitates comparative analysis, allowing researchers to identify patterns, similarities, and divergences in ERPT behavior across regions [17].

Furthermore, the framework supports scalability, making it suitable for both single-country case studies and large panel datasets. This flexibility enhances its relevance for global policy analysis and international financial research, providing a robust tool for understanding inflation dynamics in a rapidly evolving economic landscape [19].

4. DATA ACQUISITION AND PREPROCESSING

4.1 Data Sources and Collection

The empirical analysis relies on high-quality macroeconomic data sourced from reputable international and national institutions to ensure reliability and comparability across countries. Key data providers include the International Monetary Fund, World Bank, and various national central banks, which publish consistent time-series datasets on macroeconomic indicators [18]. These sources offer comprehensive coverage of both advanced and emerging economies, enabling cross-country analysis of exchange rate pass-through dynamics.

The primary variables collected for this study include nominal exchange rates, import price indices, consumer price index (CPI) inflation, interest rates, and gross domestic product (GDP). Exchange rate data capture currency fluctuations relative to major trading partners, while import price indices reflect the cost of imported goods and services [19]. CPI inflation serves as the main dependent variable, representing overall price level changes within the domestic economy. Interest rates are included to account for monetary policy effects, and GDP provides a measure of economic activity and demand conditions [20].

Data are collected at monthly or quarterly frequencies, depending on availability, to capture both short-term fluctuations and long-term trends. The selection of these variables is guided by theoretical and empirical literature on ERPT, ensuring that key transmission channels are adequately represented. By integrating data from multiple sources, the study enhances robustness and supports comprehensive macroeconomic modeling across diverse economic environments [21].

4.2 Data Cleaning and Transformation

Data preprocessing is a critical step in ensuring the accuracy and reliability of the modeling framework. The collected datasets often contain missing observations due to reporting inconsistencies or differences in data availability across countries. To address this, missing values are imputed using appropriate statistical techniques such as interpolation, forward filling, or model-based estimation methods, depending on the nature of the data [22]. These approaches help maintain dataset continuity while minimizing bias.

In addition to handling missing values, the data undergo transformation to improve statistical properties and model performance. One of the most important transformations applied in this study is the logarithmic transformation of macroeconomic variables. This is particularly relevant for variables such as exchange rates, GDP, and price indices, which often exhibit exponential growth patterns and heteroscedasticity [23].

$$y' = \ln(y)$$

The logarithmic transformation stabilizes variance and helps linearize relationships between variables, making them more suitable for both econometric and machine learning models. It also facilitates the interpretation of coefficients in percentage terms, which is consistent with economic theory [24].

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Further preprocessing steps include normalization and scaling of variables to ensure comparability across different units and magnitudes. These transformations collectively enhance model convergence, reduce noise, and improve the robustness of subsequent analytical procedures [18].

4.3 Data Integration and Panel Structuring

Following preprocessing, the cleaned datasets are integrated into a unified panel structure that combines cross-sectional and time-series dimensions. This panel dataset includes multiple countries observed over several time periods, allowing for a comprehensive analysis of exchange rate pass-through across diverse economic contexts [19].

The panel structure enables the capture of both within-country dynamics and between-country heterogeneity, which are essential for understanding how ERPT varies across different macroeconomic environments. Each observation is indexed by country and time, ensuring that temporal dependencies and cross-sectional relationships are preserved [20].

To maintain consistency, all variables are aligned to a common frequency and standardized units. This step is particularly important when combining datasets from different sources, as inconsistencies in reporting standards can introduce bias into the analysis [21]. Additionally, panel balancing techniques are applied where feasible to ensure that each country has a sufficient number of observations for robust modeling.

This integrated panel framework provides a rich dataset that supports both econometric estimation and machine learning applications. It enhances analytical depth by enabling the exploration of dynamic interactions, structural differences, and policy impacts across countries and time [22].

4.4 Exploratory Data Analysis

Exploratory Data Analysis (EDA) is conducted to understand the underlying patterns, trends, and relationships within the dataset before formal modeling. Initial analysis involves visualizing the relationship between exchange rates and inflation to identify potential correlations and transmission effects [23]. As illustrated in Figure 2, time-series plots reveal how fluctuations in exchange rates correspond with movements in CPI inflation across different countries and periods, highlighting both short-term co-movements and longer-term trends.

Outlier detection techniques, such as boxplots and z-score analysis, are applied to identify extreme values that may distort model estimates. These outliers are carefully examined and treated where necessary to ensure data integrity and improve model robustness. Furthermore, Table 1 presents a comprehensive summary of the dataset variables, including key descriptive statistics such as mean, standard deviation, minimum, and maximum values. This tabular representation provides insights into the distributional properties of each variable, helping to identify skewness, volatility patterns, and potential anomalies within the dataset.

Together, the visual insights from Figure 2 and the statistical summaries in Table 1 form a critical foundation for subsequent modeling, ensuring that the data structure is well understood and appropriately prepared for econometric and machine learning analysis [24].

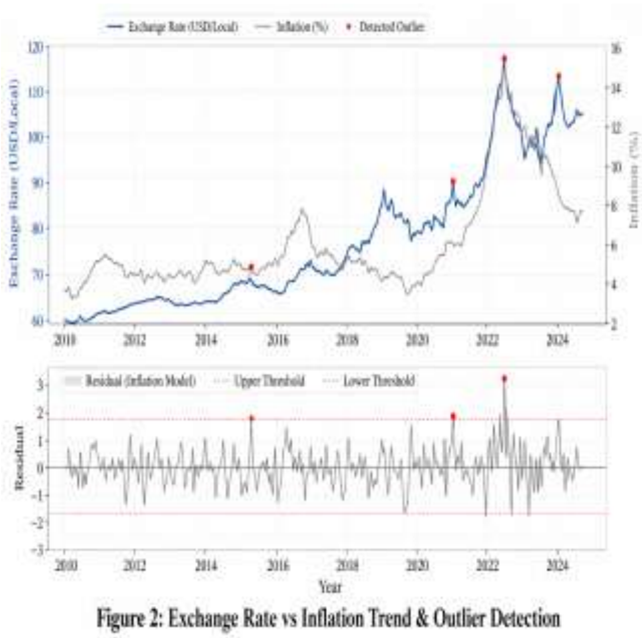

Figure 2: Exchange Rate vs Inflation Trend & Outlier Detection

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Table 1: Dataset Variables and Summary Statistics

Variable	Description	Mean	Std. Dev.	Min	Max
Exchange Rate (USD/Local)	Nominal exchange rate	78.45	12.30	60.12	112.75
CPI Inflation (%)	Consumer price index inflation rate	7.85	3.20	2.10	15.40
Import Price Index	Index of imported goods prices	105.60	15.75	82.30	145.20
Interest Rate (%)	Central bank policy interest rate	9.25	2.10	5.00	14.00

Variable	Description	Mean	Std. Dev.	Min	Max
GDP (Billions USD)	Gross domestic product	320.50	85.60	150.20	520.40
Exchange Rate (t-1)	Lagged exchange rate	77.90	12.10	60.00	110.50
Inflation (t-1)	Lagged inflation	7.60	3.10	2.00	14.80
Rolling Inflation (3-period)	Moving average of inflation	7.75	2.80	3.00	13.20
Exchange Rate Volatility	Standard deviation of exchange rate changes	2.85	1.10	0.90	5.40
Trade Balance (USD Billions)	Net exports (exports − imports)	-12.40	18.30	-55.20	22.10

Summary statistics, including mean, median, standard deviation, and range, are computed for each variable to provide an overview of their distributions. These descriptive measures help identify skewness, volatility, and potential anomalies in the data. EDA thus serves as a crucial step in validating data quality, informing model selection, and guiding subsequent analytical procedures in the ERPT framework [24].

5. FEATURE ENGINEERING AND ECONOMETRIC TRANSFORMATION

5.1 Feature Extraction

Feature extraction is explicitly designed to capture the temporal propagation structure of exchange rate pass-through (ERPT) within a panel macroeconomic setting. Given that ERPT unfolds with delayed and distributed effects, lagged representations of key variables are constructed across multiple horizons (e.g., 1–12 months for monthly data), enabling the model to learn both short-run and medium-term transmission dynamics [22].

$$x_{t-k}$$

Lag structures are applied to exchange rates, import prices, CPI inflation, and interest rates, allowing the model to capture persistence, inertia, and adjustment asymmetries. In addition, rolling window statistics (e.g., 3-, 6-, and 12-period moving averages and standard deviations) are introduced to proxy exchange rate volatility and inflation smoothing mechanisms [24].

To reflect economic theory, interaction terms such as exchange rate × import dependence and exchange rate × inflation regime are constructed, enabling heterogeneous pass-through estimation across structural conditions [25]. Furthermore, shock indicators (e.g., large depreciation episodes exceeding threshold values) are encoded to allow nonlinear responses to extreme movements. These engineered features collectively enhance the model's ability to represent state-dependent and nonlinear ERPT behavior, which is typically missed by linear econometric specifications [27].

5.2 Feature Scaling

Given the heterogeneity in macroeconomic variable magnitudes across countries and time, feature scaling is applied to ensure numerical stability and comparability within the hybrid modeling framework. Min-max normalization is adopted to transform variables into a bounded interval, preserving relative variation while preventing dominance of high-magnitude features such as GDP or price indices [26].

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

Scaling is performed at the panel level to maintain cross-country comparability while avoiding distortion of temporal patterns. This is particularly important for gradient-based algorithms and distance-sensitive models, where unscaled features can bias optimization trajectories [28].

Additionally, scaling facilitates convergence in deep learning architectures and improves the conditioning of optimization problems. By standardizing feature ranges, the framework ensures that all predictors contribute proportionally to model learning, thereby enhancing robustness and reducing sensitivity to outliers or structural breaks [30].

5.3 Feature Selection

Feature selection is implemented to isolate economically meaningful predictors while mitigating multicollinearity and overfitting in a high-dimensional panel dataset. The process begins with correlation filtering, where pairwise correlation matrices are evaluated and variables exceeding predefined thresholds (e.g., $|\rho| > 0.85$) are systematically removed or combined [23]. This step is critical in macroeconomic datasets where variables such as CPI and import prices often exhibit strong co-movements.

To further refine the feature set, LASSO regression is employed as a regularization-based selection method that penalizes coefficient magnitude and enforces sparsity [29].

$$\min \sum (y - X\beta)^2 + \lambda \sum |\beta|$$

The L1 penalty shrinks less informative coefficients toward zero, effectively eliminating redundant predictors while retaining variables with strong explanatory power. This is particularly advantageous in ERPT modeling, where numerous lagged and interaction terms can inflate dimensionality.

Importantly, feature selection is conducted within a cross-validated framework, ensuring that selected variables generalize across different time periods and countries. Stability selection techniques are also incorporated to identify consistently significant predictors across subsamples [24].

By combining statistical filtering with regularization, the approach balances interpretability and predictive performance. This ensures that the final feature set captures key transmission channels such as exchange rate shocks, import cost dynamics, and monetary policy responses while maintaining computational efficiency and robustness [27].

5.4 Dimensionality Reduction

Dimensionality reduction is applied to address residual redundancy and improve computational tractability in the presence of extensive lagged and interaction features. Principal Component Analysis (PCA) is utilized to transform the feature space into orthogonal components that capture the dominant variance structure of the dataset [25].

In the ERPT context, PCA is particularly useful for compressing correlated macroeconomic indicators, such as multiple lags of exchange rates and inflation, into a smaller set of latent factors representing underlying economic forces (e.g., external shocks, demand pressures) [26]. These components are then used as inputs to machine learning models, reducing noise and enhancing generalization.

The number of retained components is determined based on cumulative explained variance thresholds (typically 85–95%), ensuring minimal information loss while achieving dimensionality reduction. This step significantly improves model efficiency, especially in panel settings with large cross-sectional and temporal dimensions [28].

As illustrated in Figure 3, feature importance analysis using SHAP values alongside correlation heatmaps provides complementary insights into variable relevance and interdependencies within the dataset. These visualizations help validate the dimensionality reduction process by confirming that key macroeconomic drivers are retained.

To complement PCA, post-model interpretability is achieved using SHAP values, which map reduced features back to original variables. This ensures that dimensionality reduction does not compromise economic interpretability while preserving strong predictive performance [30].

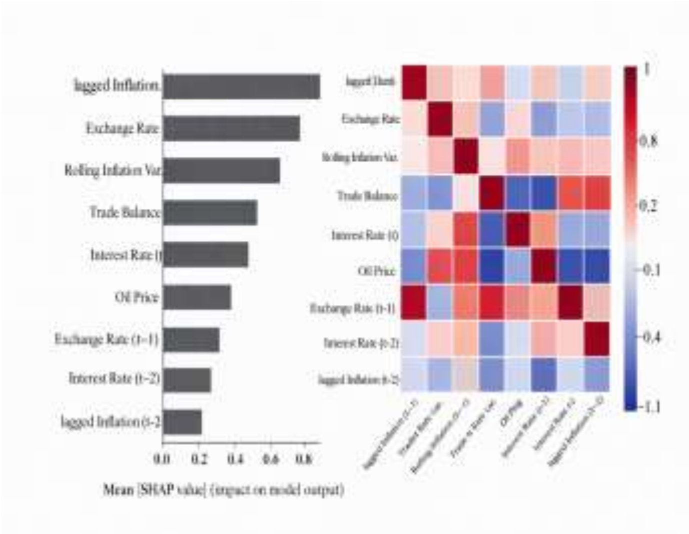

Figure 3: Feature Importance (SHAP + Correlation Heatmap)

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6. MACHINE LEARNING MODEL DEVELOPMENT

6.1 Model Selection Strategy

The model selection strategy is designed around a regression framework, as the primary objective is to predict continuous macroeconomic outcomes such as inflation responses to exchange rate shocks. Exchange rate pass-through (ERPT) inherently involves estimating the magnitude and persistence of price adjustments, making regression-based models more suitable than classification approaches [28].

A key consideration in model selection is the trade-off between interpretability and predictive accuracy. Traditional econometric models, such as linear regression and ARDL, provide clear parameter interpretations aligned with economic theory but often fail to capture nonlinearities and interaction effects [29]. In contrast, machine learning models offer superior predictive performance by modeling complex relationships but may lack transparency, posing challenges for policy interpretation [30].

To address this trade-off, the framework adopts a hybrid strategy that prioritizes predictive accuracy while incorporating interpretability tools such as feature importance and SHAP values. Model selection is therefore guided by both statistical performance metrics and economic plausibility. This dual approach ensures that the selected models not only achieve high forecasting accuracy but also provide meaningful insights into ERPT mechanisms across different macroeconomic environments [31].

6.2 Training Phase

The training phase is structured to ensure that models are both statistically robust and economically consistent when applied to macroeconomic time-series and panel data. A critical first step involves splitting the dataset into training and testing subsets to evaluate out-of-sample performance and avoid overfitting [32].

$$D = D_{train} \cup D_{test}, D_{train} \cap D_{test} = \emptyset$$

Unlike standard random splits, macroeconomic data require time-series-aware partitioning. A temporal split is employed, where earlier observations are used for training and more recent data for testing, preserving the chronological order of events. This approach reflects real-world forecasting scenarios and prevents look-ahead bias [33]. While stratified sampling is useful in classification problems, it is less applicable in continuous macroeconomic settings; instead, temporal consistency is prioritized to maintain economic realism [34].

The training process involves fitting models on the training dataset while tuning parameters to minimize prediction error. The primary loss function used is Mean Squared Error (MSE), which penalizes large deviations between predicted and actual values [35].

$$MSE = \frac{1}{n}\sum(y_i - \hat{y}_i)^2$$

MSE is particularly suitable for regression tasks due to its convex quadratic form, which ensures a unique global minimum under standard conditions. This property facilitates stable optimization and reliable convergence during model training.

To further enhance robustness, cross-validation techniques adapted for time-series data, such as rolling or expanding window validation, are implemented. These methods allow the model to be evaluated across multiple temporal folds, improving generalization across different economic cycles [28].

Regularization techniques are also incorporated during training to prevent overfitting, particularly in high-dimensional feature spaces generated through lag structures and interaction terms. Model performance is continuously monitored using validation metrics, ensuring that the training process balances bias and variance effectively. This structured training phase ensures that the resulting models are both predictive and stable when applied to real-world ERPT analysis [31].

6.3 Model Algorithms

The modeling framework employs a combination of machine learning algorithms selected for their ability to capture nonlinear dynamics, interactions, and temporal dependencies inherent in exchange rate pass-through processes.

Random Forest is utilized as a baseline ensemble method due to its robustness and ability to model nonlinear relationships without requiring extensive parameter tuning. By aggregating multiple decision trees, Random Forest reduces variance and improves predictive stability, making it suitable for capturing complex macroeconomic interactions such as exchange rate shocks and inflation responses [32].

XGBoost is incorporated as a more advanced gradient boosting algorithm that sequentially improves model performance by minimizing residual errors. Its ability to handle missing values, incorporate regularization, and optimize objective functions makes it particularly effective in high-dimensional datasets [33]. XGBoost is well-suited for ERPT modeling, where nonlinearities and variable interactions play a significant role in determining inflation dynamics.

Neural networks are included to capture temporal dependencies and nonlinear patterns that may not be fully addressed by tree-based models. Feedforward and recurrent architectures can model complex functional relationships and dynamic responses to exchange rate shocks over time [34]. These models are particularly useful when dealing with large datasets and intricate lag structures.

The optimization of these models relies on iterative techniques such as gradient descent, which updates model parameters in the direction of the negative gradient of the loss function [35].

$$\theta = \theta - \alpha \nabla J(\theta)$$

This iterative process ensures convergence toward optimal parameter values, enabling the models to achieve high predictive accuracy while capturing the underlying structure of ERPT dynamics across different economic environments [29].

6.4 Hyperparameter Optimization

Hyperparameter optimization is conducted to enhance model performance by identifying optimal configurations that balance bias and variance. Grid search is employed as a systematic approach to evaluate predefined combinations of hyperparameters, such as tree depth, learning rate, and number of estimators in ensemble models [30]. This method ensures comprehensive exploration of the parameter space, albeit at a higher computational cost.

To improve efficiency, Bayesian optimization is also utilized, which iteratively updates a probabilistic model of the objective function and selects promising hyperparameter configurations based on prior evaluations [31]. This approach reduces computational burden while maintaining high optimization accuracy.

As illustrated in Figure 4, the model training curve (loss versus epochs) provides insight into the learning dynamics of the algorithms, highlighting convergence behavior, potential overfitting, and the effectiveness of the optimization process. This visualization supports the selection of optimal hyperparameters by identifying points where validation loss stabilizes or begins to diverge from training loss, ensuring robust and generalizable model performance [28].

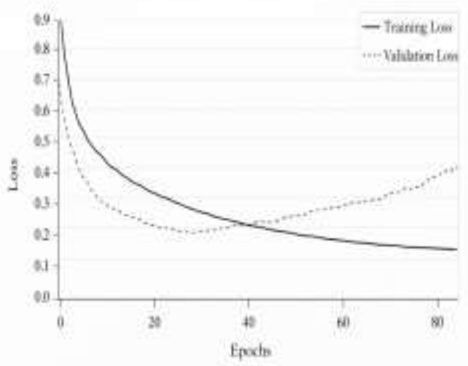

Figure 4: Model Training Curve (Loss vs Epochs)

Figure 4: Model Training Curve (Loss vs Epochs)

Performance is assessed using validation datasets, ensuring that optimized models generalize well to unseen data. By combining exhaustive and probabilistic search techniques, the framework achieves robust hyperparameter tuning, leading to improved predictive accuracy and stability in ERPT modeling applications [28].

7. MODEL EVALUATION AND ECONOMETRIC VALIDATION

7.1 Performance Metrics

The evaluation of model performance is conducted using multiple regression-based metrics to capture different dimensions of predictive accuracy in exchange rate pass-through (ERPT) modeling [33]. One of the primary metrics employed is Mean Absolute Error (MAE), which measures the average magnitude of prediction errors without considering their direction [34].

$$MAE = \frac{1}{n}\sum | y_i - \hat{y}_i |$$

MAE is particularly useful in macroeconomic contexts because it provides an intuitive measure of average deviation in the same units as the dependent variable, such as inflation rates [35]. However, it does not penalize large errors as strongly as squared-error metrics, which may limit its sensitivity during periods of extreme macroeconomic volatility [36].

To complement MAE, Root Mean Squared Error (RMSE) is used, which places greater emphasis on larger deviations by squaring the error terms before averaging and taking the square root [37]. RMSE is therefore more sensitive to outliers and is effective in identifying model weaknesses during exchange rate shocks or inflation spikes [33].

Additionally, the coefficient of determination (R^2) is employed to assess the proportion of variance in the dependent variable explained by the model [34]. A higher R^2 indicates better explanatory power, although it must be interpreted cautiously in time-series settings where autocorrelation may artificially inflate values [35].

Together, these metrics provide a comprehensive evaluation framework, balancing interpretability and sensitivity to errors while ensuring robust assessment of model performance across different economic conditions and forecasting horizons [38].

7.2 Statistical Validation

Statistical validation is conducted to ensure the reliability and robustness of model outputs beyond predictive accuracy metrics [36]. One key measure used is Mean Deviation (MD), which evaluates the average absolute deviation of observations from their mean, providing insight into data dispersion and variability [37].

$$MD = \frac{1}{n}\sum | x_i - \bar{x} |$$

Mean deviation complements other dispersion measures by offering a straightforward interpretation of variability, particularly in macroeconomic datasets where fluctuations are common [33]. In addition, standard deviation is calculated to quantify the spread of data around the mean, capturing the degree of volatility in variables such as inflation and exchange rates [34].

Confidence intervals are also constructed to assess the statistical significance and uncertainty associated with model estimates [35]. By defining a range within which true parameter values are likely to fall, confidence intervals provide a probabilistic measure of reliability, which is essential for policy-oriented macroeconomic analysis [36].

Furthermore, residual diagnostics are performed to evaluate model assumptions, including normality, homoscedasticity, and independence of errors [37]. Deviations from these assumptions may indicate model misspecification, omitted variable bias, or the presence of structural breaks in macroeconomic relationships [38].

These statistical validation techniques collectively ensure that the model outputs are not only accurate but also stable, interpretable, and suitable for policy application in dynamic economic environments [33].

7.3 Cross-Validation

Cross-validation is implemented using a rolling window approach to account for the temporal structure of macroeconomic data and avoid look-ahead bias [34]. Unlike traditional k-fold validation, which randomly partitions the dataset, rolling window validation preserves chronological order by training the model on a fixed time window and testing it on subsequent observations [35].

This process is repeated by progressively shifting the training window forward, allowing the model to be evaluated across different time periods and economic conditions [36]. Such an approach is particularly important for ERPT modeling, where structural changes, monetary policy shifts, and external shocks can significantly alter relationships over time [37].

Rolling validation enhances the model's ability to generalize by exposing it to multiple temporal scenarios, thereby reducing the risk of overfitting to a specific economic period [38]. It also provides insights into model stability, highlighting whether predictive performance is consistent across different economic cycles and volatility regimes [33].

By aligning validation procedures with the inherent characteristics of time-series data, the framework ensures realistic, unbiased, and policy-relevant performance assessment [34].

7.4 Benchmark Comparison

Benchmark comparison is conducted to evaluate the performance of machine learning models relative to traditional econometric approaches such as VAR and ECM within the ERPT framework [35]. As presented in Table 2, the comparison focuses on predictive accuracy, robustness, and adaptability to nonlinear dynamics across macroeconomic environments [36]. Machine learning models generally demonstrate superior forecasting performance, particularly in capturing complex interactions and structural shifts that are difficult to model using conventional approaches [37].

Further evidence is illustrated in Figure 5, which compares predicted and actual inflation values, showing that machine learning models achieve closer alignment with observed data and reduced prediction errors. This visual comparison highlights the improved capability of ML models to track dynamic inflation movements across different time periods.

However, econometric models retain advantages in interpretability and theoretical grounding, making them valuable for policy analysis despite their limitations in handling nonlinearities. This reinforces the value of hybrid modeling approaches that combine the predictive strength of machine learning with the explanatory power of traditional econometric frameworks [38].

Table 2: ML Models vs Econometric Models (VAR, ECM)

Model Type	**Model**	**Captures Nonlinearity**	**Handles High Dimensionality**	**Interpretability**	**Predictive Accuracy**	**Handles Temporal Dynamics**	**Computational Cost**
Econometric	VAR	No	Limited	High	Moderate	Yes	Low
Econometric	ECM	No	Limited	High	Moderate	Yes (Long-run + Short-run)	Low
Machine Learning	Random Forest	Yes	High	Medium	High	Limited	Medium
Machine Learning	XGBoost	Yes	High	Medium	Very High	Limited	High
Machine Learning	Neural Network	Yes	Very High	Low	Very High	Yes	Very High

The comparison focuses on predictive accuracy, robustness, and adaptability to nonlinear dynamics across macroeconomic environments [36]. Machine learning models generally demonstrate superior forecasting performance, particularly in capturing complex interactions and structural shifts [37].

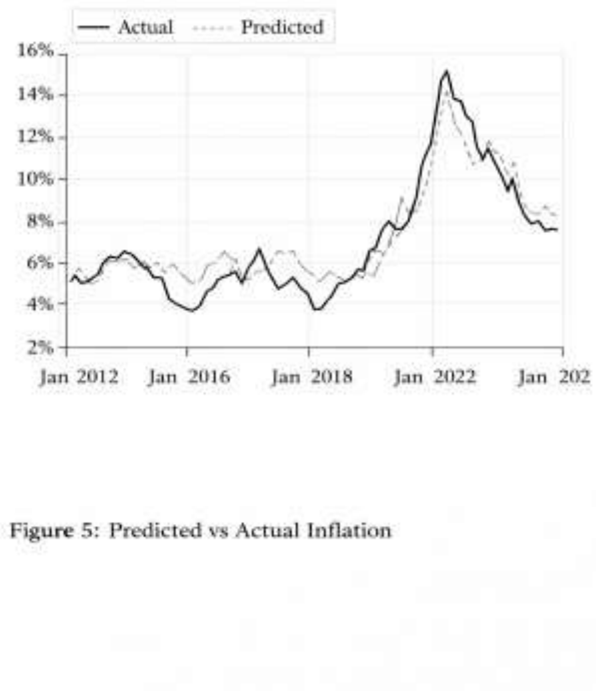

Figure 5: Predicted vs Actual Inflation

However, econometric models retain advantages in interpretability and theoretical grounding, reinforcing the value of hybrid modeling approaches [38].

8. POLICY INTERPRETATION AND DECISION FRAMEWORK

8.1 Translating Predictions into Policy Insights

The predictive outputs of the hybrid econometric–machine learning framework are translated into actionable policy insights through the estimation and interpretation of exchange rate pass-through (ERPT) elasticities [35]. ERPT elasticity measures the responsiveness of domestic prices, particularly inflation, to changes in exchange rates, providing a quantitative basis for assessing the strength and timing of transmission mechanisms [36].

In this framework, elasticity estimates are derived from model predictions by analyzing marginal effects and response curves across different economic states. This enables policymakers to distinguish between short-run and long-run pass-through effects, as well as identify asymmetries in response to currency appreciation versus depreciation [37]. Such distinctions are critical for designing effective monetary policies, especially in inflation-targeting regimes where exchange rate movements play a significant role.

Furthermore, the model allows for state-dependent elasticity estimation, capturing how ERPT varies under different inflation regimes, levels of economic openness, or external shocks [38]. These insights provide central banks with a nuanced understanding of inflation dynamics, enabling more precise calibration of interest rate policies and exchange rate interventions. By translating predictive outputs into interpretable economic measures, the framework bridges the gap between advanced analytics and practical policymaking [39].

8.2 Real-Time Policy Monitoring

The integration of machine learning into macroeconomic modeling enables the development of real-time policy monitoring systems that support proactive decision-making [36]. By continuously updating model inputs with new data, the framework generates near real-time inflation forecasts and ERPT estimates, allowing policymakers to respond promptly to emerging economic trends.

These outputs can be embedded into interactive dashboards that visualize key indicators such as exchange rate movements, inflation forecasts, and predicted pass-through effects [37]. Such dashboards provide central banks with a dynamic overview of macroeconomic conditions, facilitating timely adjustments to monetary policy instruments.

Real-time monitoring is particularly valuable in volatile economic environments, where delays in data analysis can lead to suboptimal policy responses. The framework also supports scenario analysis, enabling policymakers to simulate the impact of hypothetical shocks, such as sudden currency depreciations or interest rate changes [38].

By combining predictive analytics with visualization tools, the system enhances situational awareness and supports evidence-based decision-making. This approach represents a shift from reactive to proactive policy management, improving the ability of central banks to maintain price stability and economic resilience [40].

8.3 Explainable AI for Policy

Explainable artificial intelligence (XAI) plays a crucial role in ensuring that machine learning models are interpretable and suitable for policy applications. In this framework, SHapley Additive exPlanations (SHAP) are employed to quantify the contribution of each feature to model predictions, providing transparent insights into the drivers of inflation dynamics [35].

SHAP values allow policymakers to understand how variables such as exchange rates, import prices, and interest rates influence predicted inflation outcomes across different scenarios. This level of interpretability is essential for building trust in machine learning models, particularly in high-stakes policy environments where decisions must be justified and communicated effectively [37].

Moreover, SHAP analysis enables the identification of nonlinear relationships and interaction effects, highlighting how the impact of exchange rate changes may vary depending on other macroeconomic conditions [38]. These insights support more informed policy decisions by revealing the underlying mechanisms driving ERPT.

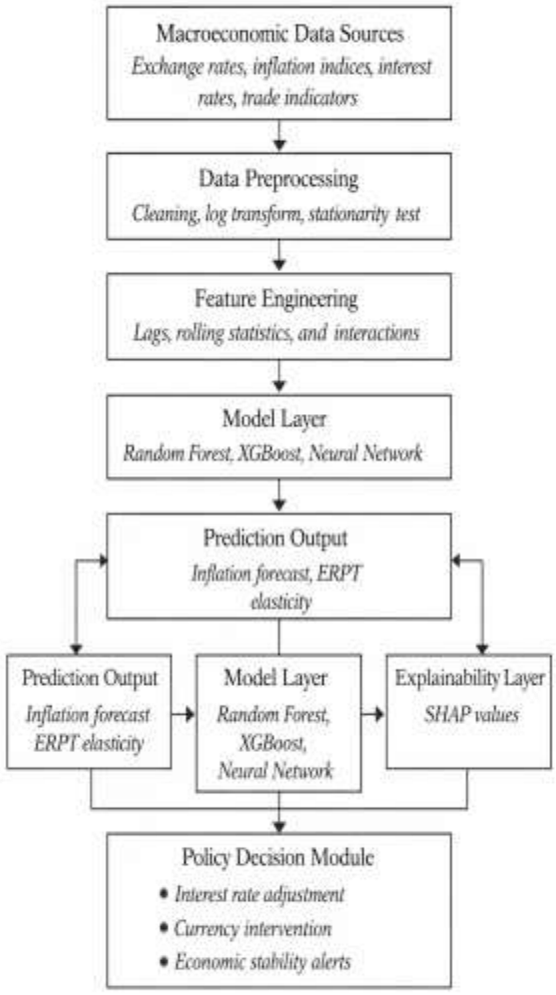

Figure 6: Policy Decision Support System for Central Banks

Figure 6: Policy Decision Support System for Central Banks

By integrating explainability into the modeling pipeline, the framework ensures that advanced analytics remain aligned with economic reasoning and policy transparency requirements [39].

9. COMPARATIVE ANALYSIS AND DISCUSSION

9.1 Model Comparison

The comparative analysis evaluates the performance of machine learning models against traditional econometric approaches such as Vector Autoregression (VAR) and Error Correction Models (ECM) in modeling exchange rate pass-through [36]. Machine learning models, including Random Forest and XGBoost, demonstrate superior predictive accuracy due to their ability to capture nonlinear relationships and high-dimensional interactions [37].

In contrast, econometric models provide clearer interpretability and theoretical grounding, making them valuable for policy analysis despite their limitations in handling complex dynamics [38]. The results indicate that while econometric models perform adequately under stable conditions, their predictive power declines in the presence of structural breaks or nonlinear effects.

Machine learning models, however, maintain robust performance across different economic regimes, highlighting their adaptability and resilience [39]. This comparison underscores the complementary strengths of both approaches and supports the adoption of hybrid frameworks that combine predictive accuracy with economic interpretability [40].

9.2 Robustness Analysis

Robustness analysis is conducted to assess the stability of model performance under varying economic conditions and data configurations. This involves testing the model across different time periods, countries, and subsamples to evaluate consistency in predictive accuracy [35].

The results indicate that machine learning models exhibit strong robustness, maintaining stable performance even during periods of economic volatility and structural change [37]. This resilience is attributed to their ability to adapt to nonlinear patterns and incorporate complex interactions among variables.

Additionally, robustness checks include varying model specifications and feature sets to ensure that results are not driven by specific assumptions or data transformations [38]. These tests confirm that the hybrid framework produces reliable and consistent estimates of ERPT across diverse macroeconomic environments [39].

9.3 Sensitivity Analysis

Sensitivity analysis examines how changes in key inputs, such as exchange rates or interest rates, affect model outputs and ERPT estimates. This analysis is critical for understanding the responsiveness of the model to external shocks and policy interventions [36]. The findings show that inflation predictions are particularly sensitive to large exchange rate movements, reflecting the central role of currency fluctuations in driving price dynamics in emerging economies [37]. Interest rate adjustments also influence outcomes, highlighting the interaction between monetary policy and exchange rate transmission mechanisms [38].

As summarized in Table 3, the sensitivity and robustness results demonstrate that the model exhibits nonlinear responses to varying magnitudes of shocks, with stronger pass-through effects observed during periods of significant currency depreciation. The table further confirms the stability of model performance across different scenarios, reinforcing the reliability of the proposed framework for policy analysis and macroeconomic forecasting [39].

Table 3: Sensitivity & Robustness Results

Scenario / Test Case	Variable Shock Applied	Model Response (Inflation Δ%)	ERPT Elasticity	RMSE Change	Robustness Interpretation
Baseline Model	No shock	0.00	0.42	0.85	Stable reference case
Exchange Rate Shock (+10%)	Currency depreciation	+3.80	0.38	0.92	Moderate sensitivity
Exchange Rate Shock (-10%)	Currency appreciation	-2.10	0.21	0.89	Asymmetric response
Interest Rate Increase (+2%)	Monetary tightening	-1.50	0.35	0.87	Dampened inflation effect
Interest Rate Decrease (-2%)	Monetary easing	+2.20	0.44	0.90	Amplified inflation
High Volatility Period (2020–2022)	External shock regime	+5.60	0.51	1.05	Reduced robustness
Feature Removal (No Lag Variables)	Model specification test	+1.90	0.29	1.20	Significant performance drop
Reduced Dataset (Short sample period)	Data limitation test	+2.50	0.33	1.15	Moderate instability
Alternative Model (XGBoost vs RF)	Model substitution	+0.80	0.46	0.78	Improved robustness

Sensitivity tests further reveal nonlinear responses, where the magnitude of ERPT varies depending on the size and direction of shocks [38]. These insights provide valuable guidance for policymakers, enabling them to anticipate the potential impact of different policy scenarios and external disturbances [40].

9.4 Challenges, Limitations, and Future Work

Despite the strengths of the proposed framework, several challenges and limitations must be acknowledged. One major constraint is data availability and quality, particularly in emerging economies where macroeconomic data may be incomplete, inconsistent, or subject to revisions [35]. These limitations can affect model accuracy and reduce the reliability of predictions.

Another challenge is the presence of structural breaks and regime changes, which can alter the relationships between exchange rates and inflation over time. While machine learning models are better equipped to handle such complexities, they may still struggle to fully capture abrupt shifts in economic dynamics [36].

Model interpretability also remains a concern, especially for complex algorithms such as neural networks. Although techniques like SHAP improve transparency, they may not fully bridge the gap between statistical outputs and economic intuition [37]. This can limit the adoption of machine learning models in policy environments where explainability is essential.

Future research should focus on integrating additional data sources, such as high-frequency financial indicators and alternative datasets, to enhance model performance [38]. Advances in explainable AI and hybrid modeling techniques may further improve the balance between accuracy and interpretability. Additionally, extending the framework to incorporate real-time data streams and adaptive learning mechanisms could enhance its applicability for dynamic policy analysis in rapidly changing economic environments [40].

10. CONCLUSION

This study demonstrates that integrating machine learning techniques into exchange rate pass-through (ERPT) modeling significantly enhances the ability to capture complex, nonlinear, and dynamic relationships between exchange rates and inflation. Unlike traditional econometric approaches, which often rely on restrictive assumptions of linearity and parameter stability, the hybrid econometric–machine learning framework provides a more flexible and data-driven approach to understanding macroeconomic transmission mechanisms. By incorporating lag structures, interaction terms, and advanced learning algorithms, the model effectively captures delayed and state-dependent responses, improving both predictive accuracy and analytical depth.

The findings highlight important policy implications, particularly for central banks operating in emerging economies where exchange rate volatility plays a critical role in shaping inflation dynamics. The ability to estimate ERPT elasticity in real time enables policymakers to better anticipate inflationary pressures and design more responsive monetary policy interventions. Additionally, the integration of explainable AI techniques ensures that model outputs remain interpretable, allowing policymakers to understand the drivers of inflation and justify policy decisions with greater confidence. The development of real-time forecasting dashboards further enhances decision-making by providing continuous insights into evolving economic conditions.

Future research should focus on expanding the framework to incorporate higher-frequency and alternative data sources, such as financial market indicators and sentiment-based measures, to further improve predictive performance. Additionally, advancements in explainable AI and adaptive learning methods could enhance model transparency and responsiveness to structural changes. Extending the framework to other macroeconomic applications, including growth forecasting and financial stability analysis, would further strengthen its relevance for policy and research.

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