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Análisis y pronóstico del tipo de cambio mediante redes neuronales profundas.

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Resumen

Este artículo realiza un análisis de alta frecuencia del mercado de divisas de Costa Rica utilizando algoritmos de redes neuronales profundas. Se emplean datos diarios de acceso público de MONEX desde 2017 hasta marzo de 2025 para identificar quiebres de tendencia, patrones estacionales y la importancia relativa de las variables explicativas que determinan los movimientos diarios del tipo de cambio en MONEX. El modelo calibrado muestra una alta precisión para comprender la información histórica y realizar proyecciones del tipo de cambio a cinco días. Los resultados sugieren que los movimientos observados del tipo de cambio en 2024 están alineados con su tendencia y que existen factores estacionales significativos que influyen en el tipo de cambio a lo largo del año.

Palabras clave: Tipo de cambio, redes neuronales, inflación.

Clasificación JEL: C45, C53, F31, O24.

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Forecasting Nominal Exchange Rate using Deep Neural Networks.

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Summary

This paper offers a daily-frequency analysis and short-term forecasting of Costa Rica's foreign currency market using deep neural network algorithms. These algo-rithms efficiently integrates multiple high-frequency data to capture trends, seasonal patterns, and daily movements in the exchange rate from 2017 to March 2025. The results indicate that these models excels in predicting the observed exchange rate up to five days in advance, outperforming traditional time series forecasting methods in terms of accuracy.

Key words: Exchange rate, forecast, deep neural network.

JEL Codes: C45, C53, F31, O24.

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1 Introduction

Understanding the high-frequency behavior of the nominal exchange rate is essential for effective monetary and macroprudential policymaking. However, structural factors—such as the shallow and imperfectly competitive nature of Costa Rica's foreign currency market—amplify the influence of seasonality, autocorrelation, and idiosyncratic patterns when analyzing and forecasting short-term exchange rate movements. As a result, effective models must rely on large sets of daily data and be flexible enough to accurately capture historical trends while reliably predicting future behavior—often at a significant computational cost.

In this paper, we apply deep neural networks to analyze Costa Rica's exchange rate, which is determined in the foreign currency market, Monex. Our focus is on daily dynamics, using publicly available data to calibrate a model that interprets the exchange rate from the perspective of an external market participant. In other words, we deliberately avoid using confidential information that, while potentially useful for more precise predictions, is accessible only to the Central Bank or select private market participants.

Advanced machine learning techniques, such as deep neural networks (DNNs), enable the efficient use of high-frequency datasets and automate much of the analytical work traditionally undertaken by researchers when integrating and interpreting complex data sources—an approach that has proven increasingly valuable in economic analysis (Athey, 2018; Mullainathan & Spiess, 2017). These methods improve the ability to identify the relative importance of key drivers, thereby enhancing the accuracy and reliability of exchange rate forecasts and other financial applications (Kelly, Xiu, et al., 2023).

We find that the implemented algorithm effectively captures recent exchange rate behavior and produces relatively accurate five-day forecasts. The inferred parameters are consistent with economic intuition and align with the literature on structural factors influencing the medium-term dynamics of Costa Rica's nominal exchange rate. Specifically, our results underscore strong seasonality patterns and highlight the important role of autocorrelation in explaining daily exchange rate movements. Additionally, the exchange rate tends to closely follow its underlying trend over time. For the 2023–2024 period, our analysis suggests that the observed appreciation is in line with this broader trend, reflecting medium-term dynamics shaped by structural features of Costa Rica's economy and an abundant supply of foreign currency during this time.

This paper contributes to the literature on exchange rate dynamics in Costa Rica by introducing a novel approach that leverages deep neural networks (DNNs) to analyze and forecast high-frequency exchange rate movements. While traditional methods—such as

ARIMA models—have been widely used, they often fall short in capturing the complex, non-linear relationships and pronounced seasonality patterns characteristic of small, open economies like Costa Rica. By employing advanced machine learning techniques, this study offers a more flexible and robust framework for understanding short-term exchange rate behavior.

Specifically, the paper makes three key contributions. First, it demonstrates the effectiveness of deep neural networks (DNNs) in capturing the complex dynamics of Costa Rica's foreign currency market—including trends, seasonality, and the impact of key market variables such as public sector demand and retail market activity. Second, it underscores the value of high-frequency data in improving the accuracy of short-term exchange rate forecasts, particularly over horizons of up to five days. Third, the paper provides empirical evidence of the model's superior predictive performance relative to traditional approaches, showing substantial gains in forecasting accuracy as measured by reductions in Root Mean Squared Error (RMSE).

The paper is organized as follows. Section 2 presents a detailed description of the data and the empirical methodology followed.

2 Empirical Strategy

Our variable of interest is the nominal exchange rate, analyzed at a daily frequency. Specifically, we focus on the weighted average exchange rate determined in each daily session of the Foreign Currency Market (Monex). The analysis is restricted to the period from January 1, 2017, through March 24, 2025.

FIGURE 1. Costa Rica's Nominal Exchange Rate

Notes: Weighted average of the exchange rates negotiated in each daily session of the Foreign Currency Market (Monex).
Source: Central Bank of Costa Rica.

As illustrated in Figure 1, the exchange rate has exhibited clear and sustained phases of appreciation and depreciation. In mid-2018, the exchange rate underwent a sharp depreciation, which gradually reversed over the following year. With the onset of the COVID-19 pandemic, depreciation resumed and intensified notably in 2022. However, by mid-2022, this trend reversed, and from that point through December 2024, the exchange rate followed a prolonged appreciation path, ultimately reaching its lowest level in nearly a decade. These dynamics, as depicted in Figure 1, underscore the strong autocorrelation present in Costa Rica's daily exchange rate—reflecting a high degree of persistence, whereby current values are closely tied to their recent history.

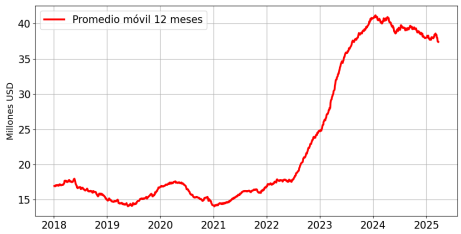
2.1 Data

We use publicly available daily data from the Central Bank of Costa Rica (BCCR) covering the period from January 1, 2017, to March 24, 2025, on foreign currency market outcomes. The dataset includes information on traded volumes, average and weighted-average exchange rates from Monex sessions, BCCR participation, and the foreign currency requirements of the public sector. Additionally, we incorporate data on net currency purchases by private financial entities through cash windows (over-the-counter, OTC, transactions), which represent the retail segment of the foreign currency market, as well as daily data on the Central Bank's net international monetary reserves.

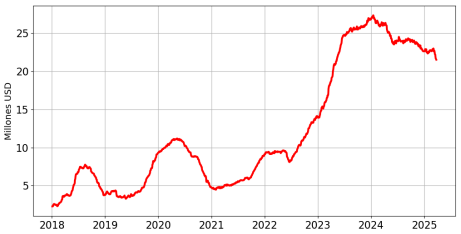
Overall, this comprehensive dataset allows for an in-depth analysis of net currency demand from both the public and private sectors, along with the Central Bank's role in the foreign exchange market.

Figure 2 presents the 12-month moving average of key market indicators[1], highlighting notable shifts in trends within Costa Rica's currency market. After mid-2022, the average daily traded volume in Monex sessions nearly doubled—from approximately US$17 million per day (2017 to early 2022) to around US$35 million daily during 2023–2024. At the same time, the BCCR's net purchases increased, reflecting higher foreign currency demand from the non-financial public sector, efforts to stabilize the market, and operations aimed at rebuilding foreign reserves to optimal levels. Additionally, average net purchases through cash windows (retail markets) also nearly doubled after 2022, signaling a clear excess supply of foreign currency during this period. This development aligns with the sustained appreciation of the exchange rate described in Figure 1.

FIGURE 2. Foreign Currency Market Variables

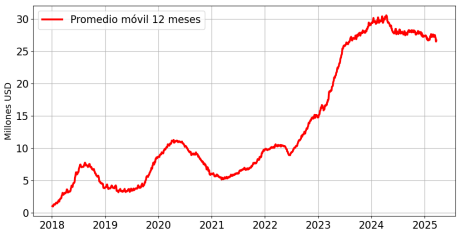


Total Traded Volume in Monex



Net Purchases by BCCR in Monex

Net demand (Purchases) by non-financial public sector



Net Purchases at Cash Windows

Notes: Net purchases by the BCCR in Monex include those for market stabilization, operational requirements, and meeting public sector foreign currency needs. The net demand from the non-financial public sector is managed by the BCCR and is not necessarily executed during the corresponding daily Monex session. Net purchases at cash windows refer to currency trading conducted by financial entities outside of Monex (retail currrency market).
Source: Central Bank of Costa Rica.

[1]For model calibration, we use the raw time series instead of moving averages.

2.2 Deep Neural Networks

Deep neural networks (DNNs) are a class of machine learning models inspired by the functioning of the human brain. They consist of multiple interconnected layers of artificial neurons that process information sequentially, enabling the model to identify complex patterns and non-linear relationships within the data.

A typical DNN is composed of the following core components:

- Input Layer: Receives the raw data and passes it to the network for processing.
- Hidden Layers: One or more intermediate layers where computations take place. Neurons in these layers apply weights and activation functions to transform the input data and extract deeper features.
- Activation Functions: Non-linear functions (such as ReLU, sigmoid, or tanh) applied at each neuron to introduce non-linearity, allowing the network to learn complex mappings.
- Output Layer: Produces the final prediction or classification result, depending on the task. The number and type of output neurons vary by application.
- Weights and Biases: Parameters learned during training that determine the strength and direction of connections between neurons.
- Loss Function: Measures the error between the predicted and actual values. The network uses this to guide learning during training.
- Optimizer: An algorithm (such as SGD or Adam) used to minimize the loss function by updating the model's weights and biases through backpropagation.

The learning process in a deep neural network (DNN) involves adjusting the weights of connections between neurons to approximate complex, non-linear functions. This is achieved through backpropagation, an algorithm that iteratively minimizes the error between the network's predictions and the actual outputs by updating weights in the direction that reduces the loss. Through repeated optimization, the network gradually improves its performance, effectively "learning" from the data.

DNNs are widely used in a variety of fields, including image recognition, natural language processing, and time series forecasting. Their capacity to uncover intricate patterns and relationships within large datasets makes them a powerful and versatile tool in modern machine learning.

2.3 Implementation

For the empirical implementation, we use NeuralProphet (Triebe et al., 2021), a hybrid forecasting framework built on PyTorch and trained using standard deep learning techniques.

Our variable of interest is the daily weighted-average session exchange rate at time t, with a forecasting horizon of h business days ahead, denoted as y_{t+h}. The model is structured as a modular system, where each module contributes an additive component to the overall forecast. While each module operates with its own inputs and modeling process, all are required to produce h forecasted values. These components are then aggregated to form the predicted values $\hat{y}t, \ldots, \hat{y}_{t+h-1}$, which correspond to the forecasted future values of the time series $y_t, \ldots, y_{t+h-1}$.

Specifically, we consider the following modules as key components in explaining the daily movements of the exchange rate:

$$\hat{y}_{t+h} = T(t) + S(t) + E(t) + A(t) + L(t)$$

where,
$T(t)$ = Trend at time t

$S(t)$ = Seasonal effects at time t

$E(t)$ = Events and Costa Rica and US holidays effects at time t

$A(t)$ = Auto-regression effects at time t based on past observations

$L(t)$ = Regression effects at time t for lagged observations of exogenous variables

The model accounts for potential monthly and weekly seasonality. Additionally, we incorporate Costa Rican[2] and U.S. holidays that could influence the foreign currency market. Furthermore, we include bi-weekly periodic events, defined as two business days before the 15th and 28th of each month, when firms—particularly multinational corporations and exporters—typically demand local currency to meet obligations such as wages, taxes, and social security contributions.

We incorporate market variables such as foreign exchange total traded volume, public sector foreign currency requirements, and the central bank's market participation, includ-

[2]For Costa Rica, we account for days when Monex did not operate, either due to official holidays or because lawmakers rescheduled holidays to create extended weekends aimed at promoting tourism.

ing net purchases for market stabilization, operational needs, and fulfilling public sector foreign currency demands.[3]. Finally, we include daily data on the Costa Rican average passive rate (tasa básica pasiva) and the U.S. federal funds rate. Given the model's daily calibration, we prioritize variables that exhibit meaningful day-to-day variation and offer significant predictive power.

The algorithm includes hyperparameters, which are key components within the model that are not learned during training but are predefined by the user prior to the training process[4]. Choosing the appropriate hyperparameters is crucial to ensure the model aligns with economic intuition while minimizing computational costs. To determine the initial setup, we partition the data, reserving the last 90 days of market activity as a validation dataset. We then conduct a search across an extensive hyperparameter space to identify the optimal values that maximize the model's predicting accuracy on the validation dataset.

[3]After X of 2020, the BCCR began directly managing public sector foreign currency needs to mitigate significant exchange rate fluctuations. Consequently, the BCCR can use its foreign reserves to meet the public sector's dollar demands and later participate in the foreign currency market to replenish those reserves.

[4]For example, this includes the maximum number of lags and allowable trend point changes, the learning rate, the number of hidden layers, among others.

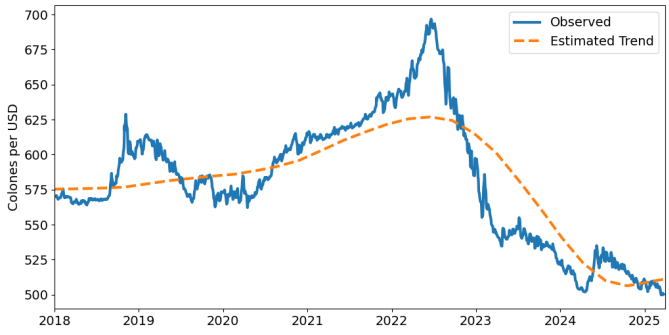
3 Results

3.1 Exchange Rate Trend

A key feature modeled by the algorithm is the trend component of the exchange rate. Alfaro-Ureña and Sandoval Alvarado (2022) shows that medium-term exchange rate dynamics—or the underlying trend—are primarily driven by structural real factors, such as productivity, external imbalances, and potential output growth. These factors evolve gradually over time and are unlikely to undergo abrupt changes over short time horizons, making the identification of a smooth and persistent trend essential for accurate modeling.

Given that the exchange rate is not expected to fluctuate significantly over short time horizons, we model its trend using a piecewise linear function with a sufficient number of potential breakpoints. To mitigate the risk of overfitting, the model is restricted from placing breakpoints within the final 60 business days of the dataset. Additionally, the hyperparameter tuning process, described in Section 2, is carefully designed to strike a balance—allowing the model enough flexibility to detect meaningful trend shifts and slope changes, while constraining excessive adaptability that could lead to an overly volatile or noisy trend.

FIGURE 3. Observed Exchange Rate and Inferred Trend Component



Notes: Weighted average of the exchange rates negotiated in each daily session of the Foreign Currency Market (Monex).
Source: Central Bank of Costa Rica and authors' calculations.

Figure 3 illustrates the trend component inferred by the model to explain exchange rate dynamics. Between 2018 and 2022, the model identifies a steady upward trend, with the exchange rate closely tracking this path. Deviations—most notably the depreciations observed in the second half of 2018 and the first half of 2022—were short-lived and quickly reverted to the underlying trend.

However, the model detects a notable change in the trend's slope beginning in April

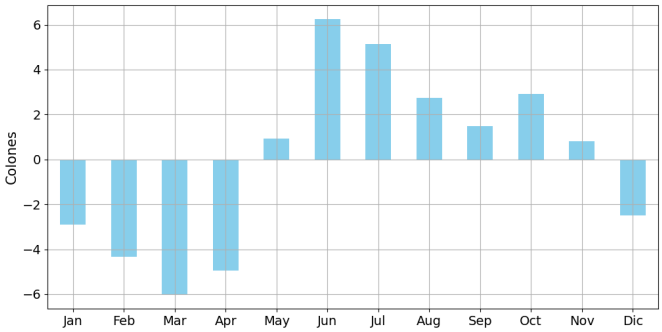
2022, signaling a shift from depreciation to appreciation dynamics. From that point onward, the model infers a downward trend, which gradually stabilizes by the third quarter of 2024. Throughout this period, the exchange rate remained broadly consistent with the inferred trend, ultimately ending 2024 in close alignment with the model's projection. For the first quarter of 2025, the model infers a trend reversal, following the exchange rate reaching 500 colones per USD.

What drives deviations from the trend? In a high-frequency, short-term context, such deviations are primarily influenced by seasonality, transitory shocks, and unobserved variables. These factors can cause temporary fluctuations around the underlying trend without necessarily signaling a shift in medium-term fundamentals.

3.2 Exchange Rate Seasonality

The model places significant emphasis on seasonality, which is a critical component of currency markets in small open economies. The algorithm identifies a seasonal pattern that aligns with the seasonality of key macroeconomic variables influencing the foreign currency supply throughout the year, such as tourism activity. To illustrate these differences across months and provide a sense of magnitude, Figure 4 depicts the additive impact that the algorithm places to each month on average. In other words, it shows the average seasonal effect each month, measured in colones. The findings reveal that from December to April, the exchange rate tends to be lower due to seasonal factors, with March and April showing the most pronounced effects. Conversely, from June to November, the model infers that the exchange rate is typically higher.

FIGURE 4. Estimated Seasonal Component of the Exchange Rate



Notes: Weighted average of the exchange rates negotiated in each daily session of the Foreign Currency Market (Monex).
Source: Central Bank of Costa Rica and authors' calculations.

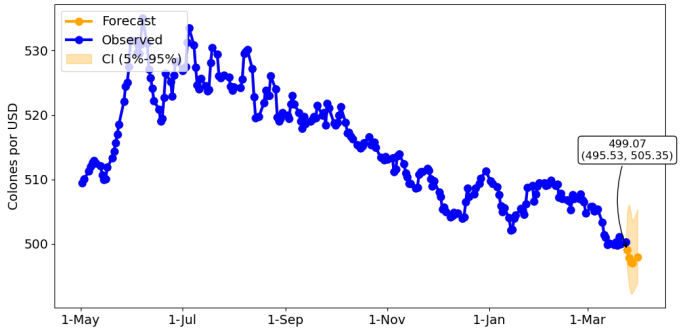
It is crucial to clarify, however, that this does not imply a perfectly predictable exchange rate pattern. Seasonality is only one component among several that explain short-

term exchange rate dynamics. Instead, these findings highlight that, controlling for other determinants, there are recurring patterns suggesting that the relative supply of foreign currency is stronger during certain months.

3.3 Exchange Rate Projection

In this paper, we evaluate the calibrated algorithm's ability to project the exchange rate five days ahead. While the algorithm is flexible enough to accommodate projections for various time horizons, such adjustments would necessitate modifications in data requirements, hyperparameter tuning, and trained parameters tailored to each specific projection window. Moreover, the structure of the chosen model is specifically optimized for short-term, high-frequency projections.

FIGURE 5. Exchange Rate and Five-Day Projection

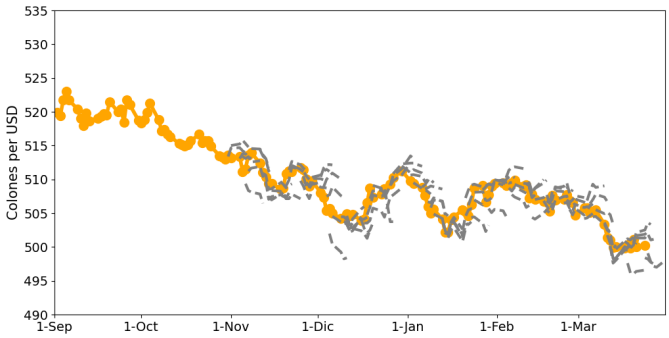


Notes: Weighted average of the exchange rates negotiated in each daily session of the Foreign Currency Market (Monex).
Source: Central Bank of Costa Rica and authors' calculations.

Figure 5 illustrates the observed exchange rate dynamics for 2024 through March 24th, 2025, along with the model's forecasted path. According to the algorithm, the projected exchange rate for March 25th, 2025 (the first day out of sample) is 499.07 colones per USD. The actual observed exchange rate on that date was 499.78, reflecting the model's high degree of accuracy in forecasting short-term exchange rate movements.

How well does the model predict? As previously explained, the model is trained to generate five-day forecast paths that closely align with observed data, based on the input variables provided. Figure 7 presents in-sample projections to evaluate the model's predictive power. Specifically, we construct daily five-day forecasting windows using data available up to each forecast date and compare these forecasts with the observed exchange rate. As illustrated, the model closely mirrors the actual exchange rate behavior, demonstrating high accuracy in inferring out-of-sample exchange rate dynamics.

FIGURE 6. Exchange Rate and Five-Day Projection



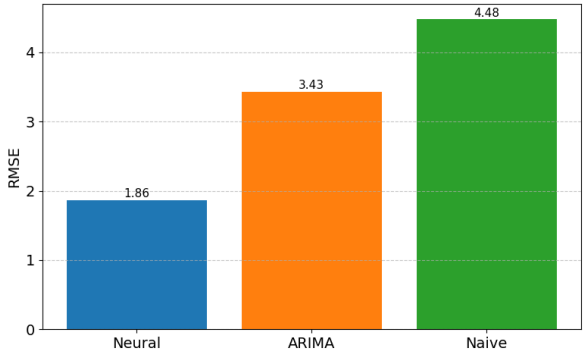
Source: Central Bank of Costa Rica and authors' calculations.

Still, Figure 7 emphasizes that the algorithm is not flawless. It is important to note that our analysis is restricted to publicly available data. Instances where the model's accuracy slips may reflect idiosyncratic shocks from significant market participants, which cannot be inferred from the data, or temporary market shocks that impact exchange rate dynamics. However, Figure 7 also demonstrates the model's resilience, as it quickly adjusts to errors and regains strong predictive performance.

3.4 Model's Performance Relative to Standard Methods

We divide the sample into training and testing datasets, using the last 60 days as the testing period. We then implement the neural model proposed in this paper, alongside a benchmark ARIMA model and a naive forecasting model. To evaluate performance, we compare the Root Mean Squared Error (RMSE) of each model.

FIGURE 7. Root Mean of Squared Error Across Selected Models



Notes: The ARIMA was estimated through a grind search defining the best parameters.
Source: Authors' calculations.

The results show that the RMSE of the neural model is substantially lower than that of the other two models. In fact, the RMSEs of both the ARIMA and naive models are nearly twice as high, indicating that the neural model demonstrates significantly greater predictive accuracy.

These findings underscore the model's superior ability to capture underlying patterns in high-frequency exchange rate data, leading to smaller prediction errors and clear out-performance relative to traditional approaches. This performance gain highlights the model's potential as a robust and efficient alternative for short-term forecasting tasks, particularly in contexts where precision and reliability are essential.

4 Conclusion

This paper presents a novel application of deep neural networks (DNNs) to forecast short-term exchange rate movements in Costa Rica, leveraging high-frequency data from the country's foreign currency market. By integrating seasonality, structural breaks, and key market variables into a flexible and data-driven framework, the proposed model captures the underlying dynamics of the exchange rate with high precision.

Our results demonstrate that the neural model significantly outperforms traditional forecasting methods, such as ARIMA and naive benchmarks, in terms of predictive accuracy. The model's ability to incorporate complex patterns, detect trend reversals, and adapt to evolving market conditions highlights its robustness and practical value for both policymakers and market participants.

These findings underscore the potential of machine learning techniques—particularly deep learning models—for improving forecasting accuracy in small, open economies with shallow and imperfectly competitive foreign exchange markets. Future research could explore the integration of real-time sentiment indicators, global financial conditions, or alternative architectures to further enhance predictive performance.

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