Stablecoin and Emerging Market Currencies: Modeling Causal Dynamics with Neural Stochastic Differential Equations

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November 29, 2025

Abstract

Stablecoins are prized for their stability amidst cryptocurrency volatility, yet their response to external economic shocks is poorly understood. This study investigates the critical, unexplored relationship between emerging market (EM) currency volatility and stablecoin dynamics. We model the interplay between Tether (USDT) and the currencies of Turkey, Vietnam, Russia, and South Africa using a novel Neural SDE model with jump diffusion, designed for abrupt price changes. A Double Machine Learning (DML) framework corroborates these findings and establishes causality. We find that Tether exhibits a significant asymmetric response, moving directionally with EM currency shocks. This causal evidence contradicts the safe-haven narrative, showing stablecoins are directly exposed to EM financial crises. Our results have major implications for global financial stability and the assessment of spillover risks.

Keywords: Neural SDES, Wavelet denoising, Causal Inference, Tether, Emerging Market Currencies, Double Machine Learning

1 Introduction

1.1 Prior works

Global monetary systems are transforming with the rise of cryptocurrencies, which are redefining how value is exchanged, stored, and governed. At the foundation of this transformation lies blockchain technology, a decentralized ledger system that ensures transparency, security, and immutability throughout the distribution process (Ante et al., 2023; Hoffman et al., 2020). Each

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transaction is cryptographically linked in a chain of data blocks, eliminating the need for intermediaries (Yau, 2024). Although major cryptocurrencies such as Bitcoin and Ethereum offer decentralized value exchange, they face inherent limitations due to their price volatility, which is caused by a lack of built-in stabilization mechanisms. Their fluctuating prices hinder their ability to act as a reliable unit of account and store of value (Aquilina et al., 2025). The limitations of existing cryptocurrencies have sparked a growing interest in more reliable digital currencies that retain the technological benefits of blockchain while ensuring greater valuation stability. Among recent innovations aimed at enhancing digital currency, stablecoins have gained traction as a prominent solution.

Stablecoins maintain a collateralized peg, enabling them to achieve significantly lower volatility compared to cryptocurrencies like Bitcoin (BTC). One of the most prominent stablecoins in terms of trading volume, Tether represents over 80 percent of the market share of all stablecoins (Lyons & Viswanath-Natraj, 2020). In the case of Tether, each unit is fully backed by USD reserves. In the event of mass liquidation of Tether, the Tether Treasury would be able to draw down its reserves and still maintain the peg (Lyons & Viswanath-Natraj, 2020).

Despite stablecoins gaining traction in the global economy, many aspects of their functionality and impact remain unanswered. In particular, their influence on emerging market economies (EMEs) is profound but remains insufficiently explored (Arner et al., 2020; Liao & Caramichael, 2022). During periods of economic instability in EMEs - characterized by high inflation, currency depreciation, and capital flight- there has been substantial demand for alternative mechanisms of monetary stores and financial access (Karamti & Bouabid, 2025; Kreuzer et al., 2024). The relationship between emerging market currencies (EMCs) and stablecoins has influenced issuers and platforms to adapt stablecoins to suit the specific needs and constraints of EMEs (of Business, 2025). In addition to being recipients of stablecoin technological development, EMEs are increasingly shaping stablecoin innovation, adoption, and regulatory patterns. This relationship reframes stablecoins as not only financial instruments but also technologies co-constructed through the pressures of economically volatile regions (Aldasoro et al., 2025).

1.2 Our Contributions

To analyze the dynamics between stablecoins and EMCs, we introduce a novel approach that utilizes Neural Stochastic Differential Equations (Neural SDEs) infused with jump diffusion processes in our model, Mean Reverting JumpNet Stochastic Differential Equations (MR JumpNet SDE); using this framework, we simulate the dynamics of EMCs fluctuations and their impact on Tether. Our findings reveal that shifts in EMCs drive asymmetric effects on Tether: appreciation shocks reduce demand for Tether more strongly than depreciation shocks increase it. Additionally, our results highlight capital flight and portfolio rebalancing under economic stress, providing key insights into stablecoin dynamics and the influence of EMEs. For our experiments, we focus on Tether (USDT) to examine its interplay with the currencies of Turkey, Vietnam, Russia, and South Africa. Based on the results of our framework, we propose the existence of a causal relationship between stablecoins and EME shocks.

To verify the validity of our results and claim, we infuse classical financial engineering techniques with machine learning through a Double Debiased Machine Learning (DML) framework posed by Chernozhukov et al., 2024 to prove a causal relationship between EMCs and Tether. Our results yield policy-relevant insights into stablecoins' dual role as hedges against depreciation and potential challenges to monetary sovereignty. Our framework and findings offer regulators, economists, and developers a scalable, robust, and interpretable approach to forecast and evaluate stablecoin behavior under adverse economic conditions in emerging markets.

Figure 1 below is the workflow of our research.



Figure 1: Illustration of the MR Jump Net SDE and DML workflow. (**A**) Workflow of pre-processing the data of emerging market currencies and USDT to remove anomalies. (**B**) Train the Jump Net model with clean data to learn the dynamics. (**C**) Workflow of MR Jump Net SDE, analyzing the responses of USDT to the shocks from currencies. (**D**) Visualization of the results. (**E**) Workflow of DML, which is conducted separately from MR Jump Net SDE model to verify the causal effects.

2 Review of Literature

This literature review investigates the structural design of stablecoins and evaluates their performance under conditions of market stress in EMEs, as well as examining how macroeconomic trends and cryptocurrency market dynamics influence stablecoin behavior. The first section of this review presents a comparative analysis of stablecoin adoption and its economic impact on emerging market currencies, whose emerging markets have seen a widespread uptake of USD-backed stablecoins.

The second section outlines the economic and computational methodology employed to analyze stablecoin dynamics. These include continuous-time neural networks for modeling real-time financial flows, causal inference techniques to isolate policy effects, and stochastic modeling frameworks to simulate liquidity shocks and systemic risk, as well as DML models. Collectively, these approaches provide a robust foundation for understanding the multifaceted role of stablecoins in

emerging markets and their implications for global financial stability.

2.1 Economics

The literature on stablecoins and their pegging mechanisms presents a comprehensive examination of how different models strive to maintain price stability under various economic conditions. Stablecoins generally fall into three categories: fiat-collateralized, cryptocurrency-collateralized, and algorithmic, each with distinct architectures and risk exposures. Arner et al., 2020 differentiates between centralized and decentralized models, underscoring the significance of collateralization and governance structures in upholding the peg. Berentsen and Schar, 2018 explores how fiat-backed stablecoins adjust the money supply in response to fluctuations in aggregate demand for money, thereby stabilizing the price level.Bullmann et al., 2019 further offers a nuanced classification based on issuer accountability and value backing, showcasing that algorithmic approaches suffer from a lack of collateral buffers. Lyons and Viswanath-Natraj, 2020 compares stablecoin pegs to fixed exchange rate regimes, emphasizing the necessity of transparent reserves and liquidity access to avoid collapse during market distress.

Building on these theoretical foundations, empirical studies provide critical insights into how stablecoins behave, especially under stress. Gorton et al., 2022 introduced the idea of convenience yield, where users may tolerate minor deviations in exchange for liquidity benefits, while Lyons and Viswanath-Natraj, 2020 showcases that arbitrage mechanisms help maintain the peg by correcting price deviations, contingent on sufficient market efficiency and access. Li and Mayer, 2020 further showcases that reserve management in centralized stablecoins is a key vulnerability, showing that peg maintenance is compromised by large shocks if reserves are not dynamically and credibly managed.

More recently, scholars have turned their attention to the behavior of stablecoins during economic disruptions, particularly geopolitical crises.Karamti and Bouabid, 2025 conducted an event study and wavelet analysis on 20 stablecoins during the COVID-19 pandemic and the Russia-Ukraine war. They found that algorithmic stablecoins were especially vulnerable to short-term shocks, while fiat-backed stablecoins offered greater price stability in volatile markets.

Complementing this conceptual work, quantitative models have been employed to assess volatility and risk exposure across stablecoin types. Although earlier literature focused primarily on Bitcoin's response to macroeconomic uncertainty, the analytical lens has now shifted toward stablecoins as instruments of capital preservation. Mokni et al., 2022 the performance of the top five cryptocurrencies and gold as a hedge and haven assets against economic policy uncertainty before and amidst the pandemic. The study found that cryptocurrencies act as safe havens, surpassing gold, as gold is losing its safe-haven status. These insights are now being extended to stablecoins, which are increasingly seen as vehicles for liquidity management during crises.

Building on volatility modeling, Granger causality has become an increasingly valuable tool for analyzing how stablecoin dynamics may influence fiat currency values, particularly in emerging markets with high cryptocurrency adoption. Kristoufek, 2022 examined links between stablecoins, Bitcoin, and altcoins using Granger tests, finding that stablecoin growth is primarily driven by investor demand, challenging earlier claims of price manipulation. In contrast, Griffin and Shams, 2020 argued that Tether (USDT) issuance supported Bitcoin prices during downturns, suggesting a causal link between stablecoin supply and market stabilization. Marshall, 2020 showed that stablecoin lending activity predicted Ethereum volatility, with USDC exerting an immediate effect. Extending this, Ante (2024) applied time-varying Granger tests to Ethereum sub-systems, revealing that transaction fees can drive stablecoin activity. Recent methodological advances in Granger causality further support these applications (Shojaie & Fox, 2022). Collectively, these

studies demonstrate how Granger causality reveals the predictive and systemic roles of stablecoins in digital finance, and underscore the importance of flexible, time-sensitive models for capturing cryptocurrency's complex behavior.

2.2 Models

Improving modeling methods, the Merton Jump-Diffusion model introduced discontinuities by adding Poisson-driven jumps to geometric Brownian motion, enabling the modeling of sudden market movements and improving the fit to observed option prices (Cheang & Chiarella, 2011). The jump-diffusion technique has been especially relevant in analyzing periods of sharp stablecoin price deviations, enabling financial analysts to better assess contagion risk across crypto and fiat markets. These models, while more realistic, introduce market incompleteness, making perfect hedging impossible and necessitating alternative pricing approaches such as equality martingale measures and risk-minimizing strategies Cheang and Chiarella, 2011.

Complementing stochastic and jump-based models, wavelet analysis has emerged as a powerful tool for capturing multi-scale dynamics in financial time series. It enhanced the detection of structural breaks and improved volatility forecasting by decomposing data across multiple time series. Wavelet-based techniques have also been utilized to study co-movements between stablecoins and fiat currencies, offering a nuanced perspective on market dynamicsNguyen et al., 2019.

While Granger causality offers insights into temporal relationships, econometric modeling of stablecoin behavior must also contend with endogeneity—a pervasive issue in empirical research. Endogeneity occurs when one or more explanatory variables are correlated with the error term in a regression model. This arises from factors such as simultaneous causality, omitted variables, or measurement error, and leads to biased and inconsistent estimates when using ordinary least squares (OLS) regression (Melitz, 2003; Terza et al., 2008; Yun, 1996). The conventional remedy is the two-stage least squares (2SLS) procedure, which introduces instrumental variables (IVs) to isolate exogenous variation (Angrist et al., 1996; Staiger & Stock, 1997). Classical econometric literature, notably Stock and Yogo (2005), emphasizes the importance of instrument strength using first-stage F-statistics to detect weak instruments in linear IV models. However, 2SLS becomes inefficient when the reduced-form relationship between instruments and endogenous variables is nonlinear or high-dimensional. To address these limitations,Hartford et al., 2017 proposed the Deep IV framework, which replaces 2SLS with a two-stage neural architecture: the first stage models the endogenous variable using instruments, while the second estimates treatment effects via counterfactual prediction. This approach accommodates complex nonlinear relationships and high-dimensional data where traditional methods falter.Farrell et al., 2021 further expands on this with the use of a two-stage estimator based on neural networks to conduct inferences on the treatment effect. Bennett et al., 2019 developed an empirical analysis of DeepIV, demonstrating its empirical reliability and mapping its performance to classical IV estimators under certain assumptions. Further practical interpretation is offered in Mishkin, 2019's Instrumental Variables, DeepIV, and Forbidden Regressions, a teaching resource that demystifies the DeepIV approach through visual examples and policy scenarios, illustrating how neural networks can effectively disentangle treatment effects from confounding bias.

Expanding on earlier innovations in causal machine learning, Double Machine Learning (DML) has become a central tool for causal inference for high-dimensional and complex data structures. The foundational framework of Chernozhukov et al., 2016 formalized the utilization of orthogonal score functions and cross-fitting to enable valid inference while using machine learning to estimate nuisance parameters. This methodology has since been extended across various empirical contexts. Clarke and Polselli, 2025 adapted DML for static panel models, enhancing traditional methods in

nonlinear settings. Xiang et al., 2025 expanded this framework to accommodate multiple treatments in their interactions. Xu et al., 2024 proposed a robust variant of DML (RDML) to handle outliers and heavy-tailed noise, which improved performance in data analysis. These developments

3 Preliminaries

3.1 Wavelet Transform

Wavelet transforms decompose a signal into multiple frequencies. From a mathematical lens, an orthogonal M-Band Discrete Wavelet Transform (DWT) utilizes a set of M filters in a filter bank with specific attributes. In any such filter banks, there is one low-pass filter and M-1 high-pass filters (j) for $j = 1, \ldots, m-1$ with N vanishing moments or N regular moments. These filters satisfy the following conditions:

$$\sum_{i=1}^{n} \alpha_i = \sqrt{M} \tag{3.1}$$

$$\sum_{i=1}^{n} i^k \beta_i^{(j)} = 0, \quad \text{for } k = 0, 1, 2, \cdots, N-1,\ j = 0, 1, 2, \cdots, M-1 \tag{3.2}$$

$$\|\alpha\| = \|\beta^{(j)}\| = 1, \quad \text{for } j = 1, \cdots, M-1 \tag{3.3}$$

$$\langle \alpha, \beta^{(j)} \rangle = 0, \quad \text{for } j = 1, \cdots, M-1 \tag{3.4}$$

$$\langle \beta^{(i)}, \beta^{(j)} \rangle = 0, \quad \text{for } i, j = 1, \cdots, M-1 \text{ and } i \neq j \tag{3.5}$$

M-band DWT can decompose a signal $S \in \mathbb{R}^{Mk}$ into the sum of M different frequency components. Generally, M-band L-regular DWT matrices have M filters with each length ML, and the non-zero elements in each row are shifted by M columns. To be concise, here is a 16×16 4-band 2-regular DWT matrix:

$$T = \begin{bmatrix}
\alpha_1 & \alpha_2 & \alpha_3 & \alpha_4 & \alpha_5 & \alpha_6 & \alpha_7 & \alpha_8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & \alpha_1 & \alpha_2 & \alpha_3 & \alpha_4 & \alpha_5 & \alpha_6 & \alpha_7 & \alpha_8 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \alpha_1 & \alpha_2 & \alpha_3 & \alpha_4 & \alpha_5 & \alpha_6 & \alpha_7 & \alpha_8 \\
\alpha_5 & \alpha_6 & \alpha_7 & \alpha_8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \alpha_1 & \alpha_2 & \alpha_3 & \alpha_4 \\
\beta_1 & \beta_2 & \beta_3 & \beta_4 & \beta_5 & \beta_6 & \beta_7 & \beta_8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & \beta_1 & \beta_2 & \beta_3 & \beta_4 & \beta_5 & \beta_6 & \beta_7 & \beta_8 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \beta_1 & \beta_2 & \beta_3 & \beta_4 & \beta_5 & \beta_6 & \beta_7 & \beta_8 \\
\beta_5 & \beta_6 & \beta_7 & \beta_8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \beta_1 & \beta_2 & \beta_3 & \beta_4 \\
\gamma_1 & \gamma_2 & \gamma_3 & \gamma_4 & \gamma_5 & \gamma_6 & \gamma_7 & \gamma_8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & \gamma_1 & \gamma_2 & \gamma_3 & \gamma_4 & \gamma_5 & \gamma_6 & \gamma_7 & \gamma_8 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \gamma_1 & \gamma_2 & \gamma_3 & \gamma_4 & \gamma_5 & \gamma_6 & \gamma_7 & \gamma_8 \\
\gamma_5 & \gamma_6 & \gamma_7 & \gamma_8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \gamma_1 & \gamma_2 & \gamma_3 & \gamma_4 \\
\delta_1 & \delta_2 & \delta_3 & \delta_4 & \delta_5 & \delta_6 & \delta_7 & \delta_8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & \delta_1 & \delta_2 & \delta_3 & \delta_4 & \delta_5 & \delta_6 & \delta_7 & \delta_8 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \delta_1 & \delta_2 & \delta_3 & \delta_4 & \delta_5 & \delta_6 & \delta_7 & \delta_8 \\
\delta_5 & \delta_6 & \delta_7 & \delta_8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \delta_1 & \delta_2 & \delta_3 & \delta_4
\end{bmatrix}$$

where

$$\alpha = [-0.0674,\ 0.0942,\ 0.4058,\ 0.5674,\ 0.5674,\ 0.4058,\ 0.0942,\ -0.0674],$$
$$\beta = [-0.0942,\ 0.0674,\ 0.5674,\ 0.4058,\ -0.4058,\ -0.5674,\ -0.0674,\ 0.0942],$$
$$\gamma = [-0.0942,\ -0.0674,\ -0.5674,\ -0.4058,\ 0.4058,\ 0.5674,\ 0.0674,\ 0.0942],$$
$$\delta = [-0.0674,\ -0.0942,\ 0.4058,\ -0.5674,\ 0.5674,\ 0.4058\,0.0942,\ -0.0674]$$

are the corresponding filters.
Given the wavelet matrix W_1, the first level of DWT can be done by

$$W_1 S = \begin{bmatrix} a^1 & d_1^1 & d_2^1 & \cdots & d_{M-1}^1 \end{bmatrix} \triangleq \tilde{S}_1 \tag{3.6}$$

where

$$a^1 = \begin{bmatrix} a_1^1 & a_2^1 & \cdots & a_k^1 \end{bmatrix}^T, \tag{3.7}$$
$$d_i^1 = \begin{bmatrix} d_{i,1}^1 & d_{i,2}^1 & \cdots & d_{i,k}^1 \end{bmatrix}^T, \quad \text{for } i = 1, 2, \ldots, M-1. \tag{3.8}$$

Intuitively, $W_1 S = \tilde{S}_1$ means that we transform S into the corresponding wavelet domain, or coordinates of S under the wavelet basis.

Denote $C_1, C_2, \ldots, C_{Mk}$ as the column vectors of W_1^T, then $\{C_1, C_2, \ldots, C_{Mk}\}$ form an orthonormal basis of $\mathbb{R}^{Mk}$ and we have

$$S = s_1 C_1 + s_2 C_2 + \cdots + s_n C_N, \tag{3.9}$$

where $n = Mk$ and

$$s_i = C_i^T S = \langle C_i, S \rangle. \tag{3.10}$$

Therefore,

$$s_i = \begin{cases} a_i & \text{for } i = 1, 2, \ldots, k, \\ d_{1,i} & \text{for } i = k+1, k+2, \ldots, 2k, \\ d_{(M-1),i} & \text{for } i = (M-1)k+1, \ldots, Mk. \end{cases} \tag{3.11}$$

Let

$$A_1 = a_1^1 C_1 + \cdots + a_k^1 C_k, \tag{3.12}$$
$$D_i^1 = d_{i,1}^1 C_{ik+1} + \cdots + d_{i,(i+1)k}^1 C_{(i+1)k}, \quad \text{for } i = 1, \ldots, M-1. \tag{3.13}$$

Then A_1 corresponds to a_1 and D_i^1 corresponds to d_{i1} for $i = 1, \ldots, M-1$. And

$$S = A^{(1)} + D_1^{(1)} + \cdots + D_{M-1}^{(1)}. \tag{3.14}$$

3.2 Double Debiased Machine Learning

Traditional causal inference often relies on linear regression models, where the outcome variable is modeled as a linear function of the treatment and observed confounders. For example, in the 2 SLS framework, we have:

$$\begin{aligned} \text{First stage: } & T = \pi_0 + \pi_1 Z + \pi_2^\top X + \eta, \\ \text{Predicted treatment: } & \hat{T} = \pi_0 + \pi_1 Z + \pi_2^\top X, \\ \text{Second stage: } & Y = \alpha + \tau \hat{T} + \beta^\top X + \varepsilon. \end{aligned} \tag{3.15}$$

where X are the confounding variables, T is the treatment variable, Y is the outcome variable and Z are the instrumental variables.

While this approach works well under linearity assumptions, it fails to capture nonlinear or high-dimensional relationships, leading to biased estimates. In order to account for these complex relationships, a natural solution is to replace the linear regression with a machine learning model. However, without refinement, this approach amplifies common machine learning challenges such as regularization bias and overfitting, leading to a biased model unfit for causal inference. To address these issues, Chernozhukov et al., 2024propose a framework combining:

1. **Neyman orthogonality:** Modifies the loss function to ensure ML models are "orthogonal" to confounding, reducing bias from regularization.

2. **K-fold cross-fitting:** Splits data into K subsets, training ML models on $K-1$ folds and estimating effects on the held-out fold. This mitigates overfitting and improves robustness.

This approach, known as "double/debiased machine learning" (DML), enables valid causal inference even with high-dimensional, nonlinear relationships. We note that we introduce the framework from the context of neural networks, but this approach can be generalized to other machine learning models.

Let Y denote our outcome variable, D our treatment variable, and X our confounding variables. Define $m(X) = \mathbb{E}[Y|X]$, $g(X) = \mathbb{E}[D|X]$. These functions capture the effect of the confounding variables on the treatment and outcome variables, respectively, so by approximating them, we will be able to remove the influence of our confounding variables from our treatment and outcome. Computationally, we have

$$\hat{m}(X) \approx \mathbb{E}[Y \mid X], \quad \hat{g}(X) \approx \mathbb{E}[D \mid X], \quad X \in \mathbb{R}^{d_x} \text{ (confounding variables)}, \tag{3.16}$$

where d_x denotes the number of confounding variables and $\hat{m}, \hat{g}$ are neural networks such that $\hat{m} : X \to Y$ and $\hat{m} : X \to D$. These functions are known as nuisance functions and are critical to determining the presence of a casual relationship even though we do not use them directly. The existence of a causal relationship is measured through a parameter θ_0 known as the causal parameter, which captures the effect of the treatment on the outcome while accounting for the confounding variables. However, this is a latent variable, so there is no way to directly measure this from the data. In order to estimate θ_0, we define it implicitly through a score function ψ. Define

$$\psi(W; \theta, \eta) = (D - \hat{g}(X))(Y - \hat{m}(X) - \theta(D - \hat{g}(X))). \tag{3.17}$$

where $\eta = (\hat{m}(X), \hat{g}(X))$ and $W = (X, Y, D)$. When $\theta = \theta_0$, we have

$$\mathbb{E}\left[\psi\left(W; \theta_0, \eta_0\right)\right] \tag{3.18}$$

where $m_0 = \arg\min_{\tilde{m}} \mathbb{E}\left[(D - \tilde{m}(X))^2\right]$, $\quad g_0 = \arg\min_{\tilde{g}} \mathbb{E}\left[(Y - \tilde{g}(X))^2\right]$ and $\eta_0 = (m_0, g_0)$.

4 Theoretical Framework

4.1 Mean-Reverting Jump Neural SDE Model(MR JumpNet SDE)

Stablecoin clearly displays mean-reverting behavior and thus, it is suitable to model stablecoin as an Ornstein-Uhlenbeck process where Dipple et al., 2020:

$$dS_t = \theta(\mu - S)dt + \sigma dW_t. \tag{4.1}$$

However, this model fails to account for real-world phenomena such as asymmetric leptokurtic behavior observed in stablecoin returns (Kou, 2002). In order to account for this, we propose a new model that captures real-world phenomena displayed by stablecoins.(

$$dS_t = \theta(\mu - S)dt + \sigma dW(t) + d\left(\sum_{i=1}^{N_t}(V_i - 1)\right). \tag{4.2}$$

This model integrates Kou, 2002 with an Ornstein-Uhlenbeck process in order to account for jumps in stablecoin observed during periods of stress, such as during 2018, 2020. We select Kou's jump diffusion for its analytical tractability and flexibility when it comes to integrating with a Neural SDE, particularly when it comes to the numerical scheme. However, while this is a good model in theory, in practice, markets often display erratic behavior such as depegging periods, leading to a change in the parameters of the model and thus a change in overall market dynamics. In order to account for this nonlinear market evolution, we integrate Neural SDES with our model to more accurately analyze the relationship between stablecoin and EMEs. By replacing the constants of our model with neural networks, we are able to model all classes of events, such as moments of extreme market volatility or a sudden change in market dynamics. Our proposed model has a hidden state governed by the stochastic differential equation:

$$dS_t = f(S_t, t)\,dt + g(S_t, t)\,dW_1(t) + h(S_t, t)\,d\left(\sum_{i=1}^{N(t)}(V_i - 1)\right) \tag{4.3}$$

where S_t denotes the hidden layer of our model at layer t. Additionally, $f(S_t, t)$,$g(S_t, t)$, and $h(S_t, t)$ are set to Long-Term Short Term networks in order to capture temporal dependencies in the data and allowing the model to adapt dynamically. For d input features, we then have a readout function $h_\phi(S_t) : \mathbb{R}^d \to \mathbb{R}^+$ that maps our hidden state to a final price. In our model, we use a simple linear readout in the form $h_\phi(S) = WS + B$ where $W \in \mathbb{R}^{d\times d}$ and $B \in \mathbb{R}^d$. We use the numerical scheme outlined in Section 3.2 along with stochastic gradient descent for optimizing our drift and diffusion terms. Additionally, we use a mean-squared error. We calibrate the Jump-Diffusion process whilst also training the Neural SDE by including the mean, standard deviation and intensity of jumps as learnable scalar parameters within the gradient descent process. While backpropagation for Neural Ordinary Differential Equations is done through the adjoint, the situation pertaining to Neural SDES is vastly different; Kidger et al., 2021 constructs Neural SDES as an Infinite Dimensional Generative Adversarial Network and constructs a custom solver via the Wasserstein distance, leading to an efficient and accurate solver for Neural SDES.

$$\widehat{z}_n = 2z_{n+1} - \widehat{z}_{n+1} - f_{n+1}\Delta t - g_{n+1}\Delta W_n \tag{4.4}$$

$$f_n = f\left(t_n, \widehat{z}_n; \theta_f\right) \tag{4.5}$$

$$g_n = g\left(t_n, \widehat{z}_n; \theta_g\right) \tag{4.6}$$

$$z_n = z_{n+1} - \frac{1}{2}(f_n + f_{n+1})\Delta t - \frac{1}{2}(g_n + g_{n+1})\Delta W_n \tag{4.7}$$

$$\frac{\partial L}{\partial(z_n, \widehat{z}_n, f_n, g_n)} = \frac{\partial L}{\partial(z_{n+1}, \widehat{z}_{n+1}, f_{n+1}, g_{n+1})} \cdot \frac{\partial(z_{n+1}, \widehat{z}_{n+1}, f_{n+1}, g_{n+1})}{\partial(z_n, \widehat{z}_n, f_n, g_n)} \tag{4.8}$$

where t_n is the discrete time point at step n with step size $\Delta t_n = t_{n+1} - t_n, W_t$ is a d_w-dimensional Brownian motion with increment $\Delta W_n := W_{t_{n+1}} - W_{t_n}, z_n \in \mathbb{R}^{d_z}$ is the hidden state

approximation at time t_n, and $\hat{z}_n \in \mathbb{R}^{d_z}$ is an auxiliary hidden state used during optimization. The drift is $f_n := f(t_n, \hat{z}_n; \theta_f) \in \mathbb{R}^{d_z}$ and the diffusion is $g_n := g(t_n, \hat{z}_n; \theta_g) \in \mathbb{R}^{d_z \times d_w}$, where θ_f, θ_g are trainable parameters. Finally, L denotes the loss functional, and the term

$$\frac{\partial L}{\partial (z_{n+1}, \hat{z}n+1, fn+1, g_{n+1})} \cdot \frac{\partial (z_{n+1}, \hat{z}n+1, fn+1, g_{n+1})}{\partial (z_n, \hat{z}_n, f_n, g_n)} \tag{4.9}$$

is the application of the chain rule for backpropagation through the solver, computed using the continuous adjoint method.

4.2 Data Collection, Preprocessing and Training

4.2.1 Retrieving data

The countries of interest, Vietnam, Russia, South Africa, and Turkey, collectively present a compelling array of conditions to examine the predictive capacity of stablecoins in EMCs, each representing a distinct intersection of economic instability, regulatory adoption, and digital innovation. In Vietnam, stablecoins such as USDT have gained traction as an informal hedge against the depreciation of the Vietnamese dong, driven by inflationary pressure and restricted access to foreign currency; their widespread use for savings and cross-border transactions reflects broader Southeast Asian patterns of digital asset adoption (Carney, 2019; Minh, 2024). Turkey's prolonged lira devaluation has similarly fueled popular migration toward stablecoins, which are perceived as more reliable stores of value amid rising inflation and capital controls - USDT consistently dominates trading volumes on domestic exchanges (Liao & Caramichael, 2022; Oefele et al., 2025). Meanwhile, Russia underscores a strategic utilization of stablecoins at the state level, turning to digital currencies to bypass Western sanctions and exclusion from the SWIFT payment system, thereby positioning stablecoins not only as individual financial tools but also as instruments of geopolitical maneuvering and macroeconomic resilience Karamti and Bouabid, 2025; Kreuzer et al., 2024. These cases jointly illustrate the nuanced and increasingly significant role stablecoins play in shaping financial behavior and currency perception within EMEs.

The data for the present study were obtained from Yahoo Finance through the Python-based yfinance library. This data set includes historical exchange rate information for four EMCs, South African Rand (ZAR = X), Russian Ruble (RUB = X), Vietnamese Dong (VND = X), and Turkish Lira (TRY=X), against the US Dollar. The data consists of daily closing prices, trading volumes, and other market indicators spanning the time period July 25, 2020, to July 14, 2025. These exchange rates are sourced from centralized financial platforms and reflect real-time market conditions.

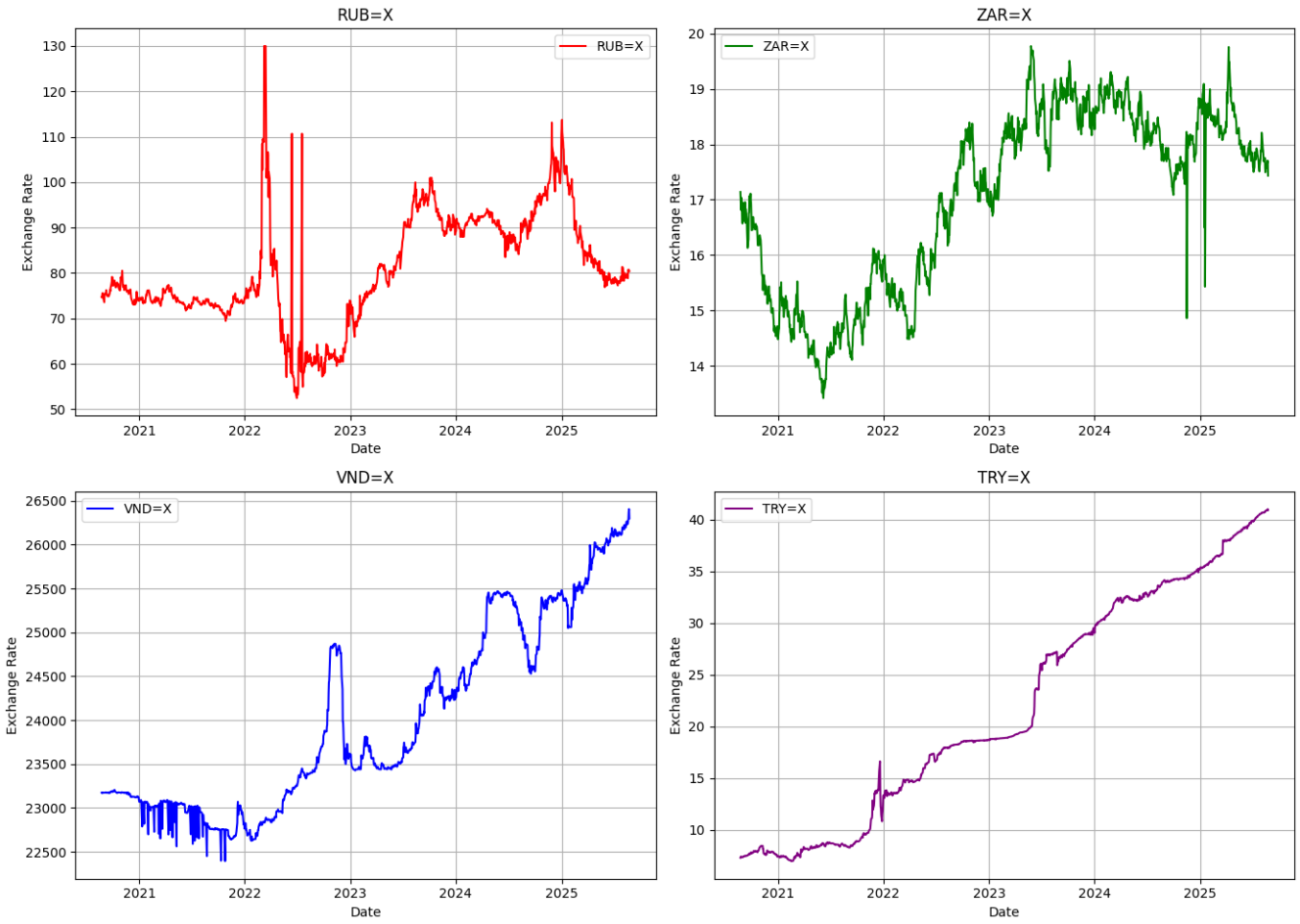


Figure 2: Exchange Rates to USD: ZAR, RUB, VND, TRY

The graphs illustrate the daily exchange rate fluctuations of the currencies we analyze against the US dollar for the period studied. For example, RUB=X is $\frac{USD}{RUB}$. While the South African Rand and Russian Ruble display moderate volatility, the Turkish Lira shows a more pronounced downward trend in value. The Vietnamese Dong remains relatively stable. The visualizations suggest that the currency stability varies significantly across regions. Overall, the visualizations suggest that currency stability varies significantly across regions and that external shocks can have measurable impacts on valuation.

Additionally Table 1 presents the summary statistics of the EMCs used in this study, as well as Tether.

Ticker	count	mean	std	min	25%	50%	75%	max
RUB=X	535	90.852	6.986	76.893	87.071	91.320	95.465	113.722
TRY=X	536	33.359	3.950	25.905	30.300	33.168	35.959	40.810
USDT-USD	752	1.000	0.001	0.998	0.999	1.000	1.000	1.002
VND=X	535	25079	658	23655	24530	25280	25455	26245
ZAR=X	536	18.362	0.549	14.860	17.972	18.406	18.780	19.758

Table 1: Summary statistics of EMC exchange rates.

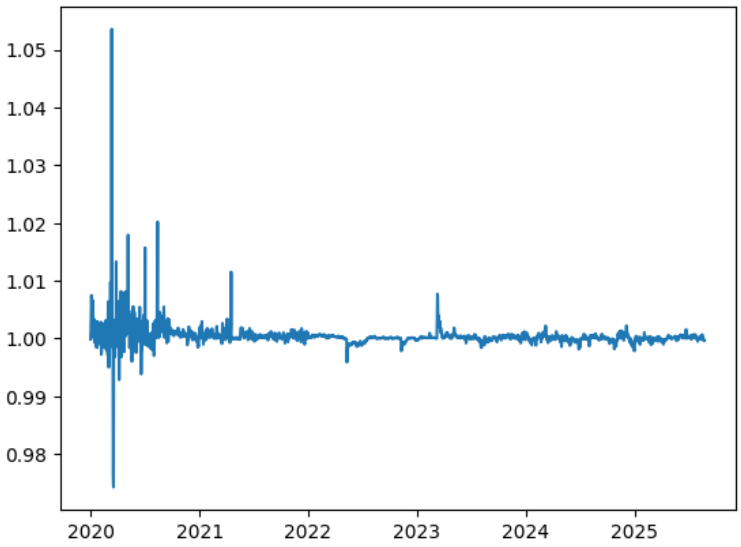


Figure 3: Tether price from 2021 to 2025

4.2.2 Preprocessing

We begin with raw prices, denoted as $\{x_t\}_{t=1}^{N}$. We apply wavelet denoising to remove anomalies in our data as outlined in Section 3.3. We set values greater than $\lambda = 5\sigma + \mu$ to μ where μ and σ denote the mean and standard deviation of our prices, respectively. We let λ be a high value in order to ensure that we have enough periods of stress in our data, but just enough so that we remove extreme periods of stress that are anomalies even within the set of anomalies.

The denoised signal $\tilde{x}_t$ is then standardized using z-score normalization:

$$z_t = \frac{\tilde{x}_t - \mu}{\sigma}, \tag{4.10}$$

where $\tilde{\mu}$ and $\tilde{\sigma}$ are the sample mean and standard deviation of $\tilde{x}_t$. We

4.2.3 Training our model

We first begin by retrieving the Tether and prices from EMCs and store them as:

$$X_t = \begin{bmatrix} \text{USDT-USD}_{t-d} & \text{EME}_{t-d} \\ \text{USDT-USD}_{t-d} & \text{EME}_{t-d} \\ \vdots & \vdots \\ \text{USDT-USD}_{t-1} & \text{EME}_{t} \end{bmatrix}, \quad Y_t = \text{USDT-USD}_t \tag{4.11}$$

where we predict a future price of Tether(Y_t) given the last d days' prices of Tether and Emerging Markets in combination with the current price of EMCs X_t. Following Section 4.1, we clean our data. We note that a sample of our training data X_t is a matrix such that $X_t \in \mathbb{L} \times \nVdash$ where L denotes the amount of lookback prices used in each sample(if $L = 45$ we utilize 45 days of past prices). In order to ensure our results are representative of the entire time period of our data, we set $L = 90$ for the entire dataset, ensuring our model accounts for long-term trends in our data. We utilize our Mean-Reverting Neural Stochastic Differential Equation model outlined in section 4.1. where we set $d = 2$.

$$\theta^* = \arg\min_{\theta} \frac{1}{N} \sum_{t=1}^{N} \left\| Y_t - \hat{Y}_t \left(X_t; \theta \right) \right\|^2, \quad \hat{Y}_t = \text{NeuraISDE} \left(X_t; \theta^* \right), t = 1, \ldots, N \tag{4.12}$$

We train the model for 40 Epochs with a batch size of 128, leading to 1600 training samples and 40 testing samples.

$$\text{Performance metric (MSE)} = \frac{1}{N} \sum_{t=1}^{N} \| Y_t - \hat{Y}_t \|^2 \tag{4.13}$$

We assess our model using the performance metric in order to ensure it has learned the correct dynamics between EMCs and Tether. Additionally, by selecting our test set over the entire time-frame, we ensure that the model has generalized to the overall dynamics and not just a specific period.

4.3 Shock Implementation and Scenario Analysis

In section 4.2, we set up our model so that it learned the dynamics between stablecoin and EMCs, and we now use this in order to determine how the relationship between these two currencies evolves during times of stress. However, we make the assumption that our model has learned the correct market dynamics, where we use empirical to justify this claim. In order to bolster the validity of our results, in section 4.5, we provide a theoretical justification for this assumption via the Double Debiased Machine Learning Framework, thus demonstrating our model is unbiased and confirming the validity of our results.

We first begin analyzing the dynamics by retrieving current prices of Tether and EMCs in the form we had in section 4.2, allowing us to pass the data to the model.

$$X_{\text{new}} = \begin{bmatrix} \text{USDT-USD}_{T-45} & \text{EME}_{T-44} \\ \text{USDT-USD}_{T-44} & \text{EME}_{T-43} \\ \vdots & \vdots \\ \text{USDT-USD}_{T-1} & \text{EME}_{T} \end{bmatrix} \tag{4.14}$$

Then, in order to analyze the relationship between the 2 markets, we simulate a market shock in the EMC where we add a price change of n standard deviations to the most recent price.

$$\text{EME}_{t-1}^{\text{new}} = \text{EME}_{t-1} + n \cdot \sigma_{\text{Price}} \tag{4.15}$$

$$X_{\hat{t}} = X_{\text{new}} \text{ with USDT-USD}_{t-1} \text{ replaced by Price}_{t-1}^{\text{new}} \tag{4.16}$$

We then pass this new data to our model in order to infer the effect of an EMC crash on stablecoin. We let our $\hat{Y}_{orig}$ denote the future predicted price with no crash and $\hat{Y}_{new}$ denote the price with a crash.

$$\hat{Y}_{\text{orig}} = \text{NeuralSDE}(X_{\text{new}}; \theta^*), \quad \hat{Y}_{\text{adj}} = \text{NeuralSDE}(X_{\hat{t}}; \theta^*) \tag{4.17}$$

With these 2 prices, we then perform a statistical analysis using Z-scores, p-values, and the t-test in order to determine whether our

$$Z_t = \frac{\hat{Y}_{\text{adj}} - \hat{Y}_{\text{orig}}}{\sigma_{\hat{Y}}}, \quad p\text{-value} = 2\,P(Z > |Z_t|) \tag{4.18}$$

$$t = \frac{\bar{\hat{Y}}_{\text{adj}} - \bar{\hat{Y}}_{\text{orig}}}{s_p\sqrt{2/N}}, \quad s_p = \sqrt{\frac{s^2_{\text{adj}} + s^2_{\text{orig}}}{2}} \tag{4.19}$$

1. **Data Preparation:**
   - Collect the outcome variable Y, treatment variable D, and covariates X.
   - Split the dataset into training and testing folds.
2. **Nuisance Parameter Estimation:**
   - Estimate the outcome model (residualizing Y):

     $$m_0(X) = \mathbb{E}[Y \mid X], \quad \hat{m}(X) \approx m_0(X) \tag{4.20}$$

     using a machine learning model (e.g., neural network).
   - Estimate the treatment model (residualizing D):

     $$g_0(X) = \mathbb{E}[D \mid X], \quad \hat{g}(X) \approx g_0(X) \tag{4.21}$$

     using a machine learning model.
3. **Compute Residuals (Neyman Orthogonalization):**
   - Residual for the outcome:

     $$\tilde{Y} = Y - \hat{m}(X) \tag{4.22}$$

   - Residual for the treatment:

     $$\tilde{D} = D - \hat{g}(X) \tag{4.23}$$

4. **Causal Effect Estimation:**
   - Regress the residualized outcome on the residualized treatment:

     $$\tilde{Y} = \theta\tilde{D} + \epsilon \tag{4.24}$$

   - Solve for θ, which gives the estimated causal effect of D on Y.
5. **Cross-Fitting:**
   - Perform K-fold cross-fitting by repeating steps 2–4 on different folds to reduce overfitting and ensure robustness.

4.4 Causal Effect Estimation via Double Debiased Machine Learning

To estimate the causal effect of EMCs on Tether, our paper utilizes the DML framework by Chernozhukov et al., 2024. As mentioned above, DML provides a principled approach to causal inference in environments where nonlinearities and high-dimensional interactions are prevalent by combining flexible machine learning methods for nuisance estimation with orthogonalized moment conditions that deliver valid inference for the treatment effect.

Let Y_t denote the price of Tether at time t, and let D_t represent the price of an EMCs. The vector X_t contains the confounding variables, including macroeconomic controls and other cryptocurrency prices. We model the relationship as:

$$\begin{aligned} Y_t &= \theta_0 D_t + g_0(X_t) + \varepsilon_t, \quad \mathbb{E}[\varepsilon_t \mid D_t, X_t] = 0, \\ D_t &= m_0(X_t) + \nu_t, \quad \mathbb{E}[\nu_t \mid X_t] = 0, \end{aligned} \tag{4.25}$$

where θ_0 represents the causal parameter that represents the effects of the EMCs on Tether. $g_0(X_t)$ denotes the nuisance function, which maps the potential nonlinear effects of our confounding variables to the outcomes. In the second equation $m_0(X_t)$ models the treatment nuisance function, capturing the portion of the treatment explained by the confounding variables.

The estimation procedure begins by splitting the data into K folds for cross-fitting. For each fold k, the observations in that fold are held out as the "estimation set," while the remaining $K-1$ folds form the training set. On the training set, neural networks are used to estimate the nuisance functions:

$$\hat{g}^{(-k)}(X_t) \approx g_0(X_t), \quad \hat{m}^{(-k)}(X_t) \approx m_0(X_t), \tag{4.26}$$

where the superscript $(-k)$ indicates out-of-sample training excluding fold k. Using these predictions, the residualized outcome and treatment are computed for the held-out fold:

$$\tilde{Y}_t = Y_t - \hat{g}^{(-k)}(X_t), \quad \tilde{D}_t = D_t - \hat{m}^{(-k)}(X_t). \tag{4.27}$$

These residuals form Neyman-orthogonal scores, which satisfy the formal condition outlined in Theorem 3.5, Assumption 3.6.

Finally, the causal effect is estimated by regressing the residualized outcomes on the residualized treatments:

$$\tilde{Y}_t = \theta_0 \tilde{D}_t + \tilde{\varepsilon}_t, \quad \hat{\theta}_0 = \frac{\sum_{t=1}^{n} \tilde{D}_t \tilde{Y}_t}{\sum_{t=1}^{n} \tilde{D}_t^2}. \tag{4.28}$$

This process is repeated across all folds, and the results are aggregated to form a single estimate $\hat{\theta}_0$. Under standard regularity conditions, $\hat{\theta}_0$ is $\sqrt{n}$-consistent and asymptotically normal:

$$\sqrt{n}(\hat{\theta}_0 - \theta_0) \xrightarrow{d} \mathcal{N}(0, V), \tag{4.29}$$

allowing for valid confidence intervals and hypothesis testing. By combining flexible modeling of $g_0(X_t)$ and $m_0(X_t)$ with cross-fitted residualization and Neyman orthogonality, this framework isolates a robust, interpretable estimate of the direct causal effect of EMC prices on Tether, even in high-dimensional or nonlinear settings.

4.5 Establishing Causality Between EME Shocks and Tether Dynamics

To rigorously establish a causal link between emerging market price movements and price dynamics of Tether, we employ a multilayered approach combining financial and machine learning techniques with theory-based reasoning. Firstly, we use a DML framework to estimate the causal effect of EMC on Tether, controlling for confounding variables and other asset price movements. This approach enables us to isolate the impact of EMCs on tether while maintaining ceteris paribus. Secondly, to validate the unbiasedness of our baseline model, we perform a Hausman test comparing the DML-derived causal coefficient with the coefficient generated from the MR Neural SDE model that captures the structural dynamics of Tether. In periods of normal market activity, failing to reject endogeneity in the Hausman test indicates that the Neural SDE slope is consistent with the causal effect, and thus can be interpreted as unbiased. Lastly, to extend this causal claim to periods of extreme emerging market volatility or price movements, using theory-based justification, we argue that the structural dynamics that govern the Neural SDE framework ensure that the emerging market and Tether relationship persists under extreme conditions.

This empirical finding is consistent with established theoretical frameworks. Classical jump-diffusion models (Merton, 1976; Duffie, Pan, and Singleton, 2000) demonstrate that jumps in asset prices primarily affect scale, tail risk, and variance, while preserving functional dependence on underlying drivers. Similarly, limits-to-arbitrage theories (Shleifer and Vishny, 1997; Brunnermeier, Gorton, and Krishnamurthy, 2009) show that even when funding constraints or liquidity shortages limit arbitrage efficiency, correction mechanisms persist to enforce directional price relationships. Financial market microstructure further supports this view: during periods of liquidity stress, adjustment processes may slow, but fundamental pricing anchors, such as parity links between EMCs' movements and stablecoin values, remain operative.

Thus, by integrating classical jump diffusion frameworks with limits to arbitrage theory, it appears that the causal relationship between EMC shocks and Tether price dynamics is not only analyzable but also robust. The combination of DML for causal identification, the Hausman test for bias detection, the Neural SDE for structural stress testing, and theoretical support from jump-diffusion and arbitrage-limit models provides a coherent and consistent foundation. Large shocks amplify volatility and deviations, but they do not undermine the underlying causal mechanism. This reinforces both the validity and the generalizability of our causal claim.

5 Results

To evaluate the empirical validity of our proposed approach, this section presents the estimation results obtained from MR JumpNet SDE. Table 2 reports the effects of simulated shocks to the Rand, Lira, Ruble, and Dong on Tether's price across varying magnitudes. Specifically, it shows the predicted stablecoin prices under shock conditions (in thousandths of a unit from 1), the differences between prices with and without the shock, and the corresponding z-scores calculated using both the standard deviation and the median absolute deviation. In our analysis, we computed the z-scores with both the standard deviation and the Median Absolute Deviation (MAD) to assess whether the observed price deviations following shocks could be attributed to random variation. The use of MAD, in particular, provides a more robust measure of deviations by reducing sensitivity to outliers, thereby strengthening the reliability of the inference.

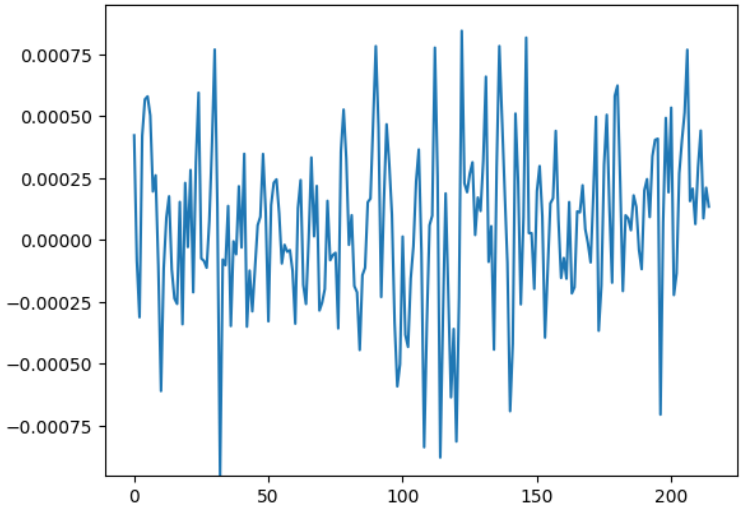


Figure 4: Residuals plot MR JumpNet SDE

Before turning to the analysis of shock responses, it is necessary to evaluate the overall performance of MR JumpNet SDE. The model demonstrates a strong fit, with a mean squared error (MSE) of 1.22^{-7}, indicating that the predictions deviate from actual values by no more than a fraction of a cent. Figure 4 presents the residual plots for each currency, showing random fluctuations that are centered and symmetric around zero, thereby suggesting no visible directional bias. In addition, the residual plots display constant variance, with no evidence of heteroskedasticity or structural misspecification. In short, these metrics confirm the model's robustness, providing a sound basis for the subsequent analysis of Tether's response to currency shocks.

Having confirmed the accuracy of the model through residual diagnostics, we examine how Tether's price reacts to currency shocks in greater detail. Due to the small prices of Tether, we adjust our metric units to be 10^{-3} in order to better illustrate the size magnitude of the jumps; we use this metric throughout all of our subsequent analysis. In Table 2, our results demonstrate a remarkable amount of symmetry in how Tether's price responds to EMC shocks. During negative shocks, where the standard deviation is less than zero, the price of Tether falls below the peg, indicating a negative price deviation, with the largest being -1.002, -2.141, -0.571, and -1.288 at -10 standard deviations for the Rand, Lira, Ruble, and Dong, respectively. Similarly, positive shocks in the EME currencies lead to positive price deviations away from the peg. For example,

a 10 standard deviation shock of Rand led the price of Tether to increase by 0.935, with a MAD z-score of 5.251. Importantly, shock values of approximately ± 3 and ± 5 standard deviations result in price deviations that are unlikely to arise from random fluctuations alone, as the z-scores exceed 2.5, indicating a 1% statistical significance level.

Table 2: Simulated Shocks Results

Countries		Std of Shocks																			
		-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10
ZAR (South Africa)	Predicted Price (Deviation from 1 ($\times 10^{-3}$))	0.201	0.304	0.400	0.507	0.606	0.707	0.808	0.900	1.000	1.096	1.197	1.298	1.389	1.486	1.582	1.688	1.771	1.873	1.967	2.053	2.138
	Difference No Shock ($\times 10^{-3}$)	-1.002	-0.899	-0.803	-0.696	-0.598	-0.496	-0.395	-0.303	-0.203	-0.107	-0.006	0.095	0.185	0.283	0.378	0.485	0.567	0.669	0.764	0.850	0.935
	Z Score STD	(-2.643)	(-2.371)	(-2.117)	(-1.836)	(-1.576)	(-1.309)	(-1.043)	(-0.800)	(-0.535)	(-0.282)	(-0.017)	(0.249)	(0.489)	(0.747)	(0.998)	(1.280)	(1.497)	(1.765)	(2.014)	(2.242)	(2.466)
	Z Score MAD	(-5.628)	(-5.050)	(-4.509)	(-3.911)	(-3.357)	(-2.787)	(-2.221)	(-1.703)	(-1.140)	(-0.602)	(-0.036)	(0.531)	(1.041)	(1.591)	(2.125)	(2.725)	(3.187)	(3.759)	(4.289)	(4.775)	(5.251)
TRY (Turkey)	Predicted Price (Deviation from 1 ($\times 10^{-3}$))	0.041	0.274	0.542	0.736	0.968	1.181	1.391	1.613	1.810	2.009	2.193	2.370	2.557	2.725	2.891	3.025	3.201	3.327	3.459	3.603	3.749
	Difference No Shock ($\times 10^{-3}$)	-2.141	-1.909	-1.640	-1.446	-1.215	-1.002	-0.792	-0.569	-0.372	-0.173	0.011	0.188	0.375	0.543	0.708	0.843	1.019	1.144	1.277	1.421	1.567
	Z Score STD	(-5.645)	(-5.033)	(-4.326)	(-3.813)	(-3.203)	(-2.641)	(-2.088)	(-1.501)	(-0.982)	(-0.457)	(0.028)	(0.495)	(0.989)	(1.432)	(1.868)	(2.223)	(2.687)	(3.018)	(3.368)	(3.746)	(4.133)
	Z Score MAD	(-12.024)	(-10.721)	(-9.213)	(-8.121)	(-6.822)	(-5.625)	(-4.447)	(-3.197)	(-2.092)	(-0.972)	(0.059)	(1.055)	(2.107)	(3.049)	(3.979)	(4.736)	(5.723)	(6.428)	(7.173)	(7.979)	(8.803)
RUB (Russia)	Predicted Price (Deviation from 1 ($\times 10^{-3}$))	0.085	0.143	0.193	0.257	0.312	0.370	0.428	0.475	0.534	0.587	0.647	0.708	0.756	0.814	0.869	0.942	0.979	1.046	1.104	1.150	1.192
	Difference No Shock ($\times 10^{-3}$)	-0.571	-0.513	-0.463	-0.398	-0.344	-0.286	-0.228	-0.180	-0.122	-0.069	-0.009	0.053	0.100	0.158	0.213	0.286	0.323	0.391	0.448	0.494	0.536
	Z Score STD	(-1.507)	(-1.353)	(-1.222)	(-1.051)	(-0.908)	(-0.754)	(-0.601)	(-0.476)	(-0.322)	(-0.182)	(-0.023)	(0.139)	(0.264)	(0.418)	(0.562)	(0.755)	(0.852)	(1.030)	(1.182)	(1.303)	(1.414)
	Z Score MAD	(-3.209)	(-2.881)	(-2.602)	(-2.238)	(-1.934)	(-1.605)	(-1.279)	(-1.013)	(-0.685)	(-0.387)	(-0.048)	(0.295)	(0.562)	(0.889)	(1.198)	(1.608)	(1.813)	(2.194)	(2.517)	(2.774)	(3.011)
VND (Vietnam)	Predicted Price (Deviation from 1 ($\times 10^{-3}$))	1.141	1.274	1.406	1.538	1.666	1.796	1.925	2.041	2.168	2.287	2.416	2.546	2.654	2.777	2.895	3.041	3.127	3.262	3.379	3.476	3.567
	Difference No Shock ($\times 10^{-3}$)	-1.288	-1.155	-1.023	-0.891	-0.763	-0.633	-0.504	-0.388	-0.261	-0.141	-0.013	0.117	0.225	0.349	0.466	0.612	0.698	0.833	0.951	1.047	1.138
	Z Score STD	(-3.398)	(-3.047)	(-2.697)	(-2.350)	(-2.012)	(-1.669)	(-1.329)	(-1.024)	(-0.688)	(-0.373)	(-0.033)	(0.309)	(0.593)	(0.920)	(1.229)	(1.614)	(1.840)	(2.196)	(2.507)	(2.763)	(3.002)
	Z Score MAD	(-7.236)	(-6.488)	(-5.744)	(-5.004)	(-4.285)	(-3.554)	(-2.829)	(-2.181)	(-1.465)	(-0.794)	(-0.071)	(0.657)	(1.262)	(1.958)	(2.616)	(3.437)	(3.918)	(4.677)	(5.339)	(5.883)	(6.392)

Note: Predicted prices are reported as deviations from 1, scaled by 10^{-3} . For example, a predicted price of 1.000201 corresponds to a deviation of 0.201.

While these results describe the general direction of price responses, it is also important to compare the relative strength of effects across different currencies. The magnitude of the effects of the shocks from each EMC differs. In Figure 5, a scatter plot shows the standard deviation of the shock on the x-axis and the price difference on the y-axis. As mentioned previously, it is apparent that all EMCs show a similar trend in increasing monotonically upward. Among the currencies, shocks to the Lira generate the strongest effect on Tether, with each one–standard deviation change in the Lira associated with a 0.185 change in the price of Tether. In contrast, the Ruble generates the least effect on Tether with a slope value of 0.056. The r^2 values for all the currencies range from 99.2% to 99.8%, indicating a strong linear fit. However, in the scatter plots, the data generally follows a linear trend, though slight curvature is visible in some regions, giving the appearance of a mild logarithmic pattern. This is most noticeable in the price deviations caused by the Lira, as shown by the data points in red.

Beyond differences in magnitude, a key question is whether Tether reacts symmetrically to positive versus negative shocks. Our results show that negative shocks produce consistently larger price deviations than positive shocks of the same magnitude, revealing a clear asymmetry in Tether's response to adverse versus favorable currency movements. To quantify this asymmetric response in Tether, we conduct a Chow test to determine whether the slope associated with positive shocks differs significantly from that of negative shocks. The results for each currency are printed in the table below.

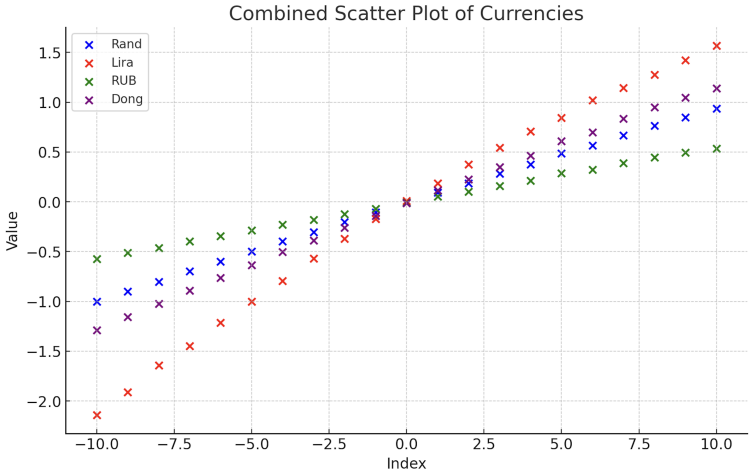


Figure 5: Combined Scatter Plot Of Currencies

Currency	Intercept (Neg)	Slope (Neg)	Intercept (Pos)	Slope (Pos)	F Statistic	P-Value
RAND	−0.002 47	0.099 59	−0.000 59	0.094 76	18.11	6.13×10^{-5}
LIRA	0.074 13	0.218 19	0.057 32	0.153 92	138.86	2.94×10^{-11}
RUB	−0.009 47	0.055 99	−0.005 59	0.055 54	0.40	6.79×10^{-1}
DONG	−0.003 13	0.128 00	0.000 00	0.116 85	16.59	1.01×10^{-4}

Table 3: Chow Test Results for Selected Currencies

The Chow test reveals asymmetric responses to positive or negative shocks for three out of the four currencies. The Lira exhibits the strongest asymmetry, with a negative-shock slope of 0.218 compared to 0.154 for positive shocks, indicating heightened sensitivity to negative shocks

compared to positive ones. The Rand and Dong also show significant, though smaller, differences in slopes, while the Ruble's slopes are nearly identical, reflecting a symmetric response. The Chow test confirms these patterns: Lira ($F = 138.86$, $p < 0.001$), Rand ($F = 18.11$, $p < 0.001$), and Dong ($F = 16.59$, $p < 0.001$) exhibit significant slope differences, whereas the Ruble does not ($F = 0.40$, $p = 0.679$).

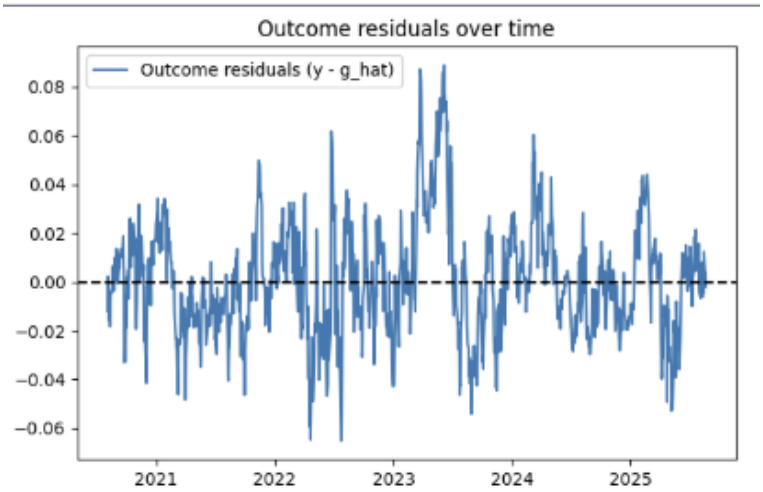


Figure 6: Outcome Residuals Over Time

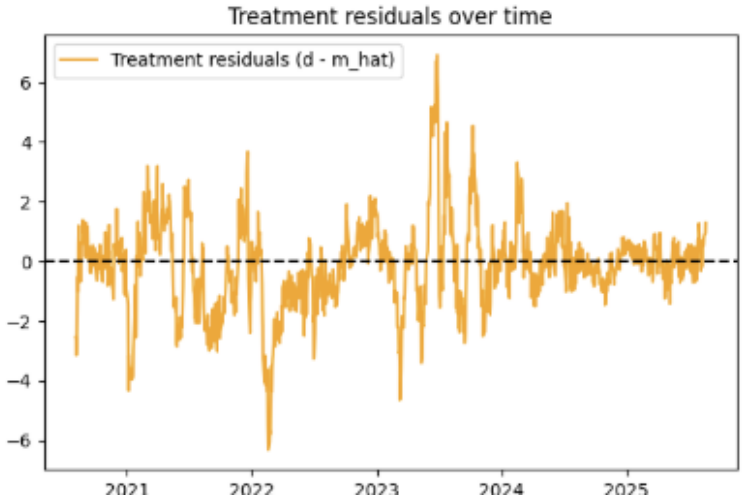


Figure 7: Treatment Residuals Over Time

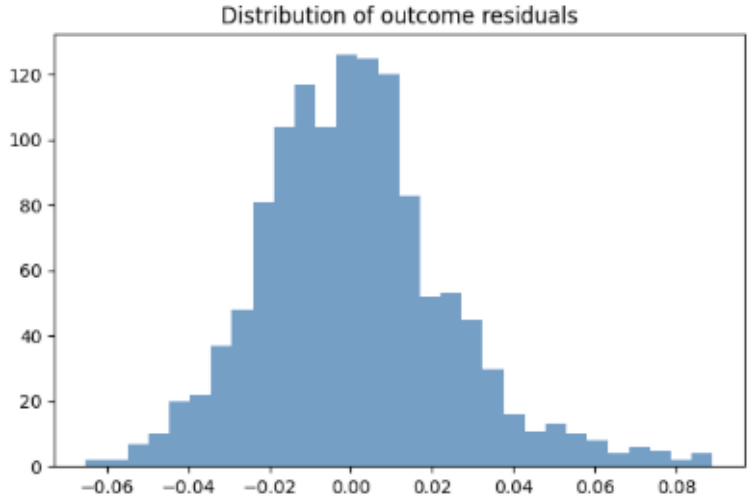


Figure 8: Distribution of Outcome Residuals

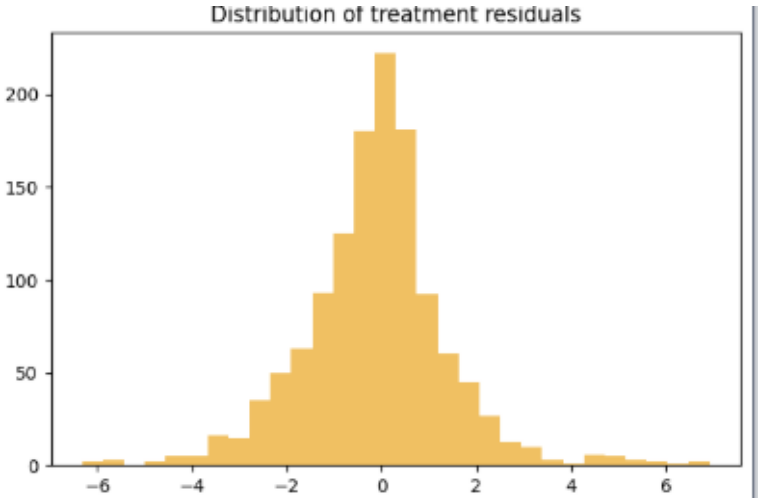


Figure 9: Distribution of Treatment Residuals

Having established the presence of asymmetry, our next step is to test whether these observed relationships reflect genuine causal effects rather than correlations. To further quantify the causal effects of EMC shocks on Tether's prices, we applied a DML framework. Firstly, prior to presenting the treatment effect estimates, Figures 6,7,8,9 display the residuals for the nuisance models estimated by machine learning frameworks. Figures 6 and 7 present a time continuous graph of the residuals for DML1 and DML2, which estimate the nuisance functions for the outcome (the price of Tether) and the treatment (the price of EMCs). As shown in these figures, the residuals are centered at zero, exhibit no obvious patterns, and show no heteroskedasticity, indicating unbiased and well-behaved nuisance predictions.

Similarly, figures 8 and 9 show the distribution of outcome residuals and the residuals vs the fitted values of both machine learning models, respectively. Each histogram resembles a Gaussian distribution centered at zero, symmetric, with no extreme outliers. In both the residuals vs the fitted value scatter plots, the data points closely cluster along the diagonal, have even spread, and don't have obvious curves or patterns. These results demonstrate the robustness and reliability of the nuisance function estimates used in our DML framework.

Estimator	**Coefficient**	**Std. Error**	**t-stat**	**p-value**
OLS	1.359	1.41	0.964	0.335
DML	1.327	6.07	2.189	0.029
Hausman Test	0.000 606	NaN	0.020	0.980

Table 4: Hausman Test Results. Test statistic = 0.0006, P-value = 0.980. Fail to reject the null hypothesis (no evidence of systematic difference).

Once the reliability of the nuisance models is confirmed, the estimated causal effects are directly interpreted. Table 4 reports the estimated causal effects between the prices of Tether and EMCs. The DML estimates reveal a positive causal effect of the selected EMCs on Tether's price, with a coefficient of 1.33×10^{-7}. The associated standard error is 6.07×10^{-8}, indicating a high degree of precision in the estimate. The effect is statistically significant with a p-value of 0.02, suggesting that the observed relationship is unlikely to have arisen by chance. While the magnitude of the coefficient is small, this is consistent with the scale of price fluctuations in Tether relative to currency movements. These results provide robust evidence of a causal linkage between the currency and Tether.

Finally, to assess the consistency of our findings across methods, we compare the Neural SDE estimates with those from the DML framework. Our Hausman test compares the slope estimated by the Neural SDE model with the causal effect obtained from the DML framework. The test yields a coefficient of 0.0006 with a p-value of 0.980, indicating a statistically insignificant difference between the two estimates. This finding suggests that the relationship inferred by the Neural SDE model aligns closely with the causal effect identified by DML, providing evidence that the model's estimates are not biased by endogeneity. From the argument presented in section 4.5, our Neural SDE captures the underlying causal relationship between EMC shocks and Tether's price dynamics.

6 Discussion

Our analysis illustrates the complex interplay between the EMC shocks and Tether's price stability, characterized by two primary findings: a significant asymmetric response and substantial

heterogeneity across currencies. The robustness of these results is first confirmed through a Chow test, which identifies significant slope differences between the Lira, Rand, Ruble, and Dong. Then, we use the DML framework in combination with MR JumpNet SDE, which establishes a statistically significant positive causal effect. Finally, the Hausman test indicates there is no significant difference between the Neural SDE and DML estimates, providing strong evidence that our model captures the underlying causal dynamics without endogeneity bias.

Our first key result reveals that Tether's price reacts asymmetrically to EMC shocks. Negative shocks, such as appreciations of the domestic currency against the U.S. dollar, generate larger deviations in Tether's price compared to positive shocks of equal size. This asymmetry is strongest in the case of the Turkish Lira, where slope differences are highly significant, while the Russian Ruble shows the weakest effect, with nearly symmetric responses across positive and negative shocks. The Chow test further supports these findings, confirming significant slope differences for the Lira, Rand, and Dong, indicating heterogeneous sensitivity across currencies. These heterogeneous sensitivities may stem from varying levels of cryptocurrency adoption, regulatory environments, or historical volatility. The Ruble's symmetric response and the Dong's muted sensitivity suggest heterogeneity in how different EMCs interact with cryptocurrency markets. These differences may stem from varying levels of cryptocurrency adoption, regulatory environments, or historical volatility. The Lira's outsized effect, on the other hand, likely reflects Turkey's inflationary history and the population's reliance on digital assets as a hedge against currency depreciation. This symmetry pattern may reflect behavioral biases among cryptocurrency users in EMEs, where downside risk triggers more immediate and pronounced shifts in demand for stablecoins.

These patterns underscore the behavioral tendency of investors to react more strongly to adverse news, which may accentuate volatility in both traditional and digital financial markets. One such emerging market is the Turkish financial markets, which exhibits heightened sensitivity to adverse macroeconomic news (Gürkaynak et al., 2023). Investors in Turkey shift to foreign currency assets or stablecoins during episodes of Lira depreciation, amplifying volatility (Oyadeyi, 2021). This behavior aligns with the principle that loss aversion and uncertainty drive stronger reactions to negative events (Coşar & Şahinoz, 2018; Ozata, 2020; Teker et al., 2023). The asymmetric nature, influencing investor reactions, makes it difficult for Turkish authorities to maintain stability using conventional tools. Additionally, as Turkish residents are increasingly adopting stablecoins like Tether during lira volatility, the cryptocurrency-fianancial channel becomes more relevant, potentially undermining domestic monetary policy and accelerating digital dollarization.

Additionally, the differential sensitivity of Tether to shocks across currencies is indicative of the underlying structural and behavioral factors within each economy. For instance, the pronounced asymmetry observed in the Lira may reflect heightened domestic reliance on informal financial instruments and cryptocurrency-based hedging strategies in response to persistent inflation and currency depreciations. The South African Rand's moderate asymmetry to Tether shocks reflects its lower domestic integration of cryptocurrency compared to Turkey. Turkey is ranked 11th globally in cryptocurrency adoption and South Africa at 30th (Chainalysis Team, 2024). This may be attributed to the tendency of Turkish households to more actively use digital assets like Tether to hedge against inflation and currency instability. In contrast, South Africa's financial system is more formalized, offering more access to regulated instruments that reduce reliance on informal cryptocurrency based strategies (Adelowotan, 2024; Roman, 2024; Sadhaseevan, 2019). The Rand's exchange rate is primarily shaped by external factors such as commodity price fluctuations and global investor sentiment (Lefatsa et al., 2025; Maveé et al., 2016). These structural differences dampen the Rand's sensitivity to cryptocurrency-linked shocks, even as it remains exposed to broader macroeconomic volatility. In contrast, the Vietnamese Dong's more dampened asymmetry compared to the Rand and Lira might be attributed a more tightly controlled exchange rate regime

with the government seeking to maintain the Dong fixed in terms of the US dollar (Dapice, 2021; Jing, 2022; Thuy & Thuy, 2019). However, the asymmetric sensitivity can be attributed to its externally driven trade dynamics, limited buffers, and high exposure to geopolitical shifts, which makes it disproportionately vulnerable to large reactions (Dapice, 2021). The Ruble, in comparison to other currencies analyzed, has shown relatively benign effects on Tether under both appreciation and depreciation shocks. Russia's strict capital controls and persistent current account surplus, due to energy exports, provide buffers that limit panic-driven selloffs and liquidity "Russia's Balance of Payments – Q3 2024", 2024, dampening the effect of the Ruble on Tether. Furthermore, the most recent sanctions have made the ruble less prone to global investor sentiment (Shin et al., 2025), making the Ruble's price movements more policy-driven and symmetric. Overall, these heterogeneous patterns highlight that Tether's responsiveness is shaped not only by global market forces but also by country-specific institutional frameworks, policy regimes, and behavioral dynamics, underscoring the need to account for cross-currency asymmetries when evaluating stablecoin stability.

In general, EMCs often display higher volatility and limited monetary credibility, which may cause markets to react more strongly to adverse movements than to favorable ones (Ahmed et al., 2021). However, since negative shocks imply an appreciation of the EMCs against the dollar, this pattern is unexpected in the context of loss aversion. Existing literature has explained capital flight through the lens of loss and risk aversion due to economic risk, political instability, and policy variability (Davies, 2010; Hasnul and Masih, 2016; Le and Rishi, 2006). These previous findings by researchers may suggest that positive shocks, which imply rapid currency depreciation, would have a larger effect on the price of Tether as a result of the influx of demand. But this is not the case in our results, which show that negative shocks have more impact than positive ones. This highlights an important financial implication: while Tether is often portrayed as a dollar-linked safe-haven asset in global markets, its stabilizing capacity appears conditional, and in times of EMC appreciation, investors reduce demand for Tether, undermining its role as a substitute for foreign currency reserves.

This suggests that stablecoins like Tether are not yet suitable as a dominant safe-haven asset during episodes of depreciation, with investors turning instead to more established stores of value, such as gold, other cryptocurrencies, or more stable assets. Indeed, in the broader context of international finance, this indicates that Tether is positioned more as a transactional hedge than a long-term reserve asset. For policymakers in EMEs, this means that capital outflows linked to cryptocurrency markets may be less destabilizing than feared, since demand for Tether does not fully offset losses in domestic credibility during depreciation.

It is important to note that existing research has demonstrated that bitcoin and other cryptocurrencies affect the price and volatility of stablecoins; however, the effects are short-lived and moderate. Although there may be a flight to cryptocurrencies more broadly, this movement does not appear to translate directly into stronger demand for Tether. Instead, it may indicate that investors are diversifying across a wider range of assets rather than a single stablecoin. From a portfolio theory perspective, this behavior aligns with the substitution effect across asset classes, where investors allocate marginal capital toward instruments with perceived higher liquidity and safety, thus diluting Tether's dominance (Jacquet et al., 2020; Robison and Barry, 1977). In this sense, Tether's role in capital flight may be limited in comparison to other assets, demonstrating why negative shocks produce larger deviations than positive ones in our results. Additionally, while our empirical models do not assume normally distributed shocks, the leptokurtic and asymmetric features highlighted in Kou, 2002 jump-diffusion model provide a theoretical lens for interpreting our results. In particular, the disproportionate impact of negative shocks is consistent with the higher probability of extreme downside events in leptokurtic distributions. Importantly, these dis-

tributional properties do not bias our findings but rather explain the underlying mechanism driving the observed asymmetry.

Moreover, our results show that Tether remains susceptible to the influence of EMEs and demonstrate that they have a remarkable ability to dampen and disperse smaller shocks. However, they remain more sensitive and elastic to certain directional shocks. While Tether contributes to financial integration between cryptocurrency and fiat systems, it may also amplify vulnerabilities in economies with fragile monetary credibility. For regulators, this raises the question of whether Tether represents a stabilizing tool or an additional channel of volatility transmission. In particular, our findings show that Tether's stabilizing role in EMEs may not be as strong as theoretical expectations suggest, making it less able to ease money movements and market swings.

7 Conclusion

This study examined the causal relationship between EMC shocks and their effect on Tether, where we leveraged both classical financial engineering and machine learning techniques to perform our analysis. Using a novel Neural SDE and the DML framework, we established that EME fluctuations exert a statistically significant and robust causal effect on Tether. Through the simulation of shocks in the EMC, MR JumpNet SDE quantifies the effects of those shocks on Tether. Then, by controlling for confounding variables, the DML framework ensures that the estimated parameter reflects a genuine causal influence rather than spurious correlation. Furthermore, the Hausman test further demonstrated the absence of meaningful endogeneity bias in our estimates, confirming the causal relationship between EMC shocks and Tether price deviations.

Our results contribute to the growing literature on stablecoins by challenging the assumption that they are insulated from emerging-market dynamics. While stablecoins are often framed as detached from traditional macroeconomic forces, we show that Tether is directly affected by emerging market currency shocks. This has broader implications for understanding the role of stablecoins in global financial markets. First, it suggests that stablecoins are not fully "safe havens" but are instead partially tethered to macroeconomic conditions in emerging markets. Second, it highlights the potential for spillover risks, where instability in foreign exchange markets can propagate into cryptocurrency markets via stablecoins. Third, it raises policy considerations regarding financial stability: as stablecoins become more widely used, their susceptibility to EMC shocks may amplify global transmission mechanisms of EME volatility.

Building on these findings, future works should aim to integrate high-frequency data to capture more granular and transient dynamics in Tether's price response to EMC volatility. This would allow for a deeper insight into short-term sensitivities and potential microstructure effects that may not be apparent in lower-resolution datasets. Additionally, it is essential to investigate the depth and extent of the causal relationship identified, assessing whether the observed effects hold across different time horizons, levels of macroeconomic stress, and to quantify the degree to which it holds. Additionally, expanding the scope to include other stablecoins, such as USDC and DAI, under similar circumstances could determine whether Tether's responsiveness is indicative of a broader systemic behavior within the stablecoin ecosystem or if it is exclusive to Tether. Furthermore, incorporating behavioral finance elements, such as investor sentiment, speculative flows, and macroeconomic factors, may enhance the causal narrative and uncover nonlinear feedback mechanisms that influence price dynamics during periods of heightened uncertainty. These extensions would contribute to a more comprehensive and multidimensional interpretation of stablecoin behavior in volatile macroeconomic environments.

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