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STRUCTURAL TIME SERIES MODEL IN PREDICTING CRYPTOCURRENCIES PRICES

(Model Siri Masa Berstruktur dalam Meramal Harga Mata Wang Kripto)

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ABSTRACT

Cryptocurrency prices exhibit high volatility and dynamic behavior, posing significant challenges for accurate prediction. These fluctuations are influenced by external factors such as macroeconomic conditions, supply and demand dynamics, and hidden components like trends, seasonality, and irregularities. This study evaluates the performance of the Structural Time Series (STS) model in forecasting the prices of the top five cryptocurrencies, considering both external and hidden factors. Two STS modeling approaches were assessed: (1) STS without explanatory variables and (2) STS incorporating explanatory variables alongside significant intervention variables. The explanatory variables include trading volume, transaction volume, velocity, the number of whale transactions, and the Consumer Price Index (CPI), while the intervention variables consist of significant outliers and structural breaks linked to real-world events. The findings indicate that the second approach, which integrates explanatory and intervention variables within a linear STS framework, outperforms the first in terms of predictive accuracy. Additionally, the Local Level + Deterministic Seasonal model was identified as the optimal structure for estimating hidden factors in all cryptocurrency prices, except for Ethereum (ETH). These results underscore the importance of incorporating both external and hidden factors in structural time series modeling to improve cryptocurrency price predictions.

Keywords: structural time series; forecasting; volatility; cryptocurrency; macroeconomic indicators

ABSTRAK

Harga mata wang kripto mempamerkan volatiliti yang tinggi dan mempunyai tingkah laku yang dinamik, mencetuskan cabaran besar untuk mendapatkan ramalan yang tepat. Turun naik harga ini dipengaruhi oleh faktor luaran seperti keadaan makroekonomi, dinamik penawaran dan permintaan, serta komponen tersembunyi seperti trend, musim, dan ketidakteraturan. Kajian ini menilai prestasi model Siri Masa Berstruktur (STS) dalam meramal harga lima mata wang kripto teratas dengan mengambil kira kedua-dua faktor luaran dan tersembunyi. Dua pendekatan pemodelan STS telah dinilai: (1) STS tanpa pemboleh ubah penerang dan (2) STS yang menggabungkan pemboleh ubah penerang bersama-sama dengan pemboleh ubah intervensi yang signifikan. Pemboleh ubah penerang terdiri daripada volum dagangan, volum transaksi, halaju, bilangan transaksi oleh pelabur besar, dan Indeks Harga Pengguna (CPI), manakala pemboleh ubah intervensi merangkumi pencilan signifikan dan perubahan struktur yang dikesan dalam siri masa harga. Keputusan menunjukkan bahawa pendekatan kedua, yang mengintegrasikan pemboleh ubah penerang dan intervensi dalam rangka kerja STS linear, melampaui prestasi pendekatan pertama dari segi ketepatan ramalan. Selain itu, model Aras Lokal + Musiman Deterministik dikenal pasti sebagai struktur optimum untuk menganggar faktor tersembunyi dalam semua harga mata wang kripto, kecuali Ethereum (ETH). Keputusan ini menekankan kepentingan penggabungan kedua-dua faktor luaran dan tersembunyi dalam pemodelan siri masa berstruktur untuk memperbaiki ramalan harga mata wang kripto.

Kata kunci: siri masa berstruktur; peramalan; volatiliti; mata wang kripto; indikator makroekonomi

1. Introduction

Cryptocurrencies, powered by blockchain technology, have emerged as a revolutionary form of digital currency, enabling secure and decentralized transactions without intermediaries (Nakamoto 2008). Since the inception of Bitcoin (BTC) in 2009, the cryptocurrency market has experienced exponential growth, with over 10,000 cryptocurrencies now in circulation (Hossain 2021). This rapid expansion has been driven by their potential for high returns, cost efficiency, and increasing acceptance as legitimate payment methods (Hai *et al*. 2023; Seabe *et al*. 2024). However, the inherent volatility of cryptocurrency prices poses significant challenges for investors and researchers alike.

The value of Bitcoin, for instance, surged from nearly zero to approximately $65,000 by November 2021 and then to $100,000 in early 2025, highlighting both its profitability potential and unpredictability (Antar 2025). Such volatility is influenced by a myriad of factors, including economic crises, global adoption rates, geopolitical tensions, and macroeconomic news (Chauhan *et al*. 2023; Gong & Xu 2022). Recent studies emphasize the role of social media sentiment, regulatory announcements, and institutional investments in driving cryptocurrencies price fluctuations (Asif & Unar 2024; Feinstein & Werbach 2021; Ortu *et al*. 2022).

To address these challenges, numerous statistical and machine learning (ML) techniques have been proposed for cryptocurrency price forecasting. Traditional methods such as Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) have been widely used to capture time series components and volatility clustering (Khedr *et al*. 2021; Benzekri & Özütler 2021). Meanwhile, advanced ML models, including Dynamic Neural Networks (DNNs) and ensemble methods like Random Forests, have demonstrated proficiency in capturing complex relationships within data (Awoke *et al*. 2020; Patel *et al*. 2020). Despite these advancements, there remains a lack of research focusing on modeling hidden factors such as trends, seasonality, and irregular components, which are critical for understanding the underlying dynamics of cryptocurrency prices.

However, recent studies emphasize that traditional statistical models have notable limitations in handling nonstationary series, which is a common characteristic of cryptocurrency price data (Abdul Rashid *et al*. 2023). These traditional models generally assume stationarity, where the statistical properties of the series such as mean and variance remain constant over time. However, cryptocurrency data often exhibit strong nonstationary behavior, including abrupt structural breaks, evolving seasonal patterns, and irregular fluctuations due to external shocks or speculative activity. Applying models that assume stationarity to such data may result in biased parameter estimates, unreliable forecasts, and a failure to capture underlying market dynamics. Furthermore, they typically do not decompose time series into interpretable components, making it difficult to isolate and understand the contribution of long-term trends, cyclical effects, or short-term volatility. In contrast, STS models are specifically designed to accommodate nonstationary series by modeling level, trend, and seasonal components as stochastic processes. This flexibility allows STS models to preserve important dynamic features without requiring transformation or differencing, thus making them more suitable for analyzing and forecasting complex financial time series (Khosravi & Ghazani 2023).

Structural Time Series (STS) models offer a flexible framework for analyzing nonstationary time series data. By decomposing the series into trend, seasonal, and irregular components, STS models provide a comprehensive view of the underlying dynamics (Godolphin & Triantafyllopoulos 2006). Recent applications of STS models in finance and economics have also demonstrated their ability to handle complex seasonal patterns and incorporate explanatory variables (Syaharuddin 2024).

Therefore, this study aims to evaluate the effectiveness of Structural Time Series (STS) models in predicting cryptocurrency prices by comparing two approaches: (1) the basic STS model without explanatory variables, and (2) the enhanced STS model that incorporates both explanatory and intervention variables. The explanatory variables represent external economic and market related factors such as trading volume, transaction volume, velocity, number of whale transactions, and the Consumer Price Index (CPI) that influence price trends over time. Meanwhile, intervention variables account for sudden and irregular events such as structural breaks or significant outliers linked to major market disruptions. By integrating these components and applying the models to data from the top five cryptocurrencies, this research builds on recent advances in econometrics and contributes to the growing literature on cryptocurrency forecasting, offering practical insights for both investors and policymakers.

2. Data Collection

This study focuses on a comprehensive analysis of the top five cryptocurrencies by market capitalization as of December 2022. These cryptocurrencies—Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Binance Coin (BNB), and USD Coin (USDC)—were selected due to their prominence in the cryptocurrency ecosystem and their diverse price behaviors. BTC and ETH are known for their high volatility, BNB exhibits moderate volatility, while USDT and USDC are stablecoins designed to maintain price stability relative to the U.S. dollar (Dimpfl & Elshiaty 2021; Yi *et al*. 2018; Alexander & Dakos 2020). This diversity enables the evaluation of the proposed model's ability to handle varying levels of volatility and price dynamics.

The historical price data for each cryptocurrency spans different time periods, reflecting the availability of data based on the inception dates of the respective cryptocurrencies. For instance, BTC, being the first cryptocurrency introduced in 2009, has the longest available dataset, while newer cryptocurrencies like USDC and BNB have shorter histories. The study utilizes weekly closing prices to ensure consistency and reduce noise associated with intraday fluctuations (Sinha 2024). Table 1 provides a detailed breakdown of the sample periods and total observations for each cryptocurrency.

Table 1: Sample of top five cryptocurrency

Cryptocurrency	Sample Period	Total Sample	Market Capitalization (2023)
Bitcoin (BTC)	23/12/2013 – 26/12/ 2022	470	$800 billion
	Estimation: 23/12/2013 -27/12/2021	418	
	Evaluation: 03/01/2022 – 26/12/2022	52	
Ethereum (ETH)	04/01/2016 – 26/12/2022	364	$280 billion
	Estimation: 04/01/2016-27/12/2021	312	
	Evaluation: 03/01/2022- 26/12/2022	52	
Tether (USDT)	22/01/2018 – 26/12/2022	258	$91 billion
	Estimation: 22/01/2018-27/12/2021	206	
	Evaluation: 03/01/2022- 26/12/2022	52	
Binance (BNB)	15/04/2019– 26/12/2022	194	$48 billion
	Estimation: 15/04/2019-27/12/2021	142	
	Evaluation: 03/01/2022 – 26/12/2022	52	
USD Coin (USDC)	15/10/2018 – 26/12/2022	220	$24 billion
	Estimation: 15/10/2018-27/12/2021	168	
	Evaluation: 03/01/2022- 26/12/2022	52	

In addition to price data, this study incorporates five explanatory variables to capture external factors influencing cryptocurrency prices. These variables include transaction volume, trading volume, velocity, the number of whale transactions (transactions exceeding $100,000), and the Consumer Price Index (CPI). Transaction and trading volumes serve as proxies for market activity and liquidity, while velocity measures the frequency of cryptocurrency usage within a given period (Lyukevich *et al*. 2021; Tripathi *et al*. 2022). Whale transactions are included to account for the impact of large investors on price movements (Liu & Serletis 2019), and CPI is used to assess macroeconomic influences (Boskin *et al*. 1998; Bryan & Cecchetti 1993). In this study, the Consumer Price Index (CPI) is selected to represent macroeconomic influences on cryptocurrency prices. CPI is a widely used indicator of inflation and reflects changes in the general price level of goods and services, which directly affect purchasing power and consumer sentiment. Compared to other macroeconomic indicators such as Gross Domestic Product (GDP) and the Industrial Production Index (IPI), CPI is available at a higher frequency (monthly) and is released more promptly, making it better aligned with the weekly cryptocurrency data used in this study. GDP and IPI, while important, are typically released quarterly and with a time lag, which may limit their relevance in capturing rapid market reactions. Furthermore, CPI has been used extensively in financial and cryptocurrency literature as a proxy for economic conditions that influence investor behavior and asset valuation. Therefore, CPI is considered a more suitable and timely macroeconomic variable for this modeling framework.

The availability of these explanatory variables varies across cryptocurrencies, aligning with the sample periods of the respective price datasets. Table 2 summarizes the sample periods and total observations for each cryptocurrency and its corresponding explanatory variables.

Table 2: Sample period and observations for explanatory variables

Cryptocurrency	Explanatory Variables	Sample Period	Total Sample
Bitcoin (BTC)	Trading Volume, Transaction Volume, Number of Whale Transaction, Velocity, Consumer Price Index (CPI)	23/12/2013 – 26/12/ 2022	470
Ethereum (ETH)	Trading Volume, Transaction Volume, Number of Whale Transaction, Velocity, Consumer Price Index (CPI)	04/01/2016 – 26/12/2022	364
Tether (USDT)	Trading Volume, Transaction Volume, Number of Whale Transaction, Velocity, Consumer Price Index (CPI)	22/01/2018 – 26/12/2022	258
Binance (BNB)	Trading Volume, Transaction Volume, Number of Whale Transaction, Velocity, Consumer Price Index (CPI)	15/04/2019– 26/12/2022	194
USD Coin (USDC)	Trading Volume, Transaction Volume, Number of Whale Transaction, Velocity, Consumer Price Index (CPI)	15/10/2018 – 26/12/2022	220

To ensure robustness and reliability, cryptocurrency-related data such as prices, trading volume, transaction volume, velocity, and whale transactions were obtained from reputable platforms including Santiment.net and CoinMarketCap. Meanwhile, the Consumer Price Index (CPI) data used in this study were sourced from the U.S. Bureau of Labor Statistics (BLS), which is the official provider of CPI data in the United States. These platforms provide accurate and up-to-date information on cryptocurrency metrics, ensuring the integrity of the analysis.

By integrating both price and explanatory variable data, this study aims to provide a holistic understanding of the factors driving cryptocurrency price movements. The inclusion of diverse cryptocurrencies and external variables enhances the generalizability of the findings and contributes to the development of more accurate predictive models.

3. Methodology

This study focuses on the linear STS model, which encompasses two approaches. The first approach analyzes the model without explanatory variables. In contrast, the second, known as the linear STS model with explanatory variables, integrates these variables with significant intervention variables to estimate cryptocurrency prices. The significance of this study lies in investigating how the inclusion of explanatory and intervention variables can enhance the model. However, the selection of explanatory variables is limited due to data availability constraints.

Two linear STS models have been developed to model the hidden components. The first approach analyzes a linear STS model without an explanatory variable. The second approach, known as linear STS with explanatory variables, combines these variables with significant intervention variables in a linear STS model to estimate cryptocurrency prices. This study investigates how the inclusion of explanatory and intervention variables in the model can improve the linear STS model, particularly regarding the model's assumptions.

3.1. *Structural Time Series (STS) model*

The STS model adeptly handles both trend and seasonality in time series data. Furthermore, the STS model extends beyond traditional regression models by allowing explanatory variables to be functions of time, with parameters that can vary over time. The specification of a Structural Time Series (STS) model may include any combination of trend and seasonal components, as summarized in Table 3, with the symbols μ_t represents the level component and is considered deterministic when $\mu_t = \mu$, γ_t denotes the deterministic seasonal component and is modeled using weekly seasonal dummy variables, ε_t is the irregular (error term), η_t represents the stochastic disturbance of the level component. ς_t is the disturbance of the slope component and υ_t denotes the disturbance of the seasonal component.

3.1.1. *State space form*

The state space form consists of two equations: observation or measurement equation and state equation. The measurement equation describes the relationship between the observed and unobserved state variables. Furthermore, the measurement equation may also include other observed explanatory variables. Meanwhile, the state equation describes the dynamic evolution of the state component. Following Harvey (1989), the observation and state equation can be expressed as in Eq. (1):

Table 3: Combination of various specifications of trend and seasonal components

Model / Equation	
Deterministic Level + Deterministic Seasonal	
$Y_t = \mu_t + \gamma_t + \varepsilon_t$	$\varepsilon_t \sim NID(0, \sigma_\varepsilon^2)$
$\mu_t = \mu$	
$\gamma_t = -\sum_{j=1}^{s-1} \gamma_{t-j}$	
Local Level + Deterministic Seasonal	
$Y_t = \mu_t + \gamma_t + \varepsilon_t$	$\varepsilon_t \sim NID(0, \sigma_\varepsilon^2)$
$\mu_t = \mu_{t-1} + \eta_t$	$\eta_t \sim NID(0, \sigma_\eta^2)$
$\gamma_t = -\sum_{j=1}^{s-1} \gamma_{t-j}$	
Deterministic Trend + Deterministic Seasonal	
$Y_t = \mu_{t-1} + \gamma_t + \varepsilon_t$	$\varepsilon_t \sim NID(0, \sigma_\varepsilon^2)$
$\mu_t = \mu_{t-1} + \nu_t$	
$\nu_t = \nu$	
$\gamma_t = -\sum_{j=1}^{s-1} \gamma_{t-j}$	
Smooth Trend + Deterministic Seasonal	
$Y_t = \mu_t + \gamma_t + \varepsilon_t$	$\varepsilon_t \sim NID(0, \sigma_\varepsilon^2)$
$\mu_t = \mu_{t-1} + \nu_{t-1}$	
$\nu_t = \nu_{t-1} + \varsigma_t$	$\varsigma \sim NID(0, \sigma_\varsigma^2)$
$\gamma_t = -\sum_{j=1}^{s-1} \gamma_{t-j}$	
Local Level with Drift + Deterministic Seasonal	
$Y_t = \mu_t + \gamma_t + \varepsilon_t$	$\varepsilon_t \sim NID(0, \sigma_\varepsilon^2)$
$\mu_t = \mu_{t-1} + \nu_t + \eta_t$	$\eta_t \sim NID(0, \sigma_\eta^2)$
$\nu_t = \nu$	
$\gamma_t = -\sum_{j=1}^{s-1} \gamma_{t-j}$	
Local Linear Trend + Deterministic Seasonal	
$Y_t = \mu_t + \gamma_t + \varepsilon_t$	$\varepsilon_t \sim NID(0, \sigma_\varepsilon^2)$
$\mu_t = \mu_{t-1} + \nu_{t-1} + \eta_t$	$\eta_t \sim NID(0, \sigma_\eta^2)$
$\nu_t = \nu_{t-1} + \varsigma_t$	$\varsigma_t \sim NID(0, \sigma_\varsigma^2)$
$\gamma_t = -\sum_{j=1}^{s-1} \gamma_{t-j}$	

$$Y_t = Z_t\alpha_t + \varepsilon_t,$$
$$\alpha_t = T_t\alpha_{t-1} + R_t\tau_t, \tag{1}$$

where α_t is a (*m* x 1) state vector, Y_t is a (*n* x 1) vector of the dependent variable for *t* = 1,…, *n*, Z_t is a (*n* x *m*) matrix of trend and seasonal components, and ε_t is a (*n* x 1) vector of serially uncorrelated measurements error such that $[\varepsilon_t \sim NID(0, H_t)]$. T_t is a (*m* x *m*) state transfer matrix, τ_t is a (*g* x 1) vector of serially uncorrelated error term such that $[\tau_t \sim NID(0, Q_t)]$, and R_t is a (*m* x *g*) matrix related to the error term. Consequently, Z_t, T_t, R_t, H_t and Q_t are system matrices. After expressing the STS model in an SS form, the Kalman filter can be utilized to estimate the unobserved state variable.

3.1.2. *Kalman Filter estimation*

The Kalman Filter estimation is a recursive process that, using information from all previous observations, forecasts the optimal unobserved state variable at a given time, as described by Harvey (1989). The primary goal of the filter is to update the state variable as new observations become available. Note that the recursive Kalman filter involves two passes of the data: the forward pass and the backward pass. The forward pass begins at *t* = 1 and proceeds to *t* = *n*, employing a recursive Kalman filter algorithm applied to the observed time series. Conversely, the backward pass starts at *t* = *n* and goes back to *t* = 1, utilizing a recursive algorithm known as state and disturbance smoothers applied to the output of the Kalman filter, as detailed by Commandeur and Koopman (2007).

This study is based on the work of Harvey and Koopman (1996) who assumed that the initial conditions of state vector as $\hat{\alpha}_0 \sim NID(\alpha_0, P_0)$. The Kalman filter estimation consists of two iterative procedures: predicting and updating. The first stage of the Kalman filter recursion is to estimate the 1-step-ahead of the state vector $\hat{\alpha}_{t|t-1}$ and the corresponding error covariance of the estimate, $P_{t|t-1}$. This is based on all information up to and including time *t*-1, ($Y_1, Y_2, \ldots, Y_{t-1}$) using Eqs. (2) and (3):

$$\alpha_t = E(\alpha_t \mid Y_{t-1}, Y_{t-2}, \ldots, Y_1) = T\hat{\alpha}_{t-1|t-1}, \tag{1}$$

$$P_{t|t-1} = E\left[(\alpha_t - \hat{\alpha}_{t|t-1})(\alpha_t - \hat{\alpha}_{t|t-1})'\right] = TP_{t-1|t-1} + RQR'. \tag{2}$$

Given the 1-step-ahead estimate of the state vector, the 1-step-ahead estimate of the measurement variable with the corresponding matrices of measurement error is given as Eqs. (4) and (5):

$$\hat{Y}_{t|t-1} = Z\hat{\alpha}_{t|t-1},, \tag{3}$$

$$F_t = E\left[(Y_t - \hat{Y}_{t|t-1})(Y_t - \hat{Y}_{t|t-1})'\right] = ZP_{t|t-1}Z' + H, \tag{4}$$

with the prediction error presented by the Equation (6):

$$v_t = Y_t - Z\hat{\alpha}_{t|t-1}, \tag{5}$$

The updating stage of Kalman filter recursion incorporates a new observation into the predicted state vector to obtain an improved estimate. The process involves updating the estimate $\hat{\alpha}_{t|t-1}$ and $P_{t|t-1}$ giving a new observation at time *t*, Y_t based on Eqs. (7) and (8):

$$\hat{\alpha}_{t|t} = \hat{\alpha}_{t|t-1} + P_{t|t-1} Z' F^{-1} \left(Y_t - Z\hat{\alpha}_{t|t-1} \right), \tag{6}$$

$$P_{t|t} = P_{t|t-1} - P_{t|t-1} Z' F^{-1} Z P_{t|t-1}. \tag{7}$$

The detailed derivation of the Kalman filter can be discovered in Harvey (1989). The process of predicting and updating is repeated until the end of the sample period, $t = n$. When all n observations have been processed, the Kalman filter yields the optimal estimator of the current state vector, $\hat{\alpha}_{n|n}$ as well as the predicted state vector in the next time period $\hat{\alpha}_{n+1|n}$. This estimator contains all the information needed to make predictions of future values $\hat{Y}_{n+1|n}$ of both the state and observations.

To incorporate explanatory and intervention variables into the STS model, the observation (measurement) equation can be extended as Eq. (9):

$$Y_t = Z_t \alpha_t + \beta X_t + \delta D_t + \varepsilon_t \tag{9}$$

In this equation Y_t is the observed cryptocurrency price at time *t*, Z_t is the standard state-space term, α_t contains the unobserved components (level, trend, seasonality). The vector X_t is a vector of explanatory variables at time *t*, β is a vector of corresponding coefficients for the explanatory variables. The term D_t refer to vector of intervention variables indicating significant events, while δ is a vector of coefficients for the intervention variables. Finally, ε_t is the observation disturbance term assumed to follow a white noise process.

3.2. *Model diagnostic checking*

In a linear Gaussian model, three analytical assumptions serve as the foundation for all significant residual tests. These residuals must adhere to the three properties known as independence, homoscedasticity, and normality. The diagnostic tests performed include tests for serial correlation, heteroscedasticity, and nonnormality. It is possible to verify the assumption of the residuals' independence with the Box-Ljung statistic. The assumption of homoscedasticity of the residuals may be verified using the Goldfeld-Quandt (*GQ*). The residuals are then tested for normality using the Jarque-Bera (JB) test.

4. Results

The descriptive analysis of the closing prices for cryptocurrencies Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Binance Coin (BNB), and US Dollar Coin (USDC) is presented in Table 4. BTC has the highest closing price at $65,466.84 with a standard deviation of $15,902.65 and an average price of $11,901.75, indicating greater volatility compared to the others. In contrast, USDT and USDC have the lowest maximum price values of $1.02 and $1.03, respectively, and exhibit lower risk and return, as their lower standard deviations indicate less variability than other cryptocurrencies. The average closing prices for ETH and

BNB are $857.65 and $199.97, respectively. This indicates that the BNB coin is more stable than ETH, with standard deviations of $191.39 and $1121.60, respectively.

Additionally, the skewness values for the weekly BTC, ETH, and USDC price data are greater than one, indicating that the data is highly skewed or exhibits positive skewness. Both the kurtosis and skewness suggest that the data does not follow a normal distribution. The high kurtosis indicates a leptokurtic distribution, as evidenced by the positive kurtosis values. In contrast, the skewness values for USDT and BNB price data are very close to 0, implying that the distribution of these values is not significantly skewed. However, with kurtosis values greater than 3.0, a leptokurtic distribution is indicated for USDC. For BNB, the distribution appears to be platykurtic, as indicated by a kurtosis value of less than 3, characterized by thinner tails and a more flattened peak, meaning that there are fewer outliers.

The Augmented Dickey-Fuller (ADF) test is also employed in this study to confirm the stationarity of the data. The null hypothesis failed to be rejected by the unit root test, with a p-value greater than 0.05, indicating that the closing prices of BTC, ETH, and BNB are not stationary, while USDT and USDC are vice versa.

Table 4: Descriptive analysis of cryptocurrency close price

Cryptocurrency	Mean	Standard Deviation	Median	Min	Max	Skewness	Kurtosis	Augmented Dickey-Fuller Test (*p*-value)
BTC	11901.75	15902.65	6378.26	210.34	65466.84	1.65	4.70	-1.44 (0.56)
ETH	857.95	1121.60	297.16	0.99	4626.36	1.58	4.50	-1.45 (0.56)
USDT	1.00	4.62E-03	1.00	0.98	1.02	0.87	9.68	-5.77 (0.00) **
BNB	199.97	191.39	212.25	10.44	662.23	0.53	2.00	-1.62 (0.47)
USDC	1.00	5.72E-03	1.00	0.98	1.03	1.76	8.94	-3.16 (0.02) **

**significant at 5% level *significant at 10% level

Table 5 summarizes the model estimation results both without and with the addition of explanatory variables. Upon incorporating these variables, all cryptocurrency price models shift to a stochastic trend without a slope, except for ETH, retaining its model of a stochastic trend with a fixed slope. Without slope, the long-term movement or trend in the time series data does not exhibit a consistent increase or decrease over time. In other words, it does not have a positive or negative slope; instead, the direction of the trend changes randomly over time. In terms of seasonality, the pattern remains similar to that observed in models without explanatory variables, suggesting deterministic seasonality for all top five cryptocurrencies.

After incorporating selected explanatory variables, including velocity, trading volume, transaction volume, number of whale transactions over $100,000, and CPI, the model exhibits slight improvements. These enhancements are apparent in terms of the variance of disturbance for observation (irregular component), the model's assumptions, and the AIC, as elaborated in Table 5. All models exhibit a reduction in AIC values, with the exception of the USDC model, and there is a marginal reduction in the variance of disturbance compared to the linear STS model without explanatory variables. Moreover, the assumption of residuals is satisfied for all models except for one normality assumption that is still violated. As Commandeur and Koopman (2007) indicated, this normality violation or the larger critical values in the JB test might stem from structural breaks and outliers in the series. Consequently, refining the error estimate to evaluate the impact of these outliers is advisable.

Table 5: Estimation of single linear STS (without and with explanatory variables)

Cryptocurrency		BTC	ETH	USDT	BNB	USDC
Linear STS without Explanatory Variable						
Parameter/Model		Local Level with Drift + Deterministic Seasonal	Local Level with Drift + Deterministic Seasonal	Local Level + Deterministic Seasonal	Local Level with Drift + Deterministic Seasonal	Local Level + Deterministic Seasonal
Variance disturbances	Level	0.01	0.03	5.26E-06	0.03	1.48E-06
	Slope	0.00	0.00	N/A	0.00	N/A
	Seasonal	0.00	0.00	0.00	0.00	0.00
	Irregular	0.00	0.00	9.56E-06	0.00	1.55E-05
Residual Diagnostics	Box-Ljung	91.172 [0.75]	97.02 [0.59]	83.69 [0.91]	67.21 [0.05]	117.58 [0.14]
	GQ	1.31 [0.07] *	0.42 [1.00]	0.17 [1.00]	0.69 [0.84]	0.13 [1.00]
	JB	9.73 [0.00] **	12.74 [0.00] **	39.20 [0.00] **	58.14 [0.00] **	10.71 [0.00] **
	AIC	-4.36	-3.44	-10.60	-3.36	-10.5
Linear STS with Explanatory Variables						
Parameter/Model		Local Level + Deterministic Seasonal	Local Level with Drift + Deterministic Seasonal	Local Level + Deterministic Seasonal	Local Level + Deterministic Seasonal	Local Level + Deterministic Seasonal
Variance of disturbances	Level	8.82E-03	0.02	6.49E-06	0.02	2.24E-05
	Slope	N/A	0.00	N/A	N/A	N/A
	Seasonal	0.00	0.00	0.00	0.00	0.00
	Irregular	8.14E-04	2.44E-03	7.80E-06	0.00	1.51E-05
Residual Diagnostics	Box-Ljung	97.42 [0.61]	102.96 [0.42]	86.44 [0.86]	54.37 [0.31]	118.47 [0.13]
	GQ	1.27 [0.10]	0.52 [0.99]	0.22 [1.00]	1.29 [0.26]	0.15 [1.00]
	JB	7.43 [0.02] * *	16.89 [0.00] **	11.48 [0.00] **	52.77 [0.00] **	12.94 [0.00] **
	AIC	-4.42	-3.72	-10.62	-3.54	-10.43

**significant at 5% level *significant at 10% level

Next, inspecting auxiliary residuals is crucial when a model fails to meet the normality assumption of its residuals. Auxiliary residuals, comprising standardized smoothed observation disturbances and standardized smoothed level disturbances, are instrumental in detecting outliers and structural breaks in a time series. Figure 1(a) – (e) displays the auxiliary residuals for the top five cryptocurrencies, where the standardized smoothed observation disturbances are depicted on the top. The standardized smoothed level disturbances are provided at the bottom.

Each auxiliary residual, particularly on the top side of Figure 1(a) – (e), can be interpreted as a t-test aimed at testing the null hypothesis of no structural break in the observed time series levels (Koopman & Lee 2009). Notably, the BTC price series indicates 20 points that potentially signify breaks, standing out significantly beyond the 95% confidence limit. This is followed by 17 points for ETH, 11 points each for USDT and BNB, and 15 points for USDC. It is essential to note that these potential breaks often arise due to various significant events or news, such as wars, political conflicts, cyberattacks, and economic downturns.

After incorporating explanatory variables, significant outliers, and structural breaks, the model estimation exhibits marked improvement compared to the version without these variables. Table 6 displays the performance of the linear STS model both without and with these explanatory variables, including significant outliers and structural breaks. For all top five cryptocurrencies, there is an evident improvement in terms of lower standard error and higher R-squared values. Consequently, the normality assumption is now satisfied for BTC, USDT, and USDC. However, ETH and BNB still do not meet the normality assumption.

The best-fitted models for the top five cryptocurrencies, including all explanatory variables, significant outliers, and structural breaks, are tabulated in Table 7. The trend and seasonal patterns resulting from the addition of these explanatory variables are depicted in Figure 2 and Figure 3, respectively. For comparative analysis, the price level components of the five cryptocurrencies are plotted alongside the level components derived without the explanatory variables. For all cryptocurrencies, the estimated trend with explanatory variables (represented by a green line) aligns more closely with the observation series (red line) compared to the estimated trend without the explanatory variables (blue line). The exception to this pattern is observed in USDT and USDC. This divergence might be attributed to the nature of both as stationary series, whereas the linear STS model is more suited to non-stationary series (Abdul Rashid *et al.* 2023).

As indicated in Tables 7(a) - (e), the variance disturbance of the seasonal component for the top five cryptocurrencies equals zero, implying a Deterministic Seasonal component in their prices. Specifically, for BTC, detailed in Table 7(a) and Figure 3(a), the seasonal pattern consistently exhibits the highest values in the 52nd week, even after including explanatory and significant intervention variables. This aligns with the 'Santa Claus Rally,' a phenomenon where BTC prices often rise during the last trading days of December and early January, typically linked to positive market sentiment.

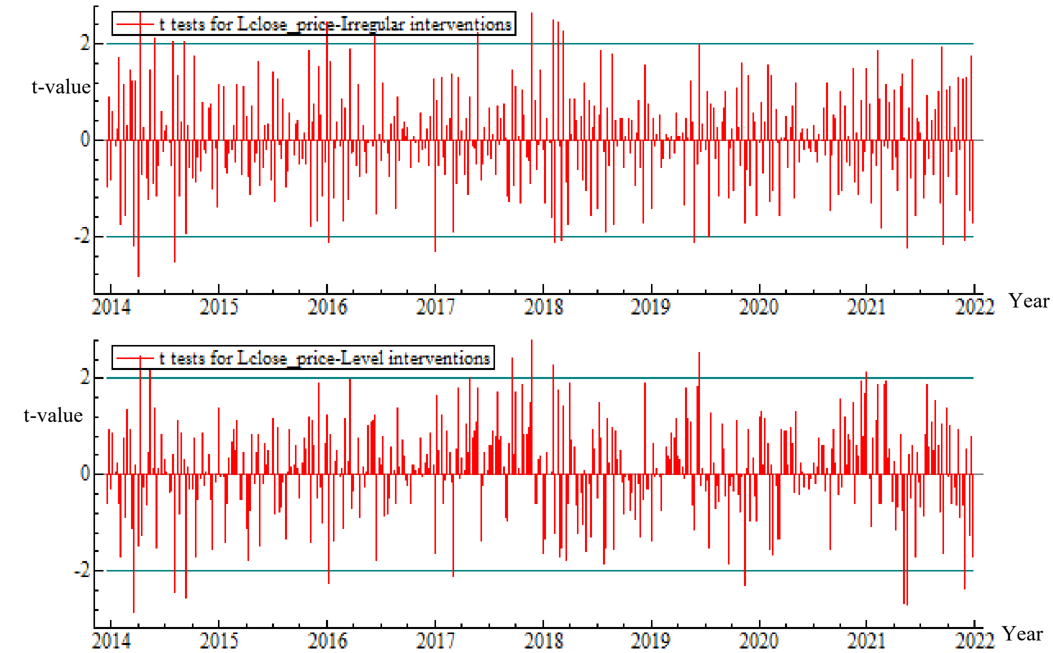
Various factors contribute to the Santa Claus Rally, including a bullish mood on Wall Street, investment in Christmas bonuses, and increased consumer activity, which can boost demand for BTC. Bursa (2019) suggested that these factors collectively lead to the seasonal price increase. Additionally, significant low prices for BTC occur around September (38th and 39th weeks) and a notable 11% weekly price decrease in the 12th week. For ETH, as provided in Table 7(b) and Figure 3(b), the highest prices remain consistent in the 22nd and 23rd weeks, with a 31% increase. The lowest prices are observed in the 4th and 51st weeks, indicating negative effects in late January, March, and November till December but positive effects at the end of April, May, and June.

Table 6: Linear STS (without and with explanatory variables)

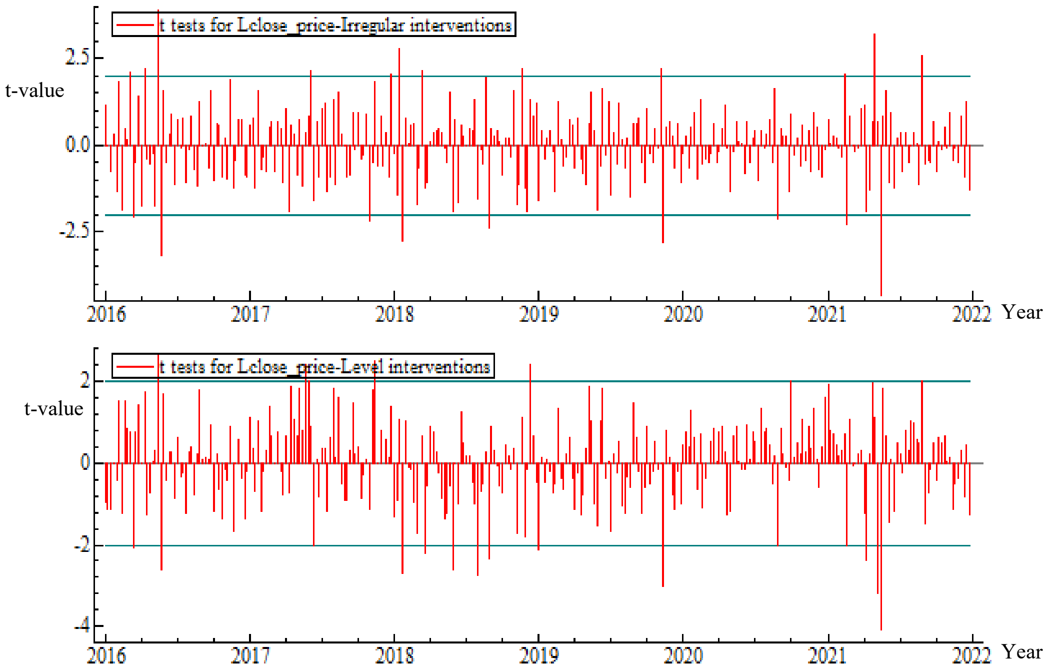
Residual Diagnostics	**BTC**		**ETH**		**USDT**	
	Linear STS without Explanatory Variables (Local Level with Drift + Deterministic Seasonal)	**Linear STS with Explanatory Variables + significant outliers and structural break (Local Level + Deterministic Seasonal)**	**Linear STS without Explanatory Variables (Local Level with Drift + Deterministic Seasonal)**	**Linear STS with Explanatory Variables + significant outliers and structural break (Local Level with Drift + Deterministic Seasonal)**	**Linear STS without Explanatory Variables (Local Level + Deterministic Seasonal)**	**Linear STS with Explanatory Variables + significant outliers and structural break (Local Level + Deterministic Seasonal)**
Box-Ljung	91.172	90.07	97.02	86.37	83.69	86.88
(Independence)	[0.75]	[0.79]	[0.59]	[0.85]	[0.91]	[0.86]
GQ	1.31	1.09	0.42	0.82	0.17	0.36
(Homoscedasticity)	[0.07]	[0.32]	[1.00]	[0.81]	[1.00]	[0.99]
JB	9.73	5.23	12.74	17.80	39.20	1.19
(Normality)	[0.00] **	[0.07]	[0.00] **	[0.00] **	[0.00] **	[0.55]
Standard error	0.10	0.08	0.15	0.10	3.86E-03	2.77E-03
R-Square	0.12	0.46	0.16	0.62	0.37	0.71

Residual Diagnostics	**BNB**		**USDC**	
	Linear STS without Explanatory Variables (Local Level with Drift + Deterministic Seasonal)	**Linear STS with Explanatory Variables + significant outliers and structural break (Local Level + Deterministic Seasonal)**	**Linear STS without Explanatory Variables (Local Level + Deterministic Seasonal)**	**Linear STS with Explanatory Variables + significant outliers and structural break (Local Level + Deterministic Seasonal)**
Box-Ljung	67.21	57.17	117.58	84.81
(Independence)	[0.05]	[0.23]	[0.14]	[0.89]
GQ	0.69	1.39	0.13	0.22
(Homoscedasticity)	[0.84]	[0.20]	[1.00]	[1.00]
JB	58.14	10.13	10.71	1.07
(Normality)	[0.00] **	[0.00] **	[0.00] **	[0.54]
Standard error	0.13	0.08	3.80E-03	3.00E-03
R-Square	0.37	0.76	0.43	0.68

**significant at 5% level *significant at 10% level



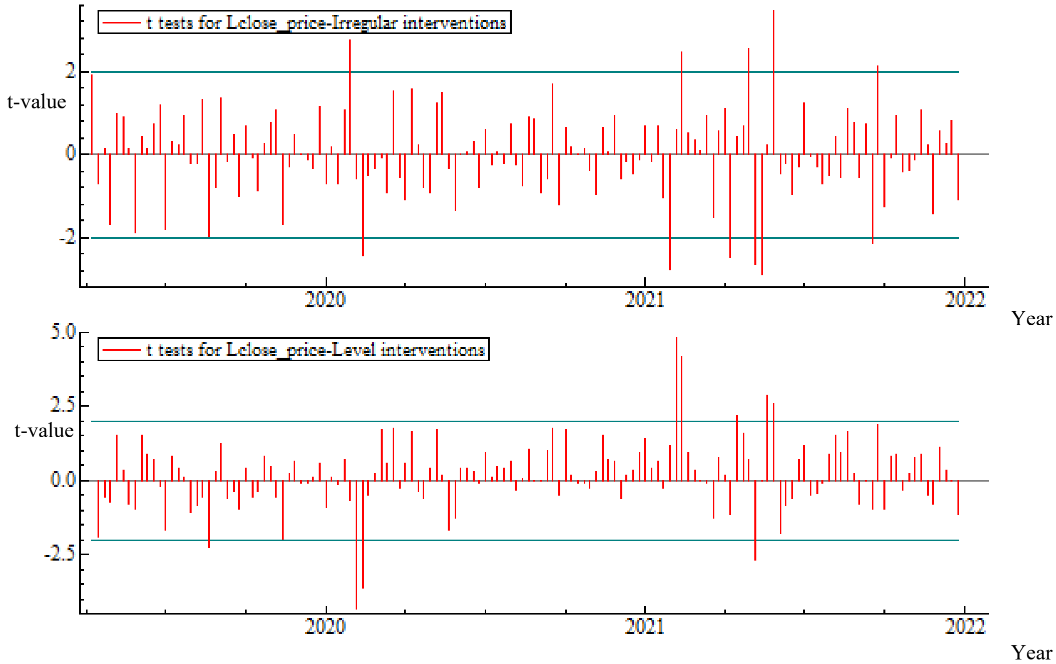
a) BTC



b) ETH

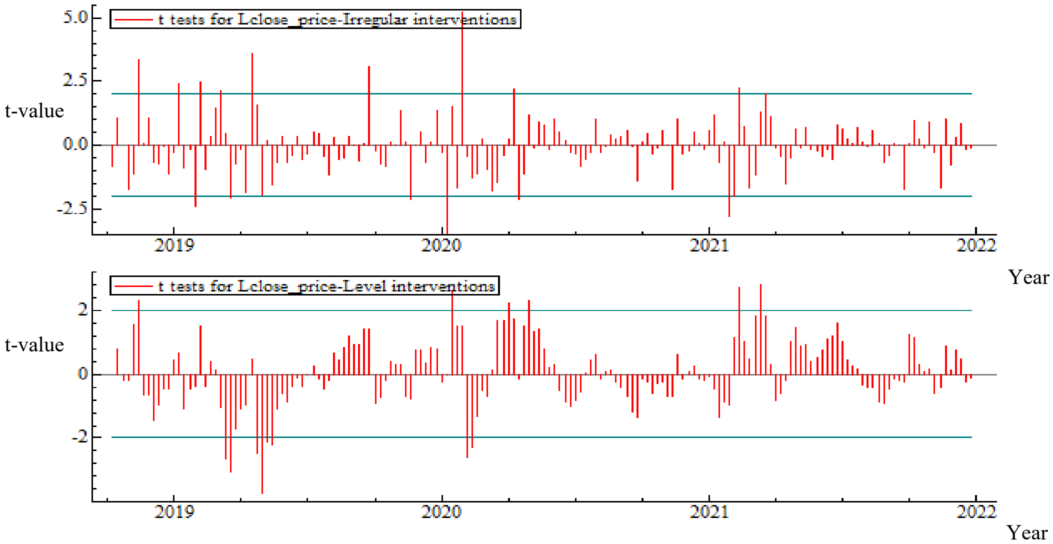
Figure 1: Smoothed estimates of the irregular and level disturbances

c) USDT



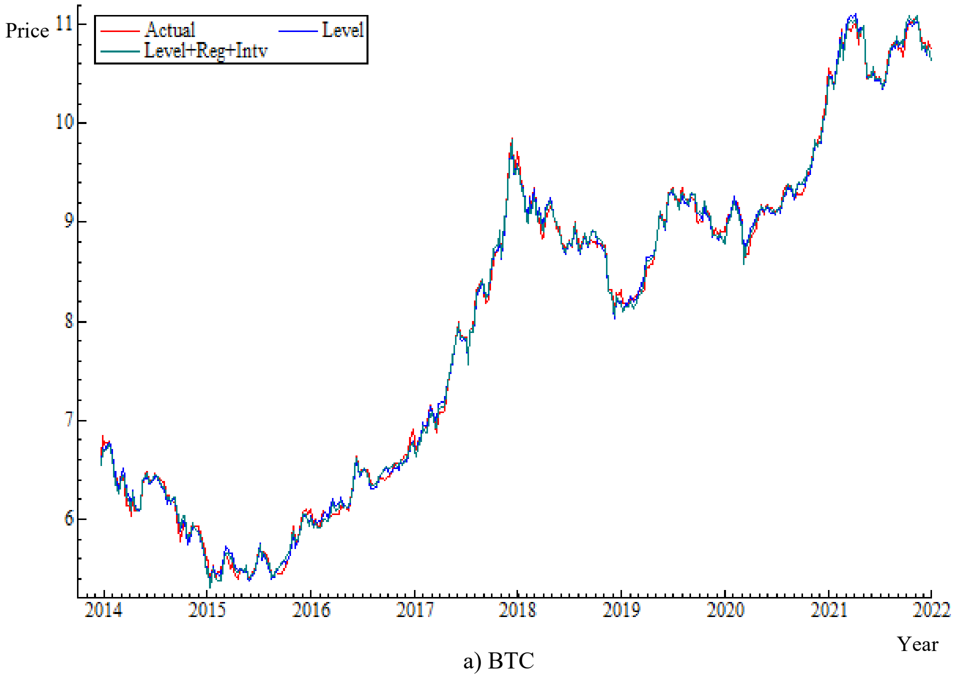
d) BNB

Figure 1 (Continued)



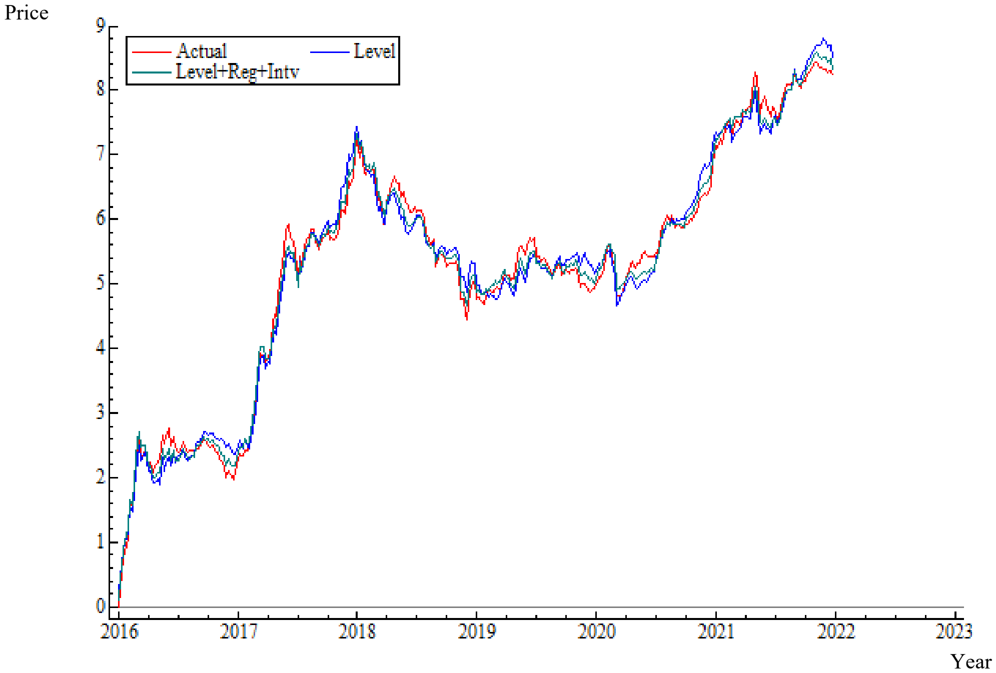
e) USDC

Figure 1: Continued

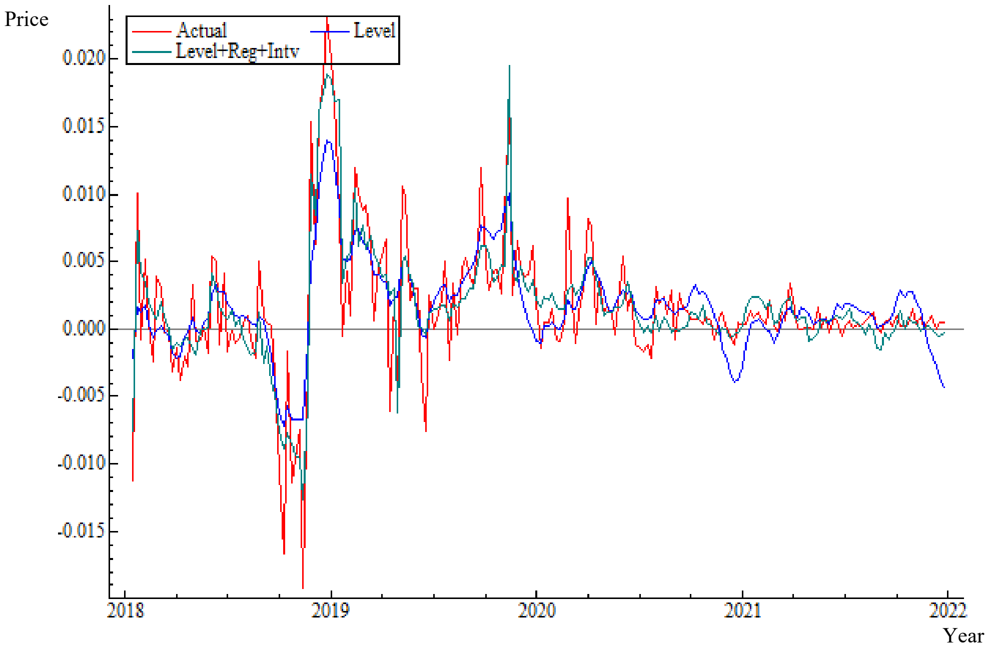


a) BTC

Figure 2: Trend pattern of top five cryptocurrencies

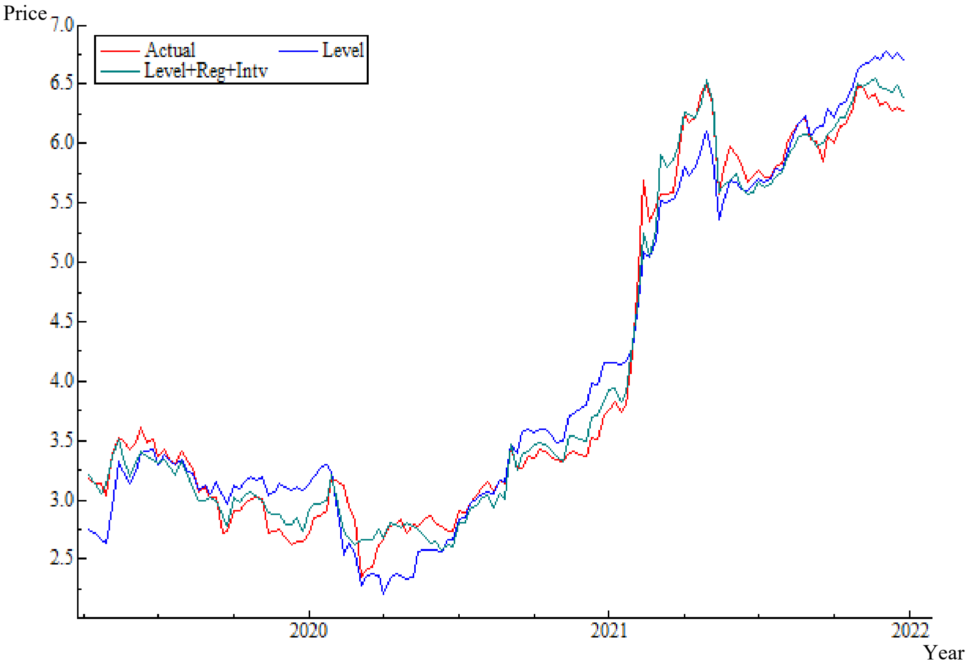


b) ETH

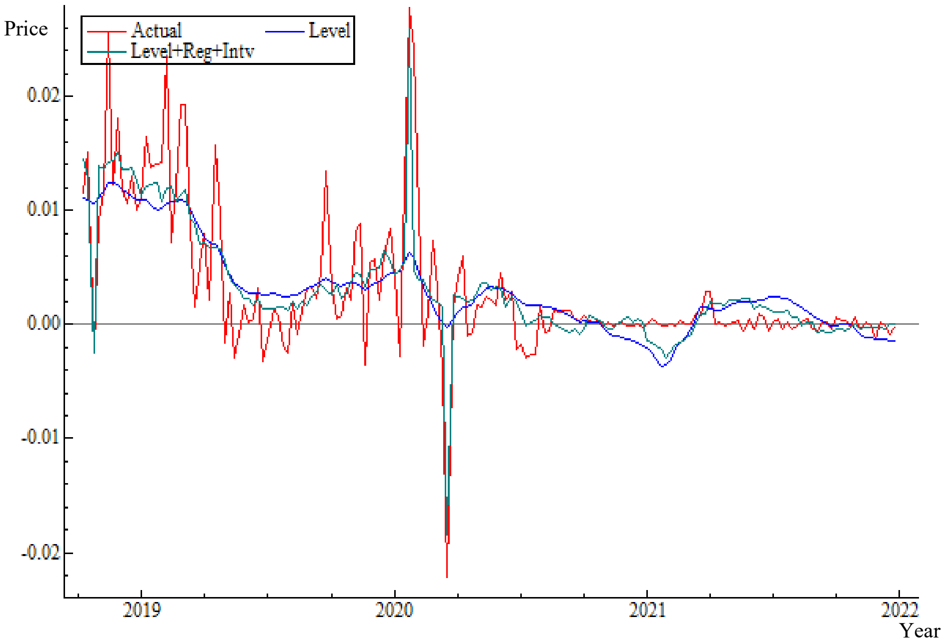


c) USDT

Figure 2 (Continued)



d) BNB



e) USDC

Figure 2 (Continued)

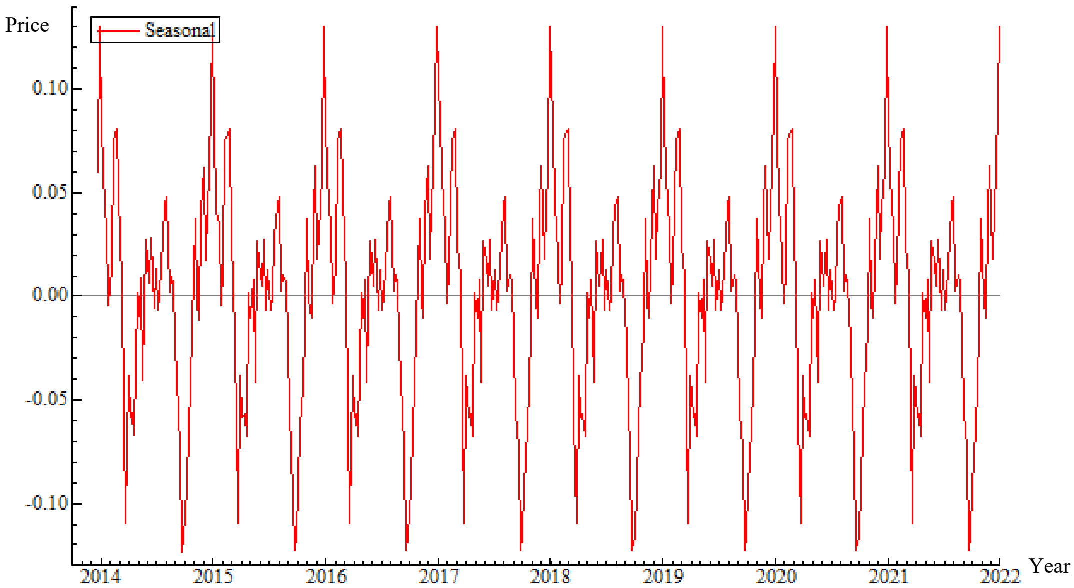
For USDT, as provided in Table 7(c) and Figure 3(c), the highest price is in the 51st week, similar to BTC, and the lowest in the 3rd week. A significant price decrease of 0.3% per week is noted in early April (16th week). For BNB, as provided in Table 7(d) and Figure 3(d), the highest week is the 7th, and the lowest is the 10th. Seasonal price effects are positively significant in late February and June, with increases ranging from 20% to 40% and 20%-24%, respectively. Negative effects are observed in March, with a 20% to 30% price decrease.

Finally, for USDC, as provided in Table 7(e) and Figure 3(e), the highest value occurs in the 5th week, while the lowest occurs in the 12th week. Significant seasonal effects are observed from January to March and in late September and mid-November, with positive impacts. The 12th and 26th weeks demonstrate negative effects, with price decreases of 0.87% and 0.38% per week, respectively.

Overall, similar to the initial linear STS approach, the updated model exhibits a significant effect towards the end of December. This trend aligns with the 'Santa Claus Rally,' a phenomenon observed in cryptocurrency markets. However, in the initial approach, BTC and USDT did not exhibit significant seasonal effects during this period. After incorporating explanatory variables and significant intervention variables, both BTC and USDT demonstrated a notable price increase at the end of December. In contrast, ETH continues to exhibit significant negative effects during this time, while BNB and USDC do not exhibit significant seasonal impacts.

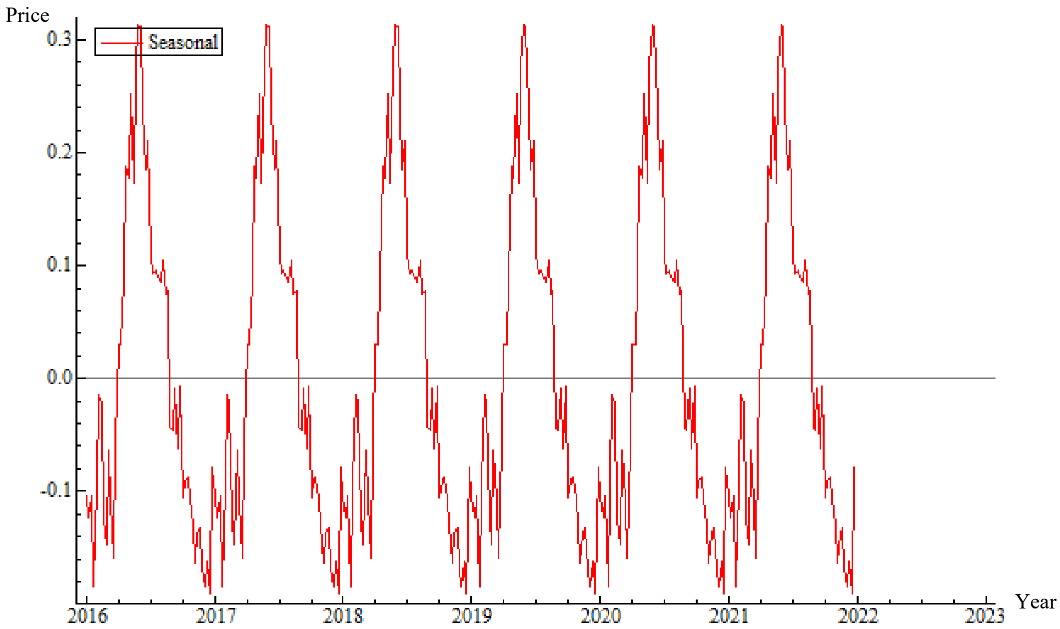
Other than that, most of the top five cryptocurrencies indicate a significant month-of-the-year effect from November to May. This finding is in line with Kaiser's (2019) study, which noted that the prices have significantly higher volatility and spread during the non-summer months.

Based on the results discussed above, it is apparent that the inclusion of explanatory variables with significant interventions impacts cryptocurrency price modeling. This is evident through price trends and seasonal pattern changes, which differ from the cryptocurrency price model without significant interventions and explanatory variables.

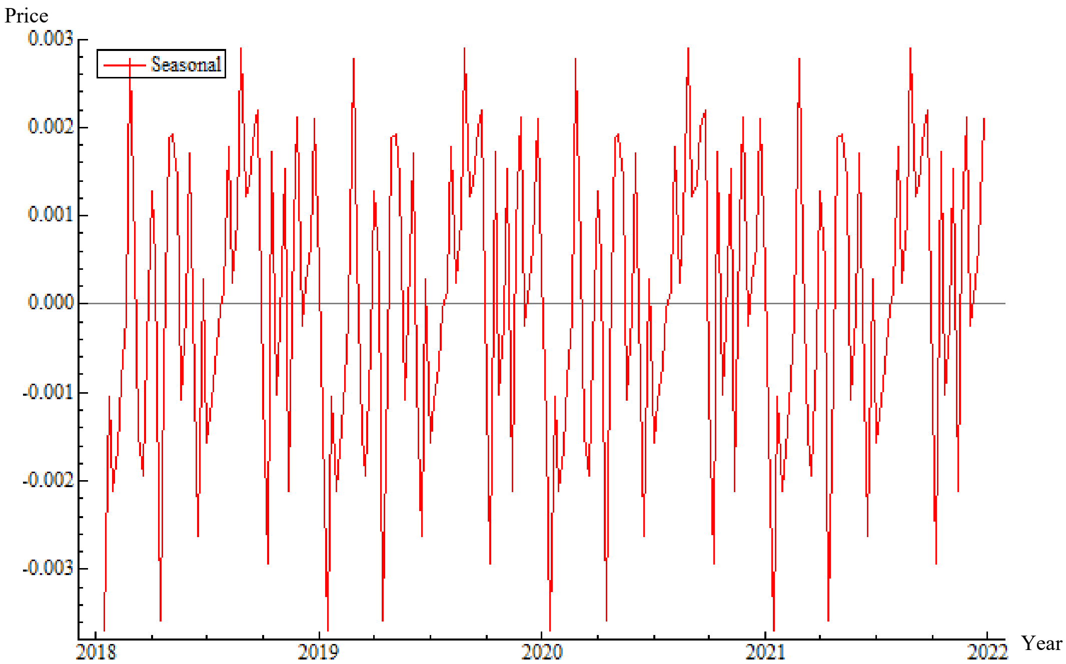


a) BTC

Figure 3: Seasonal pattern of top five cryptocurrencies

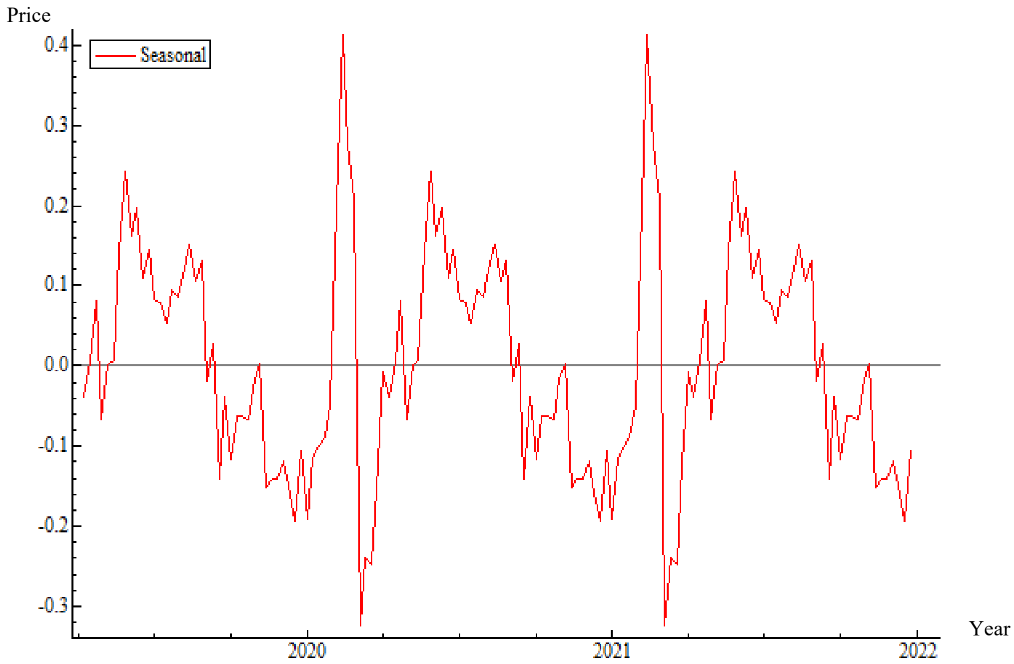


b) ETH

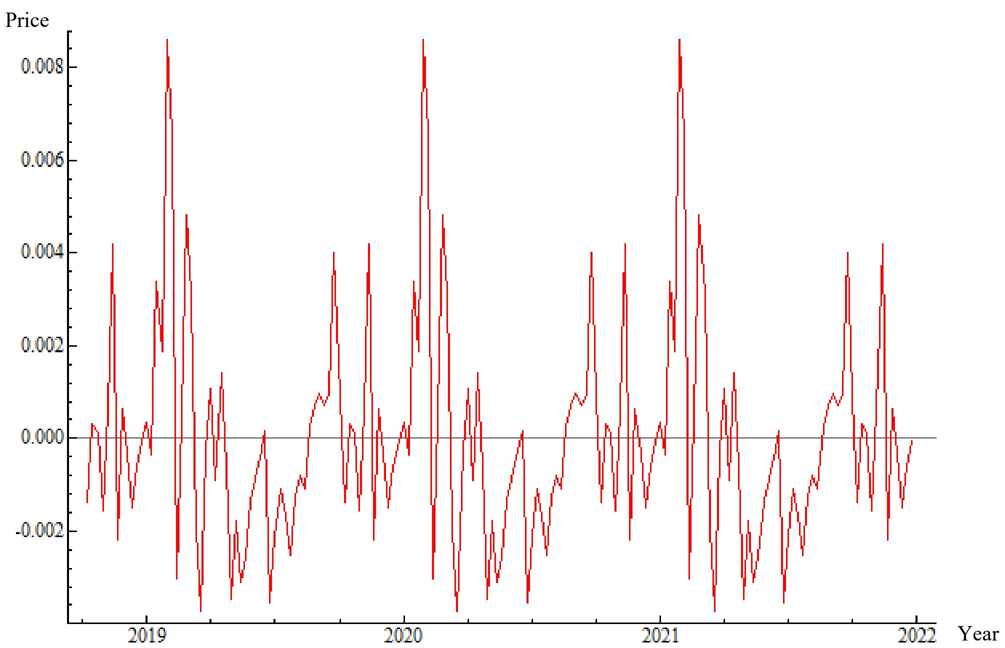


c) USDT

Figure 3 (Continued)



d) BNB



e) USDC

Figure 3 (Continued)

Hence, referring to Table 7(a) – (e) as well, this study will discuss further the impact of explanatory variables on cryptocurrency price behavior. Firstly, 'Trading Volume' refers to the total amount of cryptocurrencies bought or sold during a specific period. The results indicate that Trading Volume significantly affects cryptocurrency prices, with a positive relationship observed for BTC, ETH, and BNB. This suggests that the high Trading Volume often correlates with increased market participation and significant price movements. For example, when the price of an asset like BTC, ETH, or BNB rises, increased trading activity usually follows, potentially contributing to further price increases. The results of these studies are corroborated by Conlon *et al.* (2024), who discovered that trading volume is the most crucial explanatory factor contributing to the price movement of BTC.

Regarding the impact of demand and supply effects, 'Transaction volume' has a significant influence on prices (Sun *et al.* 2023). This volume is quantified by aggregating the total value of all BTC network transactions, subsequently multiplied by BTC's weekly average price (Kjærland *et al.* 2018). From our findings, BTC and ETH have a negative relationship with Transaction Volume, implying that as transaction volume increases, the price tends to decrease, and vice versa. Conversely, for USDT, the effect is positive for Transaction Volume. However, this variable does not significantly affect USDC and BNB prices. Nevertheless, these results exhibit varying degrees of significance due to the different data timeframes.

Another factor studied is 'Velocity,' which measures the frequency of transactions involving a cryptocurrency token within a week. The results reveal that only USDT exhibits a positive and significant correlation with Velocity, while other cryptocurrencies do not demonstrate a significant impact. This implies that for USDT, a higher token velocity, indicative of increased trading and usage, is associated with a price increase. These findings are in line with the outcomes reported by Jermann (2021), where Velocity is considered less important in affecting cryptocurrency prices.

'Number of Whale Transactions' refers to the number of weekly transactions over $100,000 in the cryptocurrency market. The results reveal a significant positive correlation with BTC, ETH, and BNB prices. This finding is consistent with Arumugam *et al.* (2022), who asserted that the presence of BTC whales contributes to price volatility in the cryptocurrency market. This suggests that large transactions by influential entities can significantly impact these cryptocurrencies' prices.

Finally, the CPI is not significantly correlated with the price of any cryptocurrency, except for a negative correlation between USDC. This is in line with Corbet *et al.* (2020), who discovered no statistically significant relationship between CPI news and cryptocurrency returns.

Table 7: The best final estimation performance

(a) BTC: Local Level + Deterministic Seasonal with explanatory variables					
Parameter	**Coefficient**	**Parameter**	**Coefficient**	**Parameter**	**Coefficient**
σ_η^2	7.42E-03	γ_{21}	0.02	γ_{46}	-5.19E-03
σ_ς^2	N/A	γ_{22}	8.89E-03	γ_{47}	0.05
σ_ω^2	0.00	γ_{23}	-5.03E-03	γ_{48}	0.07
σ_ε^2	3.53E-05	γ_{24}	0.02	γ_{49}	0.03
μ_t	10.71	γ_{25}	-0.02	γ_{50}	0.06
γ_1	0.09	γ_{26}	6.27E-03	γ_{51}	0.07
γ_2	0.05	γ_{27}	-0.01	γ_{52}	0.14*
γ_3	0.05	γ_{28}	-6.28E-03	Outlier 2014(39)	-0.22**
γ_4	7.09E-03	γ_{29}	0.02	Outlier 2015(2)	-0.20**
γ_5	0.02	γ_{30}	0.04	Outlier 2017(27)	-0.31**
γ_6	0.08	γ_{31}	0.04	Outlier 2017(44)	-0.36**

Table 7 (Continued)

γ_7	0.09	γ_{32}	-3.60E-03	Outlier 2017(49)	0.28**
γ_8	0.10	γ_{33}	4.89E-03	Outlier 2020(10)	-0.25**
γ_9	0.02	γ_{34}	2.03E-03	Level break 2014(5)	-0.30**
γ_{10}	8.60E-03	γ_{35}	-0.03	Level break 2014(52)	-0.31**
γ_{11}	-0.06	γ_{36}	-0.06	Level break 2018(4)	-0.31 **
γ_{12}	-0.11*	γ_{37}	-0.08	Level break 2018(46)	-0.34**
γ_{13}	-0.04	γ_{38}	-0.13**	Velocity	-2.43E-03
γ_{14}	-0.06	γ_{39}	-0.12*	Trading_Volume	0.04**
γ_{15}	-0.06	γ_{40}	-0.10	Transaction_Volume	-0.08**
γ_{16}	-0.07	γ_{41}	-0.07	Number_Whale_Trans	0.12**
γ_{17}	2.00E-05	γ_{42}	-0.05	Consumer Price Index	0.04
γ_{18}	-0.02	γ_{43}	-0.02		
γ_{19}	1.90E-03	γ_{44}	0.04		
γ_{20}	-0.05	γ_{45}	3.49E-03		

(b) ETH: Local Level with Drift + Deterministic Seasonal with explanatory variables

Parameter	Coefficient	Parameter	Coefficient	Parameter	Coefficient
σ_η^2	0.01	γ_{20}	0.23**	γ_{45}	-0.16*
σ_ς^2	0.00	γ_{21}	0.27**	γ_{46}	-0.14
σ_ω^2	0.00	γ_{22}	0.31**	γ_{47}	-0.13
σ_ε^2	1.10E-03	γ_{23}	0.31**	γ_{48}	-0.17*
μ_t	8.24**	γ_{24}	0.24**	γ_{49}	-0.18*
v_t	0.17**	γ_{25}	0.18**	γ_{50}	-0.16
γ_1	-0.11	γ_{26}	0.21**	γ_{51}	-0.19*
γ_2	-0.13	γ_{27}	0.11	γ_{52}	-0.08
γ_3	-0.11	γ_{28}	0.09	Outlier 2016(24)	-0.28**
γ_4	-0.19**	γ_{29}	0.10	Outlier 2017(27)	-0.43**
γ_5	-0.09	γ_{30}	0.09	Outlier 2021(18)	0.27**
γ_6	-0.01	γ_{31}	0.09	Outlier 2021(20)	-0.38**
γ_7	-0.02	γ_{32}	0.10	Level break 2016(14)	-0.57**
γ_8	-0.13	γ_{33}	0.08	Level break 2017(10)	0.43**
γ_9	-0.15	γ_{34}	0.08	Level break 2017(49)	0.50**
γ_{10}	-0.06	γ_{35}	-0.04	Level break 2018(10)	-0.41**
γ_{11}	-0.11	γ_{36}	-0.04	Level break 2018(46)	-0.45**
γ_{12}	-0.16*	γ_{37}	-8.93E-03	Level break 2020(10)	-0.43**
γ_{13}	-0.06	γ_{38}	-0.06	Velocity	-0.01
γ_{14}	0.03	γ_{39}	-6.35E-03	Trading_Volume	0.11**
γ_{15}	0.03	γ_{40}	-0.10	Transaction_Volume	-0.21**
γ_{16}	0.09	γ_{41}	-0.09	Number_Whale_Trans	0.20**
γ_{17}	0.18*	γ_{42}	-0.09	Consumer Price Index	9.81E-03
γ_{18}	0.13	γ_{43}	-0.11		
γ_{19}	0.25**	γ_{44}	-0.13		

(c) USDT: Local Level + Deterministic Seasonal with explanatory variables

Parameter	Coefficient	Parameter	Coefficient	Parameter	Coefficient
σ_η^2	2.04E-06	γ_{21}	-1.00E-03	γ_{46}	-2.17E-03
σ_ς^2	N/A	γ_{22}	-1.00E-03	γ_{47}	8.3E-04
σ_ω^2	0.00	γ_{23}	1.68E-03	γ_{48}	2.01E-03
σ_ε^2	5.90E-06	γ_{24}	-8.80E-04	γ_{49}	-2.20E-04
μ_t	-0.09	γ_{25}	-2.66E-03	γ_{50}	2.60E-04
γ_1	5.6E-04	γ_{26}	2.00E-04	γ_{51}	6.00E-03

Table 7 (Continued)

γ_2	-1.59E-03	γ_{27}	-1.62E-03	γ_{52}	2.07E-03
γ_3	-3.85E-03	γ_{28}	-9.90E-04	Outlier 2019(18)	-0.01**
γ_4	-1.29E-03	γ_{29}	-6.20E-03	Outlier 2019(46)	0.02**
γ_5	-1.96E-03	γ_{30}	5.00E-05	Level break 2018(48)	0.02**
γ_6	-1.45E-03	γ_{31}	2.40E-04	Level break 2018(50)	0.01**
γ_7	-1.03E-03	γ_{32}	1.86E-03	Level break 2019(4)	-0.01**
γ_8	-2.90E-04	γ_{33}	4.80E-04	Velocity	3.5E-03**
γ_9	2.64E-03	γ_{34}	1.07E-03	Trading_Volume	-1.16E-04
γ_{10}	4.80E-04	γ_{35}	2.99E-03	Transaction_Volume	1.67E-03**
γ_{11}	-1.61E-03	γ_{36}	1.36E-03	Number_Whale_Trans	-2.36E-03
γ_{12}	-2.08E-03	γ_{37}	1.21E-03	Consumer Price Index	2.80E-04
γ_{13}	-3.90E-04	γ_{38}	1.94E-03		
γ_{14}	1.31E-04	γ_{39}	2.34E-03		
γ_{15}	5.1E-04	γ_{40}	-9.50E-03		
γ_{16}	-3.52E-03*	γ_{41}	-3.11E-03		
γ_{17}	-6.60E-04	γ_{42}	1.51E-04		
γ_{18}	2.03E-03	γ_{43}	-1.01E-03		
γ_{19}	2.09E-03	γ_{44}	-3.00E-04		
γ_{20}	1.62E-04	γ_{45}	1.43E-03		
σ_η^2	7.30E-03	γ_{20}	6.33E-03	γ_{44}	-0.02
σ_ς^2	N/A	γ_{21}	0.14	γ_{45}	3.83E-03
σ_ω^2	0.00	γ_{22}	0.24**	γ_{46}	-0.15
σ_ε^2	1.17E-03	γ_{23}	0.16	γ_{47}	-0.14
μ_t	6.27	γ_{24}	0.20*	γ_{48}	-0.14
γ_1	-0.19	γ_{25}	0.11	γ_{49}	-0.12
γ_2	-0.11	γ_{26}	0.15	γ_{50}	-0.16
γ_3	-0.10	γ_{27}	0.08	γ_{51}	-0.19
γ_4	-0.09	γ_{28}	0.08	γ_{52}	-0.11
γ_5	-0.05	γ_{29}	0.05	Outlier 2020(35)	-0.36**
γ_6	0.20	γ_{30}	0.09	Level break 2021(10)	0.82**
γ_7	0.41**	γ_{31}	0.09	Level break 2021(20)	-0.81**
γ_8	0.27**	γ_{32}	0.12	Velocity	-0.02
γ_9	0.21	γ_{33}	0.15	Trading_Volume	0.22**
γ_{10}	-0.32**	γ_{34}	0.10	Transaction_Volume	-0.02
γ_{11}	-0.24*	γ_{35}	0.13	Number_Whale_Trans	0.05**
γ_{12}	-0.24*	γ_{36}	-0.02	Consumer Price Index	0.05
γ_{13}	-0.12	γ_{37}	0.03		
γ_{14}	-8.92E-03	γ_{38}	-0.14		
γ_{15}	-0.04	γ_{39}	-0.04		
γ_{16}	4.87E-03	γ_{40}	-0.12		
γ_{17}	0.08	γ_{41}	-0.06		
γ_{18}	-0.07	γ_{42}	-0.06		
γ_{19}	9.0E-04	γ_{43}	-0.07		

(e) USDC: Local Level + Deterministic Seasonal with explanatory variables

Parameter	Coefficient	Parameter	Coefficient	Parameter	Coefficient
σ_η^2	8.26E-07	γ_{20}	-3.15E-03	γ_{44}	-1.57E-03
σ_ς^2	N/A	γ_{21}	-2.74E-03	γ_{45}	6.60E-04
σ_ω^2	0.00	γ_{22}	-1.54E-03	γ_{46}	4.58E-03**
σ_ε^2	8.10E-06	γ_{23}	-9.60E-04	γ_{47}	-1.81E-03

Table 7 (Continued)

μ_t	0.29**	γ_{24}	-5.00E-04	γ_{48}	9.40E-04
γ_1	8.1E-04	γ_{25}	1.10E-04	γ_{49}	1.00E-04
γ_2	1.30E-04	γ_{26}	-3.79E-03*	γ_{50}	-1.12E-03
γ_3	3.61E-03*	γ_{27}	-2.26E-03	γ_{51}	-2.40E-04
γ_4	2.16E-03	γ_{28}	-1.23E-03	γ_{52}	2.10E-04
γ_5	8.84E-03**	γ_{29}	-1.82E-03	Outlier 2018(43)	-0.02**
γ_6	6.71E-03**	γ_{30}	-2.60E-03	Outlier 2020(4)	0.02**
γ_7	-2.92E-03	γ_{31}	-1.20E-03	Outlier 2020(12)	-0.02**
γ_8	5.3E-04	γ_{32}	-7.20E-04	Outlier 2021(12)	9.39E-03**
γ_9	4.95E-03**	γ_{33}	-1.19E-03	Velocity	-1.09E-03
γ_{10}	3.41E-03*	γ_{34}	1.50E-04	Trading_Volume	4.80E-04
γ_{11}	-1.99E-03	γ_{35}	8.10E-04	Transaction_Volume	4.90E-04
γ_{12}	-8.67E-03**	γ_{36}	1.17E-03	Number_Whale_Trans	-1.28E-03
γ_{13}	-3.0E-04	γ_{37}	9.10E-04	Consumer Price Index	-1.15E-03**
γ_{14}	5.90E-04	γ_{38}	1.25E-03		
γ_{15}	-1.32E-03	γ_{39}	4.26E-03**		
γ_{16}	1.07E-03	γ_{40}	1.38E-03		
γ_{17}	-7.40E-04	γ_{41}	-2.70E-04		
γ_{18}	-3.43E-03	γ_{42}	4.80E-04		
γ_{19}	-2.13E-03	γ_{43}	5.00E-04		

**significant at 5% level *significant at 10% level

5. Conclusions and Recommendation

This study highlights the complexity of predicting cryptocurrency prices due to the multiple influencing factors and considering the hidden behaviors and dynamic characteristics in predictive models. In the first approach for linear STS without explanatory variables, the preferred model for BTC, ETH, and BNB shares the same model: Local Level with Drift + Deterministic Seasonal. This indicates that, to describe the trend in these cryptocurrency prices, the level varies over time, the slope is fixed in the model, and the seasonality is deterministic. Meanwhile, stablecoins like USDT and USDC follow the Local Level + Deterministic Seasonal model. This means the level changes significantly over time; however, a slope is not included, while the seasonality is also a deterministic component.

In short, for the first approach to the linear STS model, the overall results suggest that most cryptocurrencies exhibit a significant effect from November to June. Additionally, all cryptocurrency prices at the end of December have a significant seasonal effect, except for BTC and USDC. For ETH and BNB, there is a decreasing price, while USDT, on the contrary, exhibits an increasing price rate. However, the selected model in this approach does not meet the certain assumption of the residual model.

Then, for the second approach of linear STS with explanatory variables and a significant intervention model, it was discovered that the preferred model in estimating the hidden behavior for all cryptocurrency prices, except for ETH, is Local Level + Deterministic Seasonal. Meanwhile, ETH still maintains the Local Level with Drift + Deterministic Seasonal model. After incorporating explanatory variables, significant outliers, and structural breaks, the model estimation demonstrates marked improvement compared to the version without these variables. For all top five cryptocurrencies, there is an evident improvement in terms of lower standard error and higher R-squared values, as well as the fulfilled model residual assumption. However, ETH and BNB still do not meet the normality assumption.

Based on the results discussed above, it is clear that the inclusion of explanatory variables with significant interventions has an impact on cryptocurrency price modeling. This is evident through price trends and seasonal pattern changes, which differ from the cryptocurrency price model without significant interventions and explanatory variables. In terms of explanatory variables, the model also identifies the variables' influence on cryptocurrency prices, revealing key relationships. The results suggest that Trading Volume significantly influences BTC, ETH, and BNB prices, suggesting that high trading activity often correlates with price movements. Transaction Volume has a negative effect on BTC and ETH, indicating that prices decrease as transactions increase, while USDT exhibits a positive correlation. Velocity, which measures transaction frequency, is positively correlated only with USDT. The Number of Whale Transactions has a significant impact on BTC, ETH, and BNB prices, underscoring the influence of large market players. Macroeconomic factors, such as CPI, do not correlate significantly with most cryptocurrency prices, except for a negative correlation between USDC and CPI. These findings highlight the diverse relationships between economic activities and cryptocurrency prices, varying across digital currencies.

Due to some models does not meet the normality criteria for residuals, the study suggests to examine the nonlinearity of residuals. Then, if nonlinearity exists, the study recommends integrating the residuals of each linear STS model approach with deep learning model to improve the accuracy of predicting the closing prices of these cryptocurrencies.

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