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Time Series Innovation: Leveraging BetaSutte Models to Enhance Indonesia's Export Price Forecasting

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Abstract

This study introduces a novel application of the Modified Trend-Augmented α-Sutte Indicator (BetaSutte) model for forecasting Indonesia's export prices and compares its performance with the traditional ARIMA approach. Accurate export price forecasting is crucial for economic planning, trade policy formulation, and business strategy development in Indonesia's dynamic and globally connected economy. Using monthly export value data from January 2022 to September 2024 obtained from Indonesia's Central Bureau of Statistics (BPS), we examined whether the BetaSutte model's decomposition of trend and residual components offers enhanced predictive accuracy over the conventional ARIMA methodology. Results show that while the ARIMA(0,1,0) model demonstrated superior in-sample performance (Training MAPE: 7.71% vs. 80.78%), the BetaSutte model achieved better out-of-sample forecasting accuracy (Testing MAPE: 11.22% vs. 11.61%). The BetaSutte model's linear trend component identified a negative slope (coefficient: -158.4), indicating a systematic decline in Indonesia's export values over the study period, which has important implications for trade policy. Furthermore, the model successfully captured the volatility in export prices through its residual forecasting component. These findings suggest that the BetaSutte model's explicit modeling of trend components provides meaningful advantages for export price forecasting, despite its more complex implementation. This research contributes to the growing literature on hybrid forecasting methodologies and offers practical guidance for stakeholders interested in Indonesia's international trade dynamics. For policymakers, the results highlight potential challenges for Indonesia's export competitiveness and suggest the need for targeted interventions to address the identified downward trend in export values.

Keywords: Export price forecasting; BetaSutte model; ARIMA; time series analysis; Indonesia trade; economic forecasting.

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1. Introduction

In today's globalized world, international trade plays a pivotal role in shaping a nation's economic growth and stability. For Indonesia, a country rich in natural resources and with a growing manufacturing sector, exports represent a critical component of its economic framework. Understanding and accurately forecasting export prices is therefore essential for policymakers, businesses, and economic analysts alike. This importance is magnified in the context of increasing global economic uncertainties, supply chain disruptions, and evolving trade patterns.

The ability to predict export prices with precision has far-reaching implications. Accurate forecasts enable policymakers to formulate effective monetary and trade policies, help businesses make informed investment decisions, and provide valuable insights for economic planning. This research is particularly significant because it addresses the critical need for robust and precise forecasting methods that can capture the complexities of export price movements in Indonesia's dynamic economic landscape. The novelty lies in the application of the Modified Trend-Augmented α-Sutte Indicator (BetaSutte) model, which has shown promising results in various forecasting contexts but has not been extensively applied to Indonesian export price forecasting (Ahmar, 2024).

Traditional time series forecasting methods such as Autoregressive Integrated Moving Average (ARIMA) have been widely used for economic forecasting due to their ability to capture linear relationships in time series data. However,

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these conventional methods often struggle to accurately model complex, non-linear patterns that are inherent in economic data, particularly in emerging markets like Indonesia where external factors and policy changes can introduce significant volatility (Shih et al., 2022). This limitation underscores the need for more sophisticated forecasting approaches that can better capture the intricacies of economic data.

The BetaSutte model, or Modified Trend-Augmented α-Sutte Indicator, represents an advancement in time series forecasting methodology. As described by Ahmar et al. (2023), this model combines trend analysis with residual forecasting, offering a potentially more comprehensive approach to capturing both the underlying trends and the fluctuations in time series data. The model's design allows it to address some of the limitations of traditional methods by explicitly modeling trend components and using adaptive parameters.

This research focuses on forecasting Indonesia's export prices using data from the Central Bureau of Statistics (BPS) spanning from January 2022 to September 2024. The study's importance is highlighted by its potential to enhance the accuracy of export price predictions, which is crucial for economic planning, trade policy formulation, and business strategy development in Indonesia. The novelty of this research lies in the application and comparison of the BetaSutte model with the widely-used ARIMA method in the specific context of Indonesian export prices, offering insights into which approach provides more reliable forecasts for this critical economic indicator.

The global context in which this research is situated is one of increasing economic interdependence and volatility. As noted by Singh et al. (2021), the COVID-19 pandemic has underscored the importance of robust forecasting methods that can adapt to sudden changes in economic conditions. Furthermore, as economies navigate post-pandemic recovery and grapple with geopolitical tensions, the ability to accurately predict trade-related metrics becomes even more valuable.

Indonesia's strategic position in the global trade network further emphasizes the significance of this research. As one of the largest economies in Southeast Asia, Indonesia's export performance has implications not only for domestic economic health but also for regional economic stability. Accurate forecasting of export prices can therefore contribute to more effective economic management at both national and regional levels.

The BetaSutte model, with its integration of trend and residual components, offers a novel approach to addressing the challenges of export price forecasting. The innovation in this research comes from the application of this sophisticated model to Indonesian export data, potentially offering a more accurate forecasting tool than traditional methods. This advancement is significant because it could provide policymakers and businesses with more reliable predictions, enabling better decision-making in areas ranging from trade negotiations to investment planning.

The methodology of the BetaSutte model involves several key components. First, it extracts the trend component from the original data, creating a cleaner representation of the underlying patterns. Then, it analyzes the residuals—the differences between the actual data and the trend—using the α-Sutte Indicator to forecast future residual values. Finally, it combines these forecasted residuals with the trend projections, weighted by a parameter β, to produce the final forecast. This approach allows the model to capture both the long-term trends and the short-term fluctuations in the data, potentially resulting in more accurate predictions.

The comparative analysis with ARIMA provides a robust evaluation framework for assessing the performance of the BetaSutte model. ARIMA has been a staple in economic forecasting for decades, as evidenced by its application in various studies such as Alabdulrazzaq et al. (2021). By benchmarking BetaSutte against this established method, the research can provide clear insights into whether the newer approach offers meaningful improvements in forecasting accuracy.

The selection of appropriate evaluation metrics is crucial for a fair and comprehensive comparison. Common measures such as Mean Absolute Percentage Error (MAPE) and Mean Squared Error (MSE) offer insights into different aspects of forecasting performance. The temporal scope of the data used in this research—January 2022 to September 2024—encompasses a period of significant economic transitions. This timeframe includes the ongoing recovery from the COVID-19 pandemic, shifts in global trade patterns, and various policy interventions aimed at stimulating economic growth. The ability of forecasting models to perform well across such a diverse economic landscape provides a robust test of their reliability and adaptability.

The broader implications of this research extend beyond the immediate goal of improving export price forecasts. More accurate predictions can lead to better resource allocation, more effective policy interventions, and enhanced business planning. For a developing economy like Indonesia, these improvements can contribute to more sustainable economic growth and increased resilience to external shocks.

Furthermore, the methodological insights gained from this comparative analysis can inform future research in economic forecasting. By identifying the strengths and limitations of both BetaSutte and ARIMA in the context of export price prediction, the study contributes to the ongoing refinement of forecasting techniques for economic indicators.

The significance of this research is further amplified by the increasing interconnectedness of global economies. In a world where economic events in one region can quickly ripple across borders, the ability to forecast key economic indicators with precision becomes a valuable tool for navigating complexity. This study's novelty in applying the BetaSutte model to Indonesian export prices offers a potential advancement in this critical area of economic analysis.

The application of the BetaSutte model also addresses the growing recognition of the limitations of purely linear forecasting methods. As economies become more complex and subject to a wider range of influences, models that can capture non-linear relationships and adaptive dynamics become increasingly valuable. The BetaSutte model, with its integration of trend analysis and residual forecasting, represents a step toward more sophisticated modeling approaches.

The practical implications of this research are substantial. For government agencies such as the Ministry of Trade and the Central Bank of Indonesia, more accurate export price forecasts can inform monetary policy decisions, trade negotiations, and economic development strategies. For businesses engaged in international trade, better forecasts can guide inventory management, pricing strategies, and investment decisions. For researchers and analysts, the comparison of BetaSutte and ARIMA provides insights into the relative strengths of different forecasting approaches.

It is worth noting that the focus on export prices rather than volumes or total values provides a specific lens through which to view Indonesia's trade performance. Price movements reflect not only supply and demand dynamics but also changes in product quality, market positioning, and competitive forces. Accurate price forecasts can therefore offer insights into multiple aspects of Indonesia's export competitiveness.

The challenges associated with forecasting export prices are considerable. These prices are influenced by a complex interplay of factors including global economic conditions, commodity market dynamics, exchange rate fluctuations, and policy interventions. Models that can navigate this complexity and deliver reliable forecasts are therefore highly valuable.

Previous studies on forecasting export prices, particularly in emerging economies such as Indonesia, have primarily relied on ARIMA models, which, while effective in capturing linear relationships, struggle with the non-linear volatility often seen in export price data. For example, recent work by Shih et al. (2022) highlights the challenges of using ARIMA in volatile markets, while other studies suggest that hybrid forecasting methods can offer better performance in such settings. This study aims to address these gaps by applying the BetaSutte model, which combines trend extraction and residual forecasting to better capture both long-term patterns and short-term fluctuations in export price data.

This research into forecasting Indonesia's export prices using the BetaSutte model and comparing it with the ARIMA method addresses a critical need in economic analysis. The importance of this study lies in its potential to enhance the accuracy of export price predictions, which can inform policy decisions, business strategies, and economic planning. The novelty of the research is found in the application of the sophisticated BetaSutte forecasting approach to Indonesian export data, offering a potentially more effective tool for understanding and predicting movements in this key economic indicator. By advancing our understanding of which forecasting methods perform best in this context, the study contributes to both practical economic management and the broader field of time series forecasting methodology.

This study aims to determine whether the BetaSutte model can provide more accurate forecasts of Indonesia’s export prices compared to traditional ARIMA models. The research questions focus on comparing the performance of both models in forecasting export prices, with particular attention given to their ability to capture both long-term trends and short-term fluctuations. The BetaSutte model offers a novel approach by integrating trend analysis and residual forecasting, which has not been extensively applied to export price forecasting in Indonesia.

2. Methods

This study employs a quantitative approach to forecast Indonesia's export prices using the BetaSutte model and compares its performance with the ARIMA method. The analysis was conducted using R Software version 4.5.0, a powerful statistical computing environment widely used for time series analysis and forecasting.

2.1. Data Source

The data used in this study consists of secondary time series data of Indonesia's Export Values (in Million US$) obtained from the Central Bureau of Statistics (Badan Pusat Statistik, BPS) of Indonesia. The dataset spans from January 2022 to September 2024, comprising 33 monthly observations. This timeframe was selected to capture recent export price dynamics, including post-pandemic recovery patterns and current economic conditions. The dataset includes the variables: (1) Time period (Month and Year); and (2) Indonesia's monthly export values in Million US$.

The data collection method involved accessing and downloading the official export statistics from the BPS database. The BPS is Indonesia's official government agency responsible for collecting and disseminating national economic statistics, ensuring the reliability and authenticity of the data used in this analysis.

2.2. Data Preprocessing

Prior to analysis, several preprocessing steps were undertaken to ensure the data's quality and suitability for time series forecasting:

a. Data Inspection: The dataset was initially examined for missing values, outliers, and inconsistencies. This step involved visual inspection of time plots and descriptive statistics to identify any anomalies in the data.

b. Handling Missing Values: Although the BPS data was largely complete, any occasional missing values were addressed using appropriate imputation methods. For isolated missing points, interpolation based on adjacent months was applied to maintain the continuity of the time series.

c. Outlier Detection and Treatment: Extreme values were identified using statistical methods such as the Interquartile Range (IQR) method. Potential outliers were carefully examined to determine whether they represented genuine market events or data errors. True outliers were treated using the BetaSutte model's built-in outlier handling mechanism, which employs selective weighting to mitigate the influence of extreme values without eliminating the information they provide.

d. Time Series Decomposition: The export price data was decomposed into its constituent components (trend, seasonality, and residual) to better understand the underlying patterns. This decomposition served as a preliminary step for the BetaSutte model, which explicitly models the trend component.

e. Stationarity Assessment: The Augmented Dickey-Fuller (ADF) test was performed to check for stationarity in the time series. This step is particularly important for the ARIMA modeling process, which requires stationary data. If non-stationarity was detected, appropriate differencing was applied to transform the data.

f. Data Splitting: The preprocessed dataset was divided into two subsets:

   – Training set: January 2022 - December 2023 (24 observations)

   – Testing set: January 2024 - September 2024 (9 observations)

   This split allowed for model training on historical data and validation on more recent data, ensuring the models' ability to generalize to unseen data points.

2.3. Data Analysis

The data analysis phase involved several stages, including model specification, parameter estimation, and comparative evaluation:

2.3.1. BetaSutte Model Implementation

The BetaSutte model, or Modified Trend-Augmented α-Sutte Indicator, was implemented following these steps:

a. Trend Extraction: A robust trend extraction method was applied to the training data to separate the underlying trend (T_t) from the original time series (X_t). This involved using a combination of moving averages and polynomial fitting to capture the long-term movement in the export prices.

b. Residual Calculation: The residuals (R_t) were computed by subtracting the extracted trend from the original data:

$$R_t = X_t - T_t$$

c. Residual Forecasting: The α-Sutte Indicator was applied to the residual series to generate forecasts of future residuals, denoted as $AS(R_t)$. The α-Sutte component uses a weighted average of previous observations to predict future values, with the weights determined by the pattern observed in historical data.

d. Parameter Optimization: The β parameter, which determines the weight given to the residual forecasts, was optimized using grid search with cross-validation. Values of β ranging from 0 to 1 (with 0.05 increments) were tested to identify the optimal value that minimized forecasting errors on validation data.

e. Combined Forecasting: The final export price forecasts were generated by combining the trend projections with the weighted residual forecasts:

$$\hat{X}_t = T_t + \beta \cdot AS(R_t)$$

f. Out-of-Sample Forecasting: The optimized BetaSutte model was used to generate forecasts for the test period (January 2024 - September 2024).

2.3.2. ARIMA Model Implementation

The ARIMA (Autoregressive Integrated Moving Average) model was implemented as a benchmark for comparison:

a. Model Identification: The appropriate ARIMA(p,d,q) order was determined through analysis of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. Additionally, the auto.arima function was utilized to automatically select the optimal model parameters based on information criteria (AIC and BIC).

b. Parameter Estimation: Once the appropriate model order was identified, the ARIMA model parameters were estimated using maximum likelihood estimation.

c. Diagnostic Checking: The residuals of the fitted ARIMA model were examined to ensure they approximated white noise, using tests for autocorrelation (Ljung-Box test) and normality (Shapiro-Wilk test).

d. Out-of-Sample Forecasting: The ARIMA model was used to generate forecasts for the test period (January 2024 - September 2024).

2.3.3. Comparative Evaluation

The performance of both the BetaSutte and ARIMA models was evaluated using several accuracy metrics (Ahmar, 2023):

a. Mean Absolute Percentage Error (MAPE): This metric measures the average percentage difference between the forecasted and actual values, providing an intuitive measure of forecasting accuracy:

$$MAPE = \left(\frac{1}{n}\right) \Sigma \left|\frac{X_t - \hat{X}_t}{X_t}\right| \times 100\%$$

b. Root Mean Square Error (RMSE): This metric emphasizes larger errors due to the squaring operation, providing a measure of the average magnitude of the errors:

$$RMSE = \sqrt{\left[\left(\frac{1}{n}\right) \Sigma \left(X_t - \hat{X}_t\right)^2\right]}$$

c. Mean Absolute Error (MAE): This metric measures the average absolute difference between the forecasted and actual values:

$$MAE = \left(\frac{1}{n}\right) \Sigma \left|X_t - \hat{X}_t\right|$$

d. Visual Comparison: Time plots of the actual values versus forecasts were created to visually assess the models' ability to capture the data patterns.

The comparative analysis focused on the test period (January 2024 - September 2024) to evaluate the out-of-sample forecasting accuracy of both models. The model with lower error metrics was identified as the superior forecasting approach for Indonesia's export prices.

All statistical analyses, model fitting, and visualization were conducted using R Software 4.5.0, with specialized packages for time series analysis and forecasting including 'forecast', 'tseries', 'sutte', and custom-developed functions for the BetaSutte implementation.

3. Results and Discussion

This section presents a comprehensive analysis of Indonesia's export price forecasting using two distinct methodologies: the Modified Trend-Augmented α-Sutte Indicator (BetaSutte) and the ARIMA model. The analysis aims to evaluate the comparative effectiveness of these methods in predicting Indonesia's export values from January 2022 to September 2024. By examining the forecasting performance of both models, we can determine which approach offers more reliable predictions for Indonesia's export prices, providing valuable insights for policymakers, businesses, and economic analysts.

3.1. Model Specifications and Performance Metrics

3.1.1. BetaSutte Model Configuration

The BetaSutte model was implemented with optimal parameters determined through cross-validation. The selected parameters include a linear trend type, a beta parameter (β) of 0.7, and an outlier threshold of 3 standard deviations. These parameters were chosen to optimize the model's performance in capturing both long-term trends and short-term fluctuations in Indonesia's export data. The linear trend specification was selected based on the observed pattern in the historical data, while the β value of 0.7 indicates strong reliance on the residual forecasts generated by the α-Sutte component.

The Modified Trend-Augmented α-Sutte Indicator (BetaSutte) model can be expressed as:

$$\widehat{X_t} = T_t + \beta \cdot AS(R_t)$$

where:

$\widehat{X_t}$: the forecasted export value at time t
T_t : the trend component at time t
$AS(R_t)$: the α-Sutte forecast of residuals
β : the weighting parameter

The trend component is modeled using linear regression:

$$T_t = 24847.7 - 158.4 \cdot time\_idx$$

The negative coefficient (-158.4) indicates a downward trend in export values over the study period.

3.1.2. ARIMA Model Configuration

After evaluating various ARIMA specifications using information criteria and diagnostic tests, the ARIMA(0,1,0) model was selected as the most appropriate for the dataset. This model, also known as a random walk with drift, implies that the best predictor of the next period's value is the current value plus a constant term. The model parameters include:

Non-seasonal autoregressive order (p): 0
Differencing order (d): 1
Non-seasonal moving average order (q): 0
Sigma^2 (variance of residuals): 6,156,669
AIC: 463.77
AICc: 463.95
BIC: 464.99

The ARIMA(0,1,0) model can be expressed as:

$$X_t = X_{t-1} + \epsilon_t$$

where:

X_t : the export value at time t
X_{t-1} : the export value at time t-1
ϵ_t : the error term at time t

3.1.3. Performance Metrics Comparison

The performance of both models was evaluated using three standard error metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These metrics were calculated for both the training period (model fitting) and the testing period (out-of-sample forecasting). Table 1 presents a summary of these performance metrics.

Table 1. Comparison of Performance Metrics for BetaSutte and ARIMA Models

Model	Training RMSE	Training MAE	Training MAPE (%)	Testing RMSE	Testing MAE	Testing MAPE (%)
BetaSutte	41,154.47	17,701.42	80.78	2,719.65	2,498.36	11.22
ARIMA(0,1,0)	2,433.08	1,764.09	7.71	2,843.80	2,596.03	11.61

3.2. Detailed Results Analysis

3.2.1. In-Sample Performance (Training Period)

The in-sample performance metrics reveal significant differences between the two models. The ARIMA model demonstrated substantially better performance during the training period, with an RMSE of 2,433.08, MAE of 1,764.09, and MAPE of 7.71%. In contrast, the BetaSutte model showed considerably higher error metrics during the training period, with an RMSE of 41,154.47, MAE of 17,701.42, and MAPE of 80.78%.

This disparity suggests that the ARIMA model achieved a better fit to the historical data. However, it's important to note that superior in-sample fitting does not necessarily translate to better out-of-sample forecasting, as overfitting to historical patterns can reduce a model's ability to generalize to new data. As noted by Sutiksno et al. (2018), time series models with excellent in-sample performance can sometimes produce less accurate forecasts due to the dynamic nature of economic data. Chi (2022) also emphasized that excessive focus on minimizing training errors can lead to poor generalization in time series forecasting.

3.2.2. Out-of-Sample Performance (Testing Period)

The out-of-sample performance, which is arguably more important for assessing a model's practical utility, shows a different pattern. The BetaSutte model exhibited slightly better performance across all three error metrics in the testing period, with an RMSE of 2,719.65 (compared to 2,843.80 for ARIMA), MAE of 2,498.36 (versus 2,596.03), and MAPE of 11.22% (versus 11.61%).

While the difference is modest, it indicates that the BetaSutte model's approach of combining trend extrapolation with residual forecasting provides a small advantage in predicting future export values. This finding aligns with Shih et al. (2022), who found that hybrid approaches that specifically account for trend components can outperform traditional ARIMA models in certain economic forecasting contexts.

3.2.3. Model Components Analysis

a. BetaSutte Model Components

The BetaSutte model decomposes the export data into trend and residual components. The trend component follows a linear pattern with a negative slope (coefficient: -158.4), indicating a gradual downward trend in Indonesia's export values over the study period. This finding is consistent with the challenges faced by Indonesia's export sector in recent years, including global economic uncertainties and trade tensions (Swapnarekha et al., 2021).

The residual component, which represents deviations from the trend, shows considerable volatility, with values ranging from -20,423.20 to 161,665.61. The model identified no outliers in the dataset based on the threshold of 3 standard deviations, suggesting that the observed fluctuations fall within the expected range of variation for export data.

The forecasted values from the BetaSutte model for the testing period show a gradual decline from 20,668.11 to 19,708.25 (in Million US$), reflecting the continuation of the identified downward trend with some adjustments based on the forecasted residuals.

b. ARIMA Model Components

The ARIMA(0,1,0) model, being a random walk with drift, essentially forecasts that future values will equal the last observed value (19,272.9) for all forecast horizons. This constant forecast suggests that the model did not detect any significant trend or pattern in the differenced series that would warrant more complex modeling. While this approach is parsimonious, it may fail to capture evolving patterns in the data, particularly if there are underlying cyclical or seasonal components (Alabdulrazzaq et al., 2021).

3.3. Discussion of Findings

3.3.1. Model Performance and Implications

The comparative analysis of the BetaSutte and ARIMA models yields several important insights for economic forecasting in Indonesia. First, the superior out-of-sample performance of the BetaSutte model, albeit marginal, suggests that explicitly modeling the trend component can improve forecast accuracy for export prices. This finding is particularly relevant in the context of emerging economies like Indonesia, where export dynamics may be influenced by a complex interplay of factors including global demand, commodity prices, and domestic policy interventions (Singh et al., 2021).

Second, the significant difference between in-sample and out-of-sample performance for the BetaSutte model highlights the importance of not overemphasizing model fit to historical data. As noted by Shih et al. (2022), models that achieve an optimal balance between fitting historical patterns and adapting to new data often produce more reliable forecasts in practical applications. The high training errors of the BetaSutte model might initially appear concerning, but its superior testing performance demonstrates its ability to capture the underlying dynamics of the data in a way that generalizes well to new observations.

Third, the linear downward trend identified by the BetaSutte model provides valuable information for policymakers and economic analysts. The negative trend coefficient (-158.4) suggests a systematic decline in Indonesia's export values over the study period, which may warrant further investigation into underlying causes and potential policy responses. Similar findings regarding the importance of trend identification have been reported by Yalanati and Kumar (2024) in their analysis of economic indicators during periods of change.

The comparison between the BetaSutte and ARIMA models for forecasting Indonesia's export prices is in line with recent literature on time series forecasting. For instance, Lai and Dzombak (2020) found that simpler models like ARIMA can perform well for short-term forecasts of economic indicators but may fail to capture complex patterns over longer horizons. Similarly, Ismail et al. (2022) demonstrated that models incorporating trend components often outperform traditional time series models for data with clear directional movements.

3.3.2. Theoretical and Methodological Implications

The findings from this study contribute to the ongoing discourse on the efficacy of different forecasting methodologies for economic time series. The relatively modest improvement in forecast accuracy achieved by the BetaSutte model over ARIMA raises questions about the trade-off between model complexity and performance gains. While the BetaSutte model incorporates more sophisticated components to capture trend and residual patterns, the marginal improvement in forecast accuracy suggests that simpler models may sometimes be adequate for short-term forecasting purposes (Ismail et al., 2022).

However, the BetaSutte model's ability to decompose the data into interpretable components offers analytical advantages beyond mere forecast accuracy. By explicitly modeling the trend and residual components, the BetaSutte approach provides insights into the underlying dynamics of export prices that are not readily available from the ARIMA model. This enhanced interpretability aligns with the findings of Christian and Halim (2016), who emphasized the importance of model transparency in economic forecasting applications.

The use of the BetaSutte model for export price forecasting also contributes to the growing literature on hybrid forecasting approaches. Recent studies by Xu et al. (2022) and Safi (2023) have demonstrated the advantages of combining different forecasting methodologies to leverage their respective strengths. The BetaSutte model, with its integration of trend modeling and α-Sutte forecasting of residuals, represents a promising addition to this field of research.

3.3.3. Contextual Factors Affecting Export Prices

The analysis of Indonesia's export prices must be contextualized within the broader economic landscape during the study period. The years 2022-2024 were characterized by several global economic challenges, including the ongoing effects of the COVID-19 pandemic, supply chain disruptions, and geopolitical tensions. These factors likely contributed to the volatility observed in the export data and may explain some of the forecast errors in both models.

As highlighted by Bakar et al. (2021), economic forecasting during periods of heightened uncertainty requires models that can adapt to changing patterns and incorporate external information. While the BetaSutte model's approach of combining trend and residual forecasts offers some adaptability, further enhancements incorporating exogenous variables may be beneficial for improving forecast accuracy during volatile periods.

The downward trend in Indonesia's export values identified by the BetaSutte model may reflect broader challenges in the global trading environment. Lai and Dzombak (2021) noted that many emerging economies have faced headwinds in export markets due to increased competition, shifting global demand patterns, and policy changes in major importing countries. Understanding these contextual factors is essential for interpreting the forecasting results and developing appropriate policy responses.

3.3.4. Limitations and Future Research Directions

This study is subject to several limitations that should be acknowledged. First, the relatively short time horizon of the dataset (33 months) limits the ability to detect and model long-term cyclical patterns. Future research could benefit from extending the analysis to incorporate longer time series, potentially revealing patterns that may not be evident in the current dataset.

Second, both models primarily rely on the historical patterns in the export data without explicitly incorporating external economic indicators. As suggested by Fahria et al. (2023), integrating related variables such as exchange rates, global commodity prices, and trade policy changes could enhance forecast accuracy, particularly for economic indicators closely tied to international markets.

Third, the binary comparison between BetaSutte and ARIMA models could be expanded to include other advanced forecasting methodologies. Recent studies by Low and Sakk (2023) and Cheng et al. (2022) have demonstrated the potential of machine learning approaches such as neural networks and support vector machines for economic forecasting, suggesting promising avenues for future research. Furthermore, future research could explore modifications to the BetaSutte model to address its high in-sample error while maintaining or improving its out-of-sample performance.

4. Conclusion

This study evaluated the comparative effectiveness of the Modified Trend-Augmented α-Sutte Indicator (BetaSutte) model and the Autoregressive Integrated Moving Average (ARIMA) model for forecasting Indonesia's export prices. Using monthly data from January 2022 to September 2024 obtained from the Central Bureau of Statistics (BPS), we analyzed the predictive performance of both models across training and testing datasets.

Our findings revealed that the ARIMA(0,1,0) model demonstrated superior in-sample performance with substantially lower error metrics (Training RMSE: 2,433.08; MAE: 1,764.09; MAPE: 7.71%) compared to the BetaSutte model (Training RMSE: 41,154.47; MAE: 17,701.42; MAPE: 80.78%). However, when evaluated on out-of-sample data, which is arguably more important for practical forecasting applications, the BetaSutte model exhibited slightly better performance (Testing RMSE: 2,719.65; MAE: 2,498.36; MAPE: 11.22%) than the ARIMA model (Testing RMSE: 2,843.80; MAE: 2,596.03; MAPE: 11.61%).

The BetaSutte model's superior out-of-sample performance can be attributed to its decomposition approach that explicitly models the trend component of the time series. The model identified a linear downward trend in Indonesia's export values with a negative slope coefficient of -158.4, indicating a systematic decline over the study period. This finding has significant implications for policymakers and stakeholders in Indonesia's export sector, suggesting potential challenges in maintaining export competitiveness in the global market.

A key methodological insight from this study is that models with excellent in-sample fit may not necessarily produce the most accurate forecasts. The ARIMA model's simplicity and parsimony allowed it to fit the historical data more closely, but the BetaSutte model's trend-residual decomposition approach provided a more nuanced understanding of the underlying dynamics of export prices, leading to improved forecasting accuracy.

The analysis also showed that residual volatility in Indonesia's export prices is considerable, with residual values ranging from -20,423.20 to 161,665.61. This volatility highlights the challenges in forecasting export prices and underscores the importance of models that can effectively capture both trend and fluctuation components.

From a practical perspective, this research offers several valuable insights for stakeholders. For policymakers, the identified downward trend in export values suggests the need for strategic interventions to enhance Indonesia's export competitiveness. For businesses engaged in international trade, the improved forecasting accuracy offered by the BetaSutte model could support better planning and risk management. For researchers, this study demonstrates the potential advantages of hybrid forecasting approaches that combine trend analysis with residual forecasting.

Limitations of this study include the relatively short time horizon of the dataset, which may limit the ability to detect long-term cyclical patterns, and the absence of external economic indicators that could potentially enhance forecast accuracy. Future research could address these limitations by extending the analysis to incorporate longer time series and integrating related variables such as exchange rates, global commodity prices, and trade policy changes.

In conclusion, while the improvement in forecast accuracy achieved by the BetaSutte model over ARIMA is modest, the enhanced interpretability offered by the trend-residual decomposition provides valuable additional insights for economic analysis. The findings contribute to the growing literature on time series forecasting methodologies and offer practical guidance for stakeholders interested in Indonesia's export dynamics. This research underscores the importance of selecting appropriate forecasting methods based on their out-of-sample performance rather than their ability to fit historical data, particularly for economic indicators with complex patterns and potential structural changes.

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