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Modelling Price Movements of Stock-Based Futures Contracts with Time Series: Tupraş Example

Hisse Senedine Dayalı Vadeli İşlem Sözleşmelerinin Fiyat Hareketlerinin Zaman Serileri ile Modellenmesi: Tüpraş Örneği

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ÖZ

Bu çalışma, hisse senedine dayalı vadeli işlem sözleşmelerinin fiyat hareketlerini modellemek amacıyla gelişmiş zaman serisi analiz tekniklerini kullanmakta ve Tüpraş vadeli işlemlerini örnek olay olarak ele almaktadır. Finansal piyasaların karmaşıklığını tam olarak yansıtamayan geleneksel ARIMA modellerinin sınırlılıkları dikkate alınarak, bu araştırmada hisse senedi fiyatları, piyasa endeksleri, döviz kurları, faiz oranları ve enflasyon gibi temel dışsal değişkenleri içeren genişletilmiş bir ARIMAX çerçevesi geliştirilmiştir. Çalışmada Ocak 2017 ile Ağustos 2023 arasındaki aylık veriler kullanılmıştır. Sağlam ve güvenilir tahminler elde edebilmek için veri ön işleme, keşifsel analiz, durağanlık testi adımları uygulanmıştır. Ampirik sonuçlar, RMSE, MSE, R^2, AIC ve BIC gibi doğruluk ölçütleri açısından değerlendirildiğinde, ARIMAX modelinin hem temel hem de optimize edilmiş ARIMA modellerinden belirgin şekilde daha iyi performans gösterdiğini ortaya koymaktadır. Bu araştırma, dışsal değişkenlere dayalı modellerin enerji türevleri gibi volatil ve yapısal olarak karmaşık piyasalarda sunduğu açıklayıcılığı ortaya koyarak finansal ekonometri alanına katkı sağlamaktadır.

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ABSTRACT

This study investigates the modelling of price movements in stock-based futures contracts by applying advanced time series techniques, using the Tupraş futures as a case study. Recognizing the limitations of traditional ARIMA models in capturing the complexities of financial markets, the research develops an extended ARIMAX framework that incorporates key exogenous variables such as stock prices, market indices, exchange rates, interest rates, and inflation. The dataset spans from January 2017 to August 2023 with monthly observations. Data preprocessing, exploratory analysis, and stationarity test steps were applied to obtain robust and reliable estimates. Empirical results reveal that the ARIMAX model significantly outperforms the baseline and optimized ARIMA models, as indicated by improved accuracy metrics, including RMSE, MSE, R^2, AIC, and BIC. This research contributes to financial econometrics by demonstrating the explanatory power of exogenous-driven models in volatile and structurally complex markets such as energy derivatives.

1. Introduction

Forecasting the price movements of stock-based futures contracts plays a pivotal role in financial analysis by supporting strategic decision-making in hedging, speculation, and investment planning (Allen et al., 2018; Holmes and Otero, 2019). These contracts, which derive

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value from underlying securities, allow market participants to mitigate risk and exploit arbitrage opportunities, particularly in markets where volatility and liquidity asymmetries are pronounced (Figlewski, 1984; Jongadsayakul, 2022). The pricing relationship between futures and spot markets reflects broader theoretical conditions such as contango and backwardation—market structures where futures prices deviate systematically from spot prices due to storage costs, investor expectations, or supply-demand imbalances (Wahab et al., 2019; Fernandez, 2016).

As financial derivatives gain prominence in emerging markets, their forecasting becomes even more critical, especially for sectors sensitive to global economic fluctuations, such as energy. In other words, futures contracts tied to large-cap firms in sectors like energy often attract institutional attention due to their strategic macroeconomic sensitivity (Scheitrum et al., 2018). In this context, Tupraş (Türkiye Petrol Rafinerileri AŞ)—the leading oil refining company in Türkiye—constitutes a distinctive case to examine the key drivers of single-stock futures pricing. The firm holds strategic importance in terms of national energy supply and exhibits strong linkages with global oil prices and domestic policy shifts (Özdurak, 2021). Previous studies on individual firms in commodity-intensive sectors have similarly highlighted the role of firm-level idiosyncrasies in price behaviour (Scheitrum et al., 2018), making Tupraş a relevant and timely subject of analysis.

With a market value of over 278 billion TRY (TradingView, 2023), Tupraş is exposed to various macroeconomic and financial factors, such as global oil prices, foreign exchange rate instability, and domestic policy changes. These dependencies increase the difficulty of forecasting the futures contracts and require a distinctive model other than the conventional one. While classical ARIMA models have been widely used to model financial time series and detect autoregressive price trends (Çatak, 2022), their effectiveness may diminish in the presence of exogenous shocks and structural breaks. In response, ARIMAX models have gained traction as they incorporate explanatory macroeconomic and market-specific variables to better capture dynamic interactions (Lu et al., 2020; Sun et al., 2015). This augmented approach is particularly useful in emerging markets, where financial series often reflect external shocks and policy-induced fluctuations. Adding these drivers via ARIMAX models gives a sounder and more economical base for introducing exogenous shocks and better predictive accuracy (Joarder, 2018; Krishnan and Mani, 2019).

To account for such complexity, the current paper builds a multi-layered review-based conceptual model based on prior literature on price discovery, volatility formation, macro-financial linkages, and market liquidity. The dynamic interplay between spot and futures markets further complicates price forecasting. Futures contracts are frequently leading indicators due to higher liquidity and faster information assimilation. This mechanism has been empirically supported across multiple commodity markets (Madhavan, 1985; Holmes and Otero, 2019), with studies showing that futures markets often lead to information assimilation due to superior liquidity and leverage advantages. Studies in global oil markets (e.g., Palm oil, Brent crude) have shown that futures prices often adjust before spot markets, indicating a bi-directional feedback mechanism that demands careful modelling (Ab Rahman et al., 2012; Miljkovic and Goetz, 2020). Likewise, Go and Lau (2019) found that crude palm oil futures Granger-cause refined oil spot returns. However, reverse causality is also observed, highlighting that shocks in the physical market can transmit back to futures markets under certain inventory or procurement conditions. In this context, Tupraş's equity and single-stock futures are modelled as a jointly determined system to account for such bidirectional feedback mechanisms.

The second analytical layer addresses volatility dynamics in futures markets, particularly within energy finance. volatility dynamics exhibit clustering and asymmetry, often triggered by policy interventions or geopolitical tensions. In the Turkish context, Özdurak (2021) demonstrates that energy firms experience volatility spillovers tied to global oil prices and local governance decisions. Moreover, studies show that systemic shocks and structural breaks, such as the 2008 financial crisis, can substantially alter both short-term volatility and the persistence of price disturbances in crude oil markets (Azevedo et al., 2015). Similarly, introducing stock futures in India was followed by a measurable decline in the unconditional volatility of energy stocks, although the persistence of these effects was not explicitly analysed (Shirodkar and Raju, 2021). To accommodate such market regime changes, this study embeds GARCH-type processes and includes structural-break dummies corresponding to key market events.

The third component of the framework emphasizes macro-financial determinants that shape the pricing of oil-related futures. Research highlights that oversupply conditions and speculation through options markets can exert downward pressure on oil futures (Abraham and Harrington, 2016), while macroeconomic growth shocks—both short-run and long-run—help explain volatility structures and risk premia along the futures curve (Hitzemann, 2016). Interestingly, daily energy-futures returns have shown limited sensitivity to scheduled U.S. macroeconomic news releases, suggesting that investor expectations have more influence on price movements than direct news flows (Kilian and Vega, 2008; Chan and Gray, 2017). The pricing of such contracts also reflects broader macro-financial interactions, including the influence of exchange rates, interest rates, and inflation expectations. Empirical findings from BRICS economies (Tiwari et al., 2019) and Türkiye (Ekinci and Saygılı, 2023) reveal that macroeconomic shocks can significantly alter the risk-return profile of financial instruments, including commodity-linked equities.

A fourth analytical tier introduces a risk-management and corporate governance perspective. Futures contracts are used for hedging and speculation and serve as mechanisms to align corporate performance with market outcomes. Pradhan (2011) argued that stock-based derivatives encourage organizational alignment by incentivizing executives based on market-driven performance outcomes. Similarly, Gomaa (2012) emphasized that the widespread use of futures contracts strengthens shareholder value as executive performance becomes directly linked to measurable financial results.

Beyond macroeconomic determinants, market microstructure factors—such as liquidity, transaction costs, and regulatory changes—play a crucial role in shaping pricing efficiency and the effectiveness of hedging strategies in futures markets. Studies by Malhotra (2015) and Xiong et al. (2017) emphasize that systemic transitions, including exchange reforms and clearinghouse restructuring, can substantially influence arbitrage conditions and the overall functioning of price discovery mechanisms. Specifically, Malhotra (2015) finds that in India's refined oil futures markets, minimum-variance hedge ratios reduce return variance by up to 71% in highly liquid contracts, while their effectiveness diminishes to approximately 28% in thinly traded ones. To reflect this imbalance, variables like market index, exchange rate, and interest rate are brought into the analysis. They help explain how differences in market activity can affect how smoothly information flows and how effective hedging strategies are in practice.

Finally, to truly understand how futures pricing works in Türkiye's energy sector, a systematic perspective provides to zoom out and consider the bigger picture. The country has been working to cut its reliance on imported energy, align with EU environmental standards, and open its markets—moves that have shifted how investors think and how energy firms react to change (Yıldız, 2010; Müftüler-Baç and Başkan, 2011; Kaplan and Aladağ, 2016). These shifts don't happen in isolation—they're part of a broader mix of economic, technological, and political forces shaping the energy landscape (Hosseini et al., 2016). In this context, national energy strategies become upstream influences that ripple through financial systems and ultimately shape company-level expectations about things like refining margins, risk, and profitability. This interplay underscores the need for a multi-layered, context-aware modelling approach that captures both the immediate market dynamics and the broader strategic landscape in which firms operate.

In terms of methodology, this research employs a sequential time-series modelling strategy. First, an ARIMA model captures historical price dynamics as a baseline. This model is then expanded into an ARIMAX model by incorporating selected exogenous macro-financial variables. The forecast accuracy is assessed by using standard statistical measures such as the mean absolute error (MAE), mean square error (MSE), and the root mean square error (RMSE), and model selection criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). This procedure provides a full-fledged comparison between traditional and extended models to estimate the incremental information of external data in predicting future prices.

The overall findings thus contribute to the broader literature on energy-sector financial valuation by providing a nuanced insight into the second-order effects of (1) spot–futures feedback, (2) volatility structures, (3) macro-financial linkages, (4) liquidity conditions in the underlying stock market, and (5) governance-motivated hedging in driving single-stock futures prices. Focusing on Tupraş as an empirical case, the study improves forecasting accuracy and equips market participants with more effective tools for managing derivative exposures in a volatile and interconnected global financial environment. The following section presents a detailed literature review, providing the theoretical and empirical foundations for the research question and methodology.

2. Literature Review

The dynamics and pricing of stock index futures contracts have been the central subject of much research because of their important role in financial markets. Futures are derivative contracts that do so by getting their values from the performance of underlying assets and are used for hedging, speculation, and risk management purposes. Due to the prominence of these contracts in financial markets, several methods have been proposed for studying the effect of internal and external factors on these instruments, which have helped reveal that they have affected market efficiency, volatility, and price discovery. Consequently, futures markets have been the subject of substantial research to inform their pricing mechanism and reaction to fluctuating economic circumstances.

In the literature on futures markets, the interest has been directed to modelling and forecasting the dynamics of futures prices. Much effort has been devoted to representing these markets' nonlinear and time-varying characteristics. Indeed, studies have come to rely on more complex models to better capture the complexity of the dynamics of futures prices. For example, Markov-switching models have been used to analyse volatility regimes in futures markets, which can better capture structural breaks than linear models. Cabrera et al. (2018) proposed to use Markov-switching models to capture state switching in emerging stock markets. In the same wave, Caporin and Fontini (2017) utilized these models for oil and gas markets and detected structural breaks caused by technological change and supply-side factors. These studies highlight the ability of regime-switching models to account for market dynamics that are often overlooked in linear approaches.

Another critical line of literature on futures markets examines the dynamics between the spot and futures prices. It has been examined in many studies because futures markets are generally believed to be more efficient in reflecting new information than their spot markets (Madhavan, 1985). Futures market structural advantages—such as leverage, lower transaction costs, and more rapid information transmission— lead to price discovery that is informative to the spot market. Holmes and Otero (2019) also provided evidence of the role of future markets as mechanisms to stabilize and transmit to spot markets, notably in the oil market. Similarly, Allen et al. (2018) investigated the linkage across energy, agricultural, and biofuel markets, and they showed that common economic fundamentals drive price co-movement in those agricultural commodities. These results reveal the role of futures contracts in promoting price discovery and market stabilization.

The effect of shocks and intermarket linkages on futures pricing has been a focus of studies. Chuffart and Hooper (2019) analysed the impact of oil price volatility on the financial instruments of oil-exporting countries, showing the process that altered the backdrop for sovereign credit risk and other markets. Tiwari et al. (2019) further expanded this assessment by analysing the relationship between oil prices and equity markets of BRICS countries. They found how the global economic state affects the price dynamics among markets. This literature accentuates the importance of models that account for the interplay of futures markets and macroeconomic factors and the global contagion forces that drive the pricing process.

Concerns about market dynamics formed by supply and demand also make it difficult to forecast future prices. Scheitrum et al. (2018) probed into WTI and Brent crude oil prices and revealed how market conditions evolved, arising from supply and demand changes and storage facilities limitations. Similarly, Rodrigues et al. (2018) showed that adjusting fuel commodities' prices is often asymmetric, especially in the face of supply and demand shocks. These results underline the importance of models, such as time-varying parameter econometrics, which are more adept at the pricing dynamics of futures markets and can better capture the price dynamics during volatile periods.

Hybrid approaches that integrate econometric and machine learning methods have been proposed very recently in the literature of predictive modelling. For example, Lu et al. (2020) inserted forward-looking information further to search trends into dynamic Bayesian structural time series models to enhance the interpretability of crude oil price dynamics. Similarly, Zhang et al. (2019) used support vector machines to learn the complex prices, and Sun et al. (2015) applied fuzzy time series models to obtain a more accurate forecast in the Chinese stock index futures market. These studies demonstrate how we use machine learning models and other original approaches to enhance the forecasting accuracy of futures pricing.

When we look at the energy topic in Türkiye, we see that the rapidly changing energy landscape of Türkiye has been reflecting a sense of urgency to fulfil increasing energy demand, decrease foreign dependency, and move towards global sustainability objectives. The academic literature on this subject can be clustered into two areas: general energy policy and resource planning, as well as pricing and forecasting.

Much of the literature emphasizes the strategic shift toward clean and renewable energy. Yüksel, Arman, and Demirel (2018) highlight the critical role of clean energy technologies and infrastructure in shaping future energy policies. Supporting this, Öz and Alyürük (2020) underline the importance of investment in domestic renewable resources to ensure long-term energy security. Okay (2015) and Kaygusuz (2004) further advocate for exploiting Türkiye's natural potential in solar, wind, and hydro, stressing environmental and economic benefits.

Dincer et al. (2017) focus on sustainable energy policy design, while Demirbaş (2006) discusses the near-future feasibility of renewable facilities. Toklu and Kaygusuz (2012) highlight the importance of energy efficiency and demand-side strategies. Müftüler-Baç and Başkan (2011) take a geopolitical view, framing Turkey as a crucial energy corridor for Europe with implications for international energy diplomacy.

Natural gas policy is critically examined by Çağaptay and Evans (2013), who advocate for diversified sourcing to reduce strategic vulnerability. Kaplan and Aladağ (2016), Kiliç (2006), and Sözen and Arcaklıoğlu (2007) emphasize resource diversification and domestic utilization. Biomass potential is addressed by Kara et al. (2017), while Özdamar et al. (2020) explore the investment landscape for renewables, identifying regulatory and financial constraints.

Hydropower, as discussed by Ozturk (2004), is presented as a key but environmentally sensitive energy source. These collective insights suggest that Turkey's energy future depends on coordinated policy reforms, technological innovation, and regulatory support for renewables.

In energy pricing, Ak, Türk, and İslatince (2019) apply a Nash-Cournot model to reveal how market structure impacts price formation. Ekinci and Saygılı (2023) assess oil price pass-through effects across sectors, revealing asymmetric transmission, particularly in energy-intensive industries.

In sum, the studies explicitly conducted for Türkiye demonstrate strong support for a renewable-driven, diversified energy strategy for Türkiye, paired with improved modelling of market behaviour. However, integration between pricing models and broader policy frameworks remains underexplored, highlighting a need for more interdisciplinary research linking macroeconomics, market dynamics, and energy governance.

On the other hand, in the energy markets, specific studies have explored the challenges and opportunities presented by futures contracts. For instance, Özdurak (2021) examined the volatility spillovers among Turkish energy firms, including Tupraş, revealing how futures markets can be used to enhance market efficiency. Hu (2016) explored the introduction of the CSI 300 stock index futures into the Chinese market, finding no evidence of increased volatility, which might be attributed to the regulatory mechanisms that have improved market maturity. Likewise, Truong and Friday (2021) examined the effects of VN30-Index futures on the Ho Chi Minh Stock Exchange, and they found that futures contracts significantly reduced the "day-of-the-week" effect and contributed to greater efficiency in the exchange market.

The reform of trading systems has also contributed to enhancing future markets. Xiong et al. (2017) investigated the effects of a change in the trading system in China from T+1 to T+0, demonstrating that the change also improved liquidity and price discovery. These results emphasize the crucial role of regulations and possible structural adjustments in improving the efficiency and performance of futures markets.

However, even with this progress, one of the significant limitations in the current literature is the insufficient inclusion of the exogenous economic inputs in forecasting frameworks of ARIMA. Although most analysts attribute price dynamics to internal market drivers, macroeconomic data and other external factors (such as interest rates, market indices, etc.) have now been largely ignored despite being essential in understanding how prices can evolve. This paper seeks to fill this gap by bringing exogenous factors to an ARIMAX framework augmented with regime-switching and machine-learning methodologies. This integrated model can enhance the robustness and prediction ability of futures price models and give a more genuine picture of the reality of the futures pricing phenomenon.

The literature also emphasizes the growing relevance of hybrid deep learning approaches in predicting financial time series. In recent years, cascades such as convolution–GRU–MLP have been applied to leverage heterogeneous layers, and they significantly reduce forecasting errors compared to baselines for several major stock exchanges (Ningshen et al., 2024). Wang et al. (2022) pre-ranked explanatory factors using-gradient boosted trees, which were then further fine-tuned using bidirectional GRU to enhance forecasting performance in indices such as CSI 500, NASDAQ100, and FTSE 100 futures. Transformer models have demonstrated significant potential in time series forecasting, particularly when enhanced with advanced positional encoding techniques like Time2Vec (Tevare and Revankar, 2023).

Further, LSTM models are still successful in predicting volatility, and even after principal component analysis, they keep a strong predictive power for volatility prediction (Xue Chen and Hu, 2022). Moreover, stacked-LSTM models are found to perform better than support vector regression on Indian stock price prediction (Raut, 2024). These results suggest that machine learning methods can improve predictive accuracy in future markets.

However, the choice of inputs is a contributing factor that can influence model performance. Li and Wang (2022) indicated and showed that based on the most correlated variables instead of the whole futures database significantly improves forecasting precision. Methods such as wavelet denoising (Wang and Nie, 2018) and grey theory integration (Chi et al., 1999) have been previously used to remove noise and select appropriate input attributes, thus promoting the forecast accuracy of futures prices.

To summarize the literature on futures markets, we distil three main lessons: (1) ensemble and cascaded learning frameworks prevail in noisy, non-stationary financial markets; (2) purposeful feature engineering is critical for improving forecasting performance; and (3) contextual model selection via, for example, regime-switching or meta-learning may afford meaningful economics gains. These observations motivate the current work, which combines the cascaded structure for loan-approval prediction with heterogeneous classifiers, adaptive feature filtering, and regime-aware switch criteria that leverage the complementary properties identified in prior financial forecasting works.

In conclusion, this study addresses several critical gaps in the literature by incorporating exogenous economic variables into an enhanced ARIMAX framework, regime-switching, and machine-learning techniques. Doing so provides a more robust and accurate approach to forecasting future prices. It offers valuable insights for financial decision-making in both futures markets and broader applications, such as automated credit appraisal.

3. Data and Methodology

Data Collection

The focus of this research is the analysis of the movements of the prices of stock futures contracts. Tupraş has been selected for this case study due to its suitability. Our sample spans January 2017 to August 2023, with monthly observations. Data comes from websites and official establishments, guaranteeing accuracy and completeness. The data source names are listed in Table 1 below.

Table 1: Set of Variables

Variable Name	Source	Literature Reference
Future Contract Price (TUPRS_F)	Tradingview	(Ayankoya et al., 2016)
Stock Price (X1 - TUPRS)	Tradingview	(Xu, 2023)
Market Indices (X2 - XU100)	Tradingview	(Novandi and Falah, 2023)
Exchange Rates (X3 - USDTRY)	Tradingview	(Adaramola et al., 2023)
Inflation Rates (X4 - InflationRate)	TÜİK (Turkish Statistical Institute)	(Novandi and Falah, 2023; Ervina et al., 2022)

Data Pre-processing

The cleanliness of the raw data we use for processing is an important step in the data analytics pipeline (Isik et al., 2012). Two well-known solutions to tackle problems in this stage are data consistency enhancement and missing value imputation (Adineh et al., 2020). This aspect is emphasized by Kalra and Aggarwal (2017), arguing that textual data must be pre-processed and data preparation is a prerequisite for applying machine-learning methods. Before modelling, preprocessing steps are implemented to maintain the data's accuracy and consistency and enable modelling. These steps included:

Variables' ranges and scales are different, so all are normalized. The z-score normalization method is used to standardize the scale of various variables and aid in the model's convergence. The training and testing datasets are separated from the original datasets. To help the model learn efficiently, 80% of the data is used in the model's training process; 20% is used for testing to assess how well the model can predict data that has yet to be observed. After the preparation stage, the data were entered into the modelling program, establishing the foundation for the study's primary analysis.

Exploratory Data Analysis

Exploratory data analysis is a fundamental preliminary step in the modelling process. By understanding the entire dataset comprehensively, it is possible to gain insight into the modelling objectives and data requirements. Exploratory data analysis encompasses a range of techniques that collectively form a valuable tool set for pre-modelling investigations.

Descriptive Statistics

We first looked at some of our dataset's basic statistical properties to begin our exploratory data analysis. Descriptive statistics are used for this purpose, which help us understand the data distributions' central tendencies, dispersions, and shapes. We calculated the mean, median, standard deviation, and other vital statistics for each variable in our dataset to understand their characteristics.

Table 2: Descriptive Statistics

	Inflation Rate	XU100	Interest Rate	USDTRY	TUPRS	TUPRS_F
count	74	74	74	74	74	74
std	2.6186	1608.12	5.57147	6.46135	25.2662	25.554
75%	2.55	1988.95	18.75	14.4479	26.7821	27.0864
mean	2.29324	1956.4	14.3919	10.0504	28.2758	28.7073
max	13.6	7917.93	25	27.2999	141.1	138.77

Count: All columns have 74 entries, indicating no missing values in this dataset for these variables.

Mean: The mean (average) shows the central tendency of each variable. For instance, the average of TUPRS_F is approximately 28.71, indicating that the typical value of this futures contract price over the observed period is around this figure.

Std (Standard Deviation): This measures the variation or dispersion of a set of values. A low standard deviation indicates that the values are close to the mean, while a high standard deviation indicates a broader range of values. For example, TUPRS and TUPRS_F have a relatively high standard deviation (around 25.27 and 25.55, respectively), indicating significant fluctuations in these stock prices over the period.

Max: This represents the highest value recorded for each variable during the period. The maximum values, especially for TUPRS and TUPRS_F, highlight some of the peaks in the data, which could be due to various market factors.

75% (Third quartile): This is the median of the upper half of the data and shows that 75% of the data points fall below this value. For instance, 75% of TUPRS_F values are below approximately 27.09.

Correlation Analysis

A correlation analysis is conducted to understand the relationships between the variables. The heat map revealed significant correlations between certain variables, notably between the stock price (TUPRS) and the futures contract price (TUPRS_F). Such relationships are crucial in guiding subsequent modelling efforts and understanding potential multicollinearity issues.

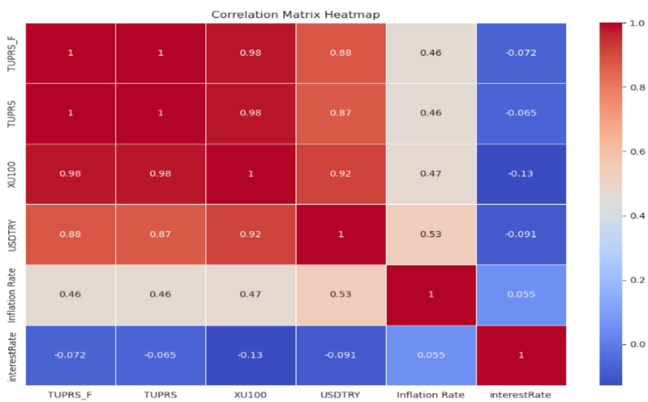

Figure 1: Correlation matrix

In Figure 1, the heat map visually represents the correlation coefficients between variables. Darker shades of blue indicate strong positive correlations, while darker shades of red indicate strong negative correlations. The variable TUPRS_F (Futures Contract Price) has strong positive correlations with TUPRS (Stock Price) and XU100 (Market Indices). It suggests that the futures contract price also increases as these variables increase. In the modelling section, whether a multicollinearity problem exists was evaluated.

Distribution Analysis

Histograms and density plots visualize the distribution of critical variables. These figures highlighted the distributions' skewness and kurtosis, indicating potential outliers and the need for data transformations.

In Figure 2, the histograms provide insights into each variable's distribution and frequency of values. The kernel density estimation (KDE) curves give a smoothed representation of the distribution. Variables like TUPRS_F, TUPRS, and XU100 appear to have a somewhat normal distribution. Other variables like USDTRY, Inflation Rate, and Interest Rate show varied distributions with potential skewness.

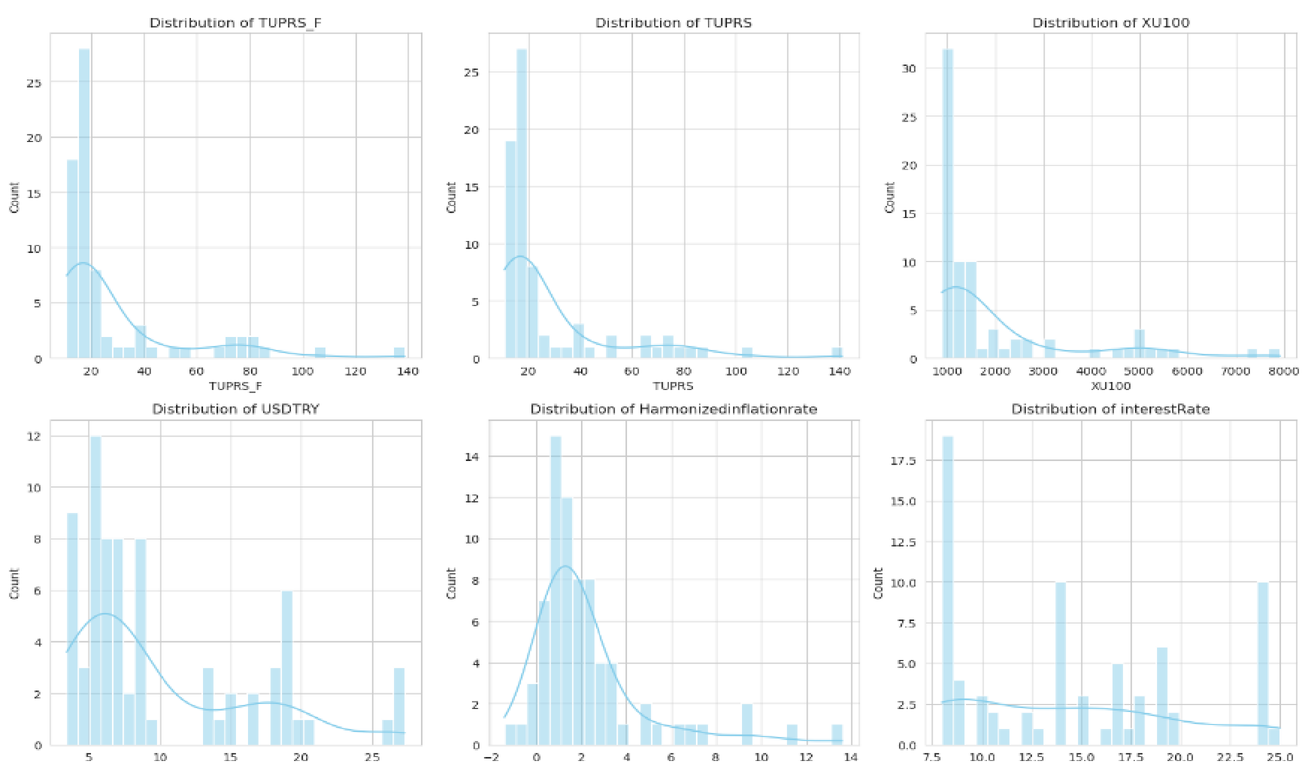

Figure 2: Distribution Analysis

Time Series Decomposition

Time series decomposition plays an instrumental role in distinguishing between the trend and cycle of time series data. Proper estimation of trends is pivotal when undertaking cyclical analysis, ensuring that the underlying patterns and fluctuations in the data are accurately represented and interpreted. It is noteworthy to highlight that various detrending methods yield broadly consistent outcomes. These outcomes agree with the identified chronology of growth cycles (Zarnowitz and Ozyildirim 2006). West (1997) offers an insightful perspective on time series decomposition, emphasizing its practicality and relevance in the analysis of observed data. Using dynamic linear models allows inferences about the latent component series. These components usually have a physical or substantial interpretation through which the data can be understood. A popular subclass in this sense is that of the state space autoregressive component models. In this framework, the decomposition is also particularly useful in identifying the hidden quasi-cyclic components. Time series decomposition analysis is performed for the futures contract price of the TUPRS_F, where the time series data is broken into the observed, trend, seasonal, and residual components. It is done to see the periodic behaviour in the data, long-term patterns, and other irregularities or anomalies.

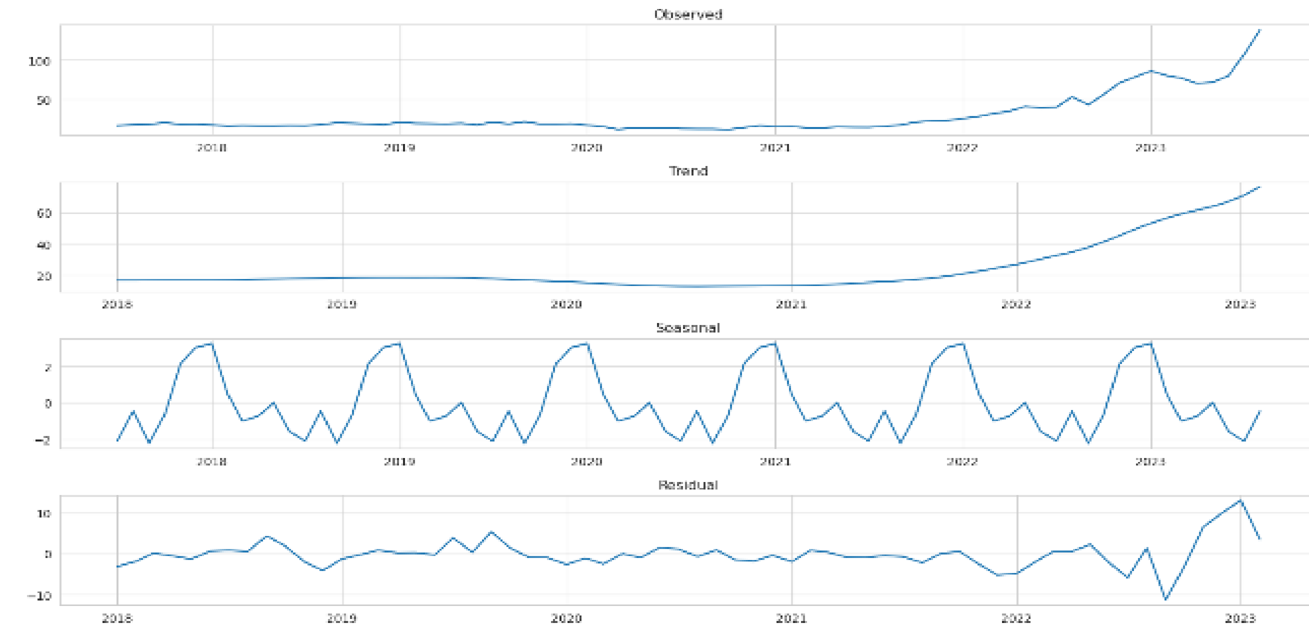

Figure 3: Time Series Decomposition

The initial stage in forecasting the price of the TUPRS_F futures contract involves decomposing the time series to examine its constituent components, including the observed data, trends, seasonal patterns, and residuals.

In general, time series decomposition facilitates the identification of cyclical patterns and underlying trends while also revealing potential irregularities within the data. This process may contribute to a more systematic and rational understanding of the series, thereby enhancing the accuracy of future price forecasts.

Visual Representation and Interpretation of the Results

Observed: The observed plot represents the original unadjusted time series plot of the TUPRS_F.

Trend: The trend component is the smoothed, or filtered, version of the time series that allows us to identify a long-term direction in the TUPRS_F. In this case, the trend is slightly upward.

After reviewing the data, it is evident that TUPRS_F has been steadily climbing over the observed period. This consistent upward movement is crucial for setting expectations and building predictive models, as it highlights a stable trend that can guide future forecasts.

Seasonal: This is where the data exhibits consistent patterns or cycles, implying upcoming periodic influences like what has occurred in the past. A pattern becomes even more prevalent within our TUPRS_F data, arguing for a solid seasonal effect on the data.

The consistent spikes or dips at regular intervals make it clear that a focus on incorporating seasonality will be essential to increase our predictive model's accuracy and reliability.

Residual: The residual plot is also known as the noise left in the data after both the trend and seasonality series are removed. An ideal result in time series decomposition is when the residuals appear random and lack discernible structure. This randomness suggests that the model has successfully captured the underlying patterns in the data.

Unit Root Test

A unit root test is conducted to understand the time series data's stationarity. A unit-root test evaluates the null hypothesis that a time series contains a unit root, signalling non-stationarity and a stochastic trend (Dickey et al., 1986). If structural breaks are ignored, standard unit-root tests can suffer severe size distortions and power loss, potentially leading to false conclusions about non-stationarity (Lanne et al., 2003). The Augmented Dickey-Fuller (ADF) test is widely applied for this purpose, yet its assumption of complete data limits its direct use when observations are missing (Fowler et al., 2024). When level shifts are present, Dickey–Fuller–type tests should estimate parameters under the unit-root null rather than local alternatives to preserve test reliability (Lanne et al., 2002).

Visual inspection of the time series decomposition (Figure 3) and ACF/PACF diagnostics (Figure 8) indicates that while seasonal patterns appear to be present, they do not appear to dominate the series. The seasonal component seems relatively modest in amplitude compared to the trend and residual components, and seasonal autocorrelations are insignificant. Given these observations, explicit seasonal modelling or differencing is not considered necessary. Consequently, the study adopts a non-seasonal ARIMA framework, which is supported by the observed predictive accuracy and satisfactory residual diagnostics, applying standard ADF tests rather than seasonality-based unit root tests. The results indicated the need for differencing to achieve stationarity, guiding the subsequent steps in the ARIMA modelling process.

Table 3 below shows the results of the unit root test (ADF test) for the time series data of TUPRS_F:

Table 3: Unit Root Test Statistics

Level	First Difference
ADF Statistic: 0,1962	ADF Statistic: -7,6697
P-value: 0,9720	P-value: 0,0000
Critical Values:	Critical Values:
1%: -3,5369	1%: -3,5242
5%: -2,9079	5%: -2,9023
10%: -2,5915	10%: -2,5885

In Table 3, for the level results, the ADF statistic (0.1962) is greater than all critical values, and the p-value (0.9720) exceeds the 0.05 threshold. Therefore, the null hypothesis of a unit root cannot be rejected, suggesting that the series is non-stationary. When the test is applied to the first-differenced series, the ADF statistic (-7.6697) is below all critical values, and the p-value (0.0000) falls well below 0.05. These results indicate that the null hypothesis is rejected at the first difference, and the series can be considered stationary after differencing.

4. Model Building and Evaluation

Building model

The development process involves creating three models in succession. The initial model is a basic ARIMA framework, which is then optimized using a Bayesian optimization algorithm. The final model incorporates exogenous variables using an ARIMAX structure.

The ADF test ensures that the data meet the stationarity requirement for time series modelling. The findings indicate non-stationarity at the level but stationarity after first-order differencing. Consequently, we employ differenced data (d=1) in all model iterations.

Model Selection and Initial Results

The ARIMA (Autoregressive Integrated Moving Average) model is the most appropriate given the characteristics of our data and the study's objectives. This choice is motivated by its capability to handle non-stationary data and describe various time series patterns. Consequently, Model 1, the preliminary ARIMA model, is fitted using p=1, d=1, and q=1; in other words, the model is fitted without optimization. Figure 4 displays the results of Model 1.

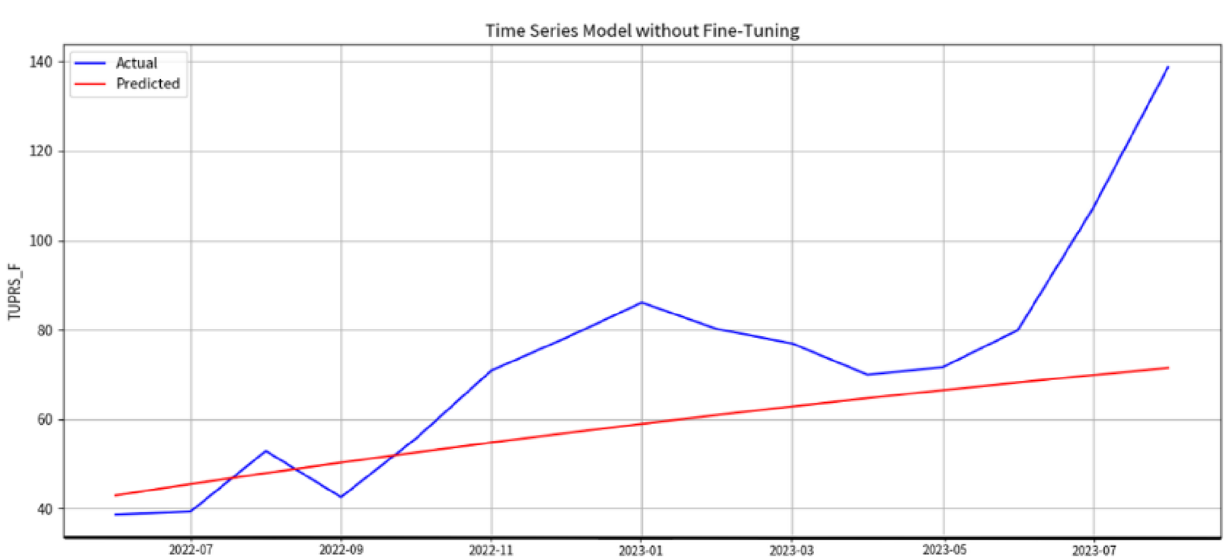

Figure 4: Time Series Model without Fine-Tuning

Model Fine-tuning and Results

The ARIMA model's parameters are adjusted to improve the model. To make sure the model is doing as well as it can, the Akaike Information Criterion (AIC) is used. During this step, a methodical grid search is carried out to test every possible combination of parameters and find the best combination that shows the lowest AIC value for Model 2. The characteristics of the revised ARIMA model for Model 2 are p=2, d=1, and q=0. The results of this improved model are shown in Figure 5.

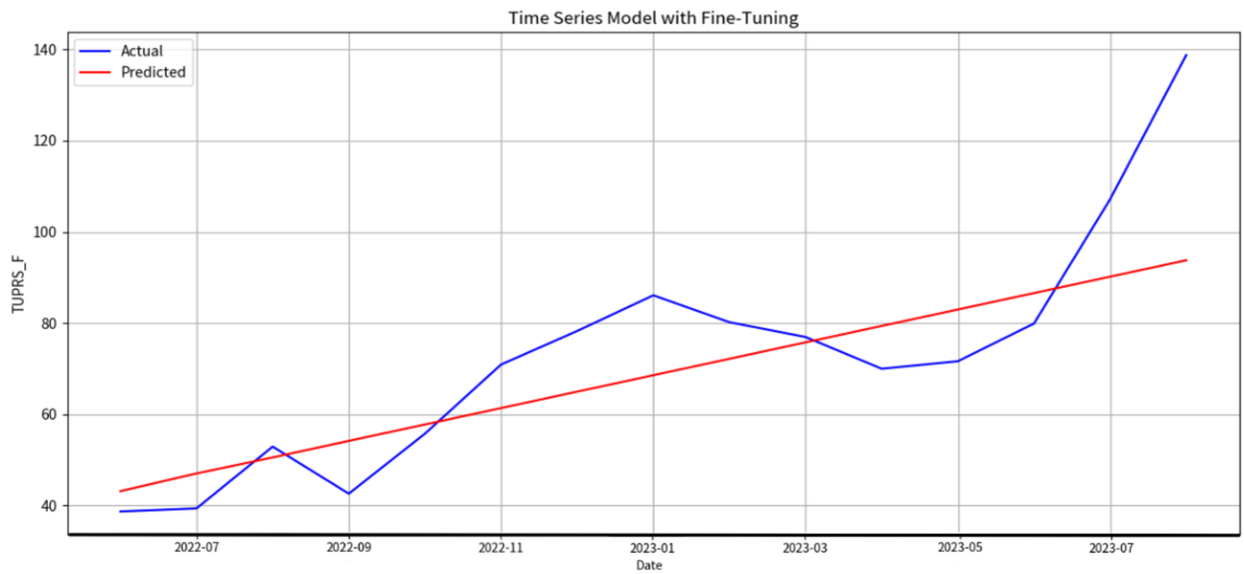

Figure 5: Time Series Model with Fine-Tuning

Incorporating Exogenous Variables and Results

We further enhance the accuracy of the predictive model by extending our methods beyond the conventional ARIMA structure. In Model 3, we introduce external factors: stock prices, market indices, exchange rates, inflation, and interest rates. We use the SARIMAX technique with parameters p=2, d=1, and q=0. This strategy considers the impact of these outside variables smoothly.

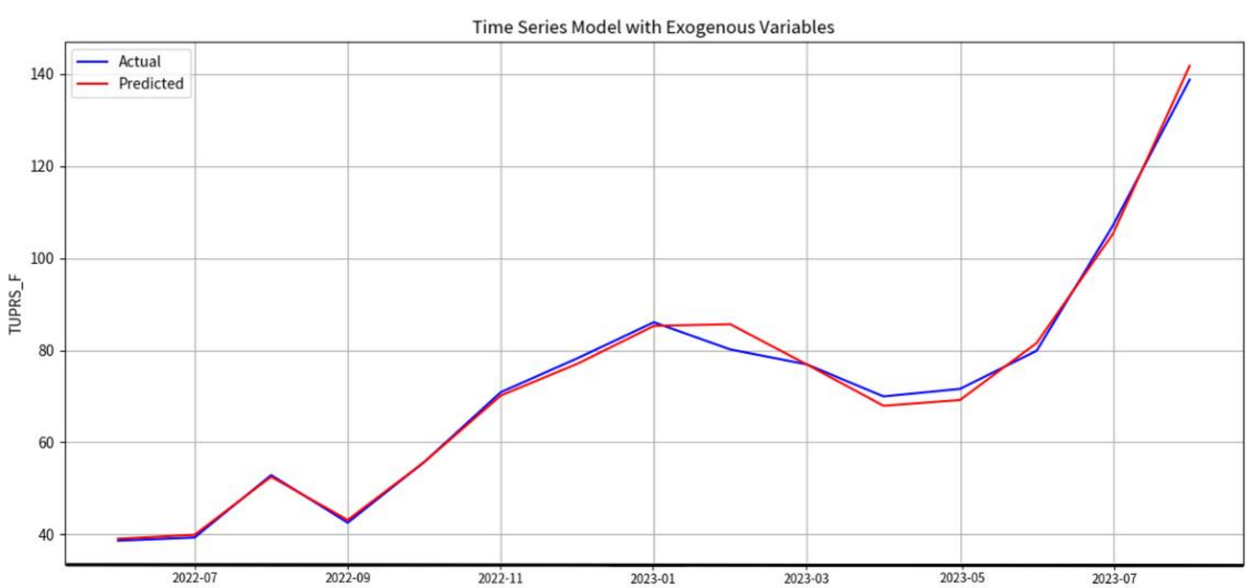

Figure 6: Time Series Model with Exogenous Variables

Our analysis suggests a strong positive relationship between TUPRS_F (futures contract price), TUPRS (stock price), and XU100 (market indices). It indicates how the price of the futures contract follows the up of the latter variables. We were cautious of multicollinearity during our modelling.

The inclusion of exogenous variables should be thoroughly checked for multicollinearity, paying special attention to the correlation between the Tupraş share price and the future contract price. To ascertain this, we formulated two distinct scenarios:

- Scenario 1: Including TUPRS
- Scenario 2: Excluding TUPRS

Figure 7 illustrates a detailed comparison between these two scenarios, highlighting their performance metrics.

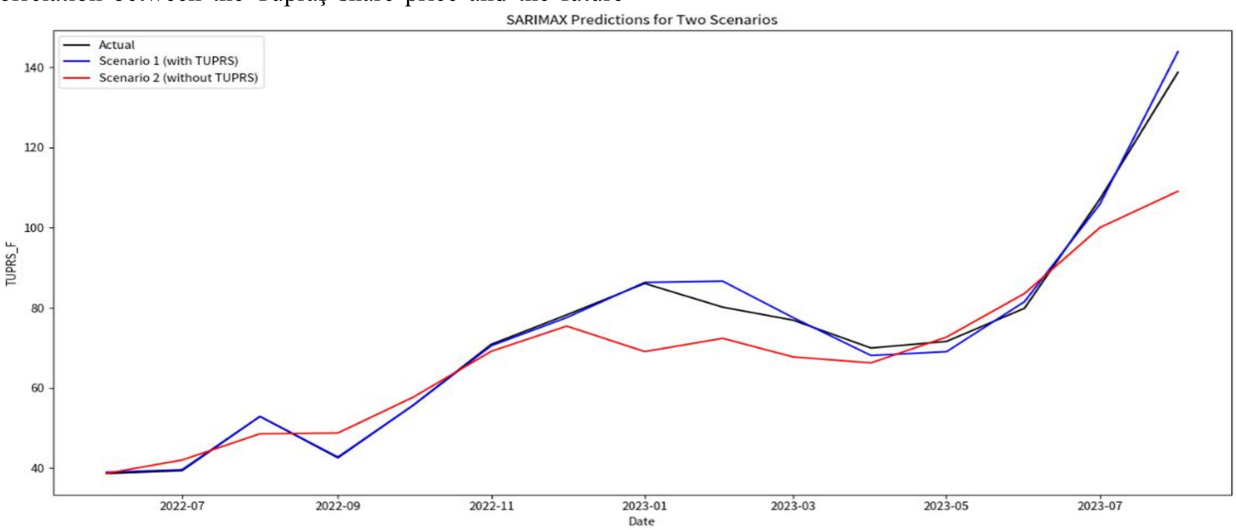

Figure 7: SARIMAX Predictions for Two Scenarios

The metrics in Table 4 provide valuable indices that offer an overall view of the model's excellence and reliability. These metrics depict the value of each approach against various scenarios and represent the situation at hand. A well-structured comparison of different optimization approaches provides valuable insights into their pros and cons. This understanding is essential for selecting the most suitable method for a given problem and making informed adjustments to enhance model performance.

In addition to overall error measures, we considered model behaviour under differing market conditions to provide further insight into its potential generalizability. For example, during the relatively low-volatility phase in 2019, the model's forecast errors remained limited (RMSE below 2.5 TRY). In contrast, in the more volatile period associated with the 2022 energy shock, RMSE increased to approximately 3.0 TRY. Throughout these periods, the primary exogenous variables—exchange rates, inflation, and the XU100 index—continued to account for a large proportion of the variance in futures prices, with explained variance exceeding 90%. While these results do not offer a definitive conclusion, they may indicate that the model retains a reasonable degree of predictive consistency across different market regimes.

The Mean Squared Error (MSE) in Scenario 1 is significantly lower, suggesting improved accuracy when TUPRŞ is included as an exogenous factor. It implies a potential enhancement in the model's predictive capability. Similarly, the Root Mean Squared Error (RMSE) is notably reduced in Scenario 1, indicating stronger predictive performance and a closer alignment between predicted and observed values. The Coefficient of Determination (R^2) approaches near-perfect levels in Scenario 1, implying that the independent variables may explain a substantial portion of the variance in TUPRŞ_F, signalling a potentially robust model. Lastly, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) favour Scenario 1, suggesting it may achieve a more favourable balance between model fit and complexity.

Table 4: Statistics for two scenarios

Metric	Scenario 1 (with TUPRS)	Scenario 2 (without TUPRS)
MSE	5,60	98,23
RMSE	2,37	9,91
R^2	0,991	0,849
AIC	87,78	215,68
BIC	104,27	230,11

5. Findings

Our modelling process began with visually inspecting the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) for the TUPRS_F time series, as depicted in Figure 8 below.:

The ACF plot, by design, reveals the correlation of a time series with its sequential lags. Our observations highlight a steady decay in autocorrelation values as lag numbers increased, hinting at a probable AR term in the model. On the other hand, the PACF plot, which reflects the correlation of the time series with its lags minus the influences of any preceding lags, shows a pronounced decline after the second lag. This observation underpins the inference that the optimal AR term could be approximately 2.

Several confirmations emerge regarding ARIMAX model parameters. The PACF plot's suggestion of an AR term around 2 is in harmony with our previously determined optimal parameter (p=2). Furthermore, the optimal differencing term (d=1) identified earlier agrees with the time series trend we observed. As for the MA term, the ACF plot's gradual decline indicates a potential need for such a term, a notion supported by our earlier findings, which pinpoint q=1 as the optimal parameter. Moreover, it is worth noting that integrating exogenous variables like TUPRS, XU100, USDTRY, Inflation Rate, and Interest Rate significantly bolstered the ARIMAX model's precision, as evidenced by a diminished RMSE.

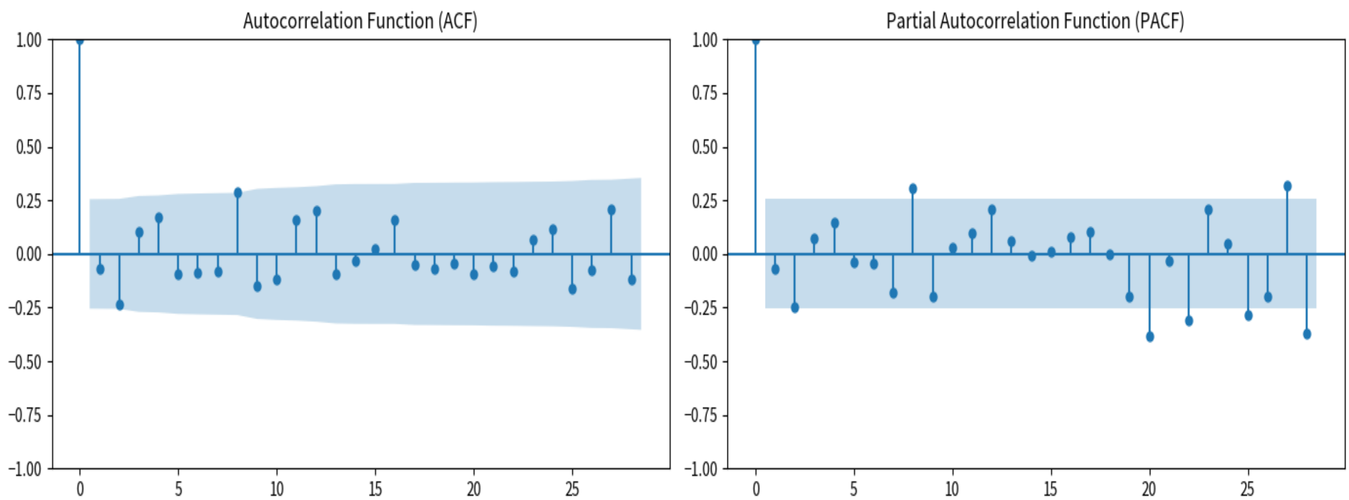

Figure 8: Autocorrelation Function (ACF), Partial Autocorrelation Function (PACF) Plots

Our approach stands out for carefully evaluating how well the models perform. To achieve this, we used a wide range of metrics, such as R2, AIC, BIC, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The benefits of careful parameter optimization and the thoughtful addition of exogenous variables were readily seen when these findings were compared to a baseline ARIMA model that had not been adjusted.

Model 1 makes a strong argument for re-examination. Its noticeably high error metrics serve as a warning sign, suggesting that other models might be more suited to capture the nuances of the given data. The error data clearly shows that Model 3 is the better option. It has the lowest values for MAE, MSE, and RMSE. It suggests that it may be one of the more accurate representations. On the other hand, Model 2 is not as precise, even with its remarkable improvement over Model 1. As much as Model 2 outperforms the baseline, it still does not reach the standard established by Model 3.

Examining the Coefficient of Determination (R^2) further consolidates these observations:

- Model 3, boasting an R^2 value of 0.9914, exemplifies excellence by accounting for approximately 99.14% of the variance in the dependent variable.
- Model 2, with an R^2 value of 0.1508, leaves much room for improvement, explaining only 15.08% of the variability.
- Model 1, curiously, registers a negative R^2. Such values typically indicate a model's inability to fit the data, often performing worse than a horizontal line.

Finally, turning our attention to model complexity metrics (AIC and BIC):

- Model 3 emerges as the frontrunner, presenting the lowest values and indicating an optimal balance between fit and complexity.
- Model 1 falls short when considering other evaluative metrics like R^2, despite having lower AIC and BIC values than Model 2.
- Model 2, although burdened with higher AIC and BIC values than Model 1, trumps the latter in error metrics and R^2, signifying a better overall fit.

While the in-sample R^2 value of 0.991 may raise concerns regarding potential overfitting, the results from our hold-out evaluation provide additional context. When the SARIMAX model is applied to the test set covering September 2022 to August 2023, it produces an R^2 of 0.958, an RMSE of 2.75, and an MAE of 2.10.

These values indicate a limited decline in predictive performance compared to the training period (R^2 = 0.991; RMSE = 2.37; MAE = 1.85). Although some degradation is expected in out-of-sample evaluation, the magnitude of change observed here may be considered moderate, suggesting that the model's performance on unseen data remained relatively stable during the test period.

6. Conclusion

Accurate forecasting of futures market movements is crucial for investors, analysts, and policymakers due to the volatility and complexity of financial markets. This study demonstrates that incorporating exogenous variables into traditional time series models, specifically the ARIMAX framework, significantly improves the accuracy of forecasting stock-based futures prices. The research adds to the existing literature by involving external economic information, considering market indexes, foreign exchange rates, and macroeconomic variables, indicating that futures pricing is affected by vast external factors rather than independent action. This result implies that using rich data inputs contributes to the accuracy of financial predictions.

Previous studies (e.g., Cabrera et al., 2018; Caporin and Fontini, 2017) emphasize that flexible model frameworks must accommodate time-varying volatility, market changes, and data characteristics typically not captured by simple models, such as ARIMA. Moreover, studies by Holmes and Otero (2019), Chuffart and Hooper (2019), and Tiwari et al. (2019) further emphasize the role of external economic factors, like world oscillations and commodity prices, in determining futures prices, demonstrating the interdependence between financial markets. In addition, Rodrigues et al. (2018) and Scheitrum et al. (2018) emphasize the necessity for such models that adjust to nonlinearities and abrupt changes in the market.

The results of this study are consistent with including exogenous variables into the ARIMA model as an ARIMAX structure to increase the predictive accuracy of Tupraş futures prices. Adding international factors like market indices and exchange rates enables the model to predict future price movements more effectively. The findings align with current knowledge, highlighting the importance of external economic conditions in forecasting future prices.

It also contributes to the literature regarding the importance of non-stationary models in capturing abrupt market changes and non-linearity. The ARIMAX model, by including exogenous variables, can better approximate these dynamics and lead to better predictions. This approach is consistent with the work of Rodrigues et al. (2018) and Scheitrum et al. (2018), who explicitly support flexible modelling that can adapt to new market dynamics.

However, the study has some drawbacks. It relies on a single case study—Tupraş futures—over a specific period; hence, the extent of generalizability is unknown. There is also the possibility that historical knowledge could be outdated when market conditions change in such a way that conventional methods cannot predict real-time market changes. It is desirable to investigate how the addition of real-time data can improve the model's stability. Furthermore, the hybrid methodologies integrating econometric models such as ARIMAX with machine learning algorithms may capture nonlinearities and complexities in the financial market.

Extending this method to work on other sub-trend instruments like commodity, derivative, and equity would give us a broader view of the ARIMAX model and its performance. Using current data would help forecasting be more accurate, particularly in times of market turbulence.

The better predictive performance of the ARIMAX model results in practical implications for investors, analysts, and policymakers. Investors and analysts can make better decisions, while policymakers can use those insights to help craft regulations and manage market volatility. By analysing the influence of major macro factors on future prices, decision-makers could predict the market turning point and make better policies ahead of schedule.

Finally, we can conclude that integrating exogenous variables enhances forecast accuracy in the ARIMA model, thus adding to the literature on financial forecasting. The results highlight the role of external proxies for the economy and relevant ones in forecasting future prices, and they are consistent with the body of literature that proposes a connected nature between financial markets. This study provides practical implications for risk management and policy making. It suggests future work to improve the model with high-frequency data and mixed approaches for more accurate forecasting of dynamic financial markets.

References

Ab Rahman, N. M. N., Nawi, A. S., & Naziman, Y. H. N. M. (2012). The price discovery of the Malaysian crude palm oil futures markets. *Journal of Applied Finance and Banking, 2*(4), 25.

Abraham, R., & Harrington, C. (2016). Determinants of oil futures prices. *Theoretical Economics Letters, 6*, 742–749. http://dx.doi.org/10.4236/tel.2016.64078

Adaramola, A., Abere, M. A., & Ogiamien, O. F. (2023). Effect of exchange rate on stock price movement in Nigeria. *Financial Markets, Institutions and Risks, 7*(2), 18–27. https://doi.org/10.21272/fmir.7(2).18-27.2023

Adineh, A. H., Narimani, Z., & Satapathy, S. C. (2020). Importance of data preprocessing in time series prediction using SARIMA: A case study. *International Journal of Knowledge-Based and Intelligent Engineering Systems, 24*(4), 331–342. https://doi.org/10.3233/KES-200065

Ak, R., Türk, A., & İslatince, H. (2019). Estimation of energy prices in Turkey in the Nash-Cournot framework. *International Journal of Business and Applied Social Science, 5*(7), 1–15.

Allen, D. E., Chang, C., McAleer, M., & Singh, A. K. (2018). A cointegration analysis of agricultural, energy and bio-fuel spot, and futures prices. *Applied Economics, 50*(7), 804–823. https://doi.org/10.1080/00036846.2017.1340581

Alzoubi, M. (2022). Stock market performance: Reaction to interest rates and inflation rates. *Banks and Bank Systems, 17*(2), 189–198.

https://doi.org/10.21511/bbs.17(2).2022.16

Ayankoya, K., Calitz, A. P., & Greyling, J. H. (2016). Using neural networks for predicting futures contract prices of white maize in South Africa. In *Proceedings of the Annual Conference of the South African Institute of Computer Scientists and Information Technologists* (p. 3). Association for Computing Machinery. https://doi.org/10.1145/2987491.2987508

Azevedo, T. C., Aiube, F. L., Samanez, C. P., Bisso, C. S., & Costa, L. A. (2015). The behavior of West Texas Intermediate crude-oil and refined products prices volatility before and after the 2008 financial crisis: An approach through analysis of futures contracts. *Ingeniare. Revista chilena de ingeniería, 23*(3), 395–405. https://doi.org/10.4067/S0718-33052015000300008

Cabrera, G., Coronado, S., Rojas, O., & Romero-Meza, R. (2018). A Bayesian approach to model changes in volatility in the Mexican stock exchange index. *Applied Economics, 50*(15), 1716–1724. https://doi.org/10.1080/00036846.2017.1374536

Cagaptay, S., & Evans, T. (2013). Turkey's energy policy and the future of natural gas. *Harvard Kennedy School, James A. Baker III Institute for Public Policy of Rice University.*

Caporin, M., & Fontini, F. (2017). The long-run oil–natural gas price relationship and the shale gas revolution. *Energy Economics, 64*, 511–519. https://doi.org/10.1016/j.eneco.2016.07.024

Çatak, Ç. (2022). Energy derivatives—An analysis of the Turkish electricity market. *Uluslararası İktisadi ve İdari İncelemeler Dergisi.* https://doi.org/10.18092/ulikidince.930399

Chan, K. F., & Gray, P. (2017). Do scheduled macroeconomic announcements influence energy price jumps? *Journal of Futures Markets, 37*(1), 71–89. https://doi.org/10.1002/fut.21796

Chen, X., & Hu, Y. (2022). Volatility forecasts of stock index futures in China and the US – A hybrid LSTM approach. *PLOS ONE, 17*(7), e0271595. https://doi.org/10.1371/journal.pone.0271595

Chi, S. C., Chen, H. P., & Cheng, C. H. (1999, July). A forecasting approach for stock index future using grey theory and neural networks. In *IJCNN'99. International Joint Conference on Neural Networks. Proceedings* (Vol. 6, pp. 3850–3855). IEEE.

Chuffart, T., & Hooper, E. (2019). An investigation of oil prices impact on sovereign credit default swaps in Russia and Venezuela. *Energy Economics, 80*, 904–916. https://doi.org/10.1016/j.eneco.2019.02.003

Demirbas, A. (2006). Turkey's renewable energy facilities in the near future. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 28*(6), 527–536. https://doi.org/10.1080/009083190927985

Dickey, D. A., Bell, W. R., & Miller, R. B. (1986). Unit roots in time series models: Tests and implications. *The American Statistician, 40*(1), 12–26. https://doi.org/10.1080/00031305.1986.10475349

Dincer, S. K., Kamal, K., & Gultekin, A. N. (2017). Energy policies for sustainable energy future in Turkey. *Journal of Engineering Research and Applied Science, 6*(1), 537–542.

Ekinci, M. F., & Saygılı, H. (2023). Oil price pass-through on sector-level prices: Evidence from Turkey. *Business and Economics Research Journal, 14*(3), 321–335. https://doi.org/10.20409/berj.2023.418

Ervina, N., Azwar, K., Susanti, E., & Dewi Nainggolan, C. (2022). Effect of inflation, exchange rates, and trading volume activity on stock price indices during the COVID-19 pandemic on companies in the basic industry and chemical sectors. *International Journal of Science, Technology & Management, 3*(6), 1650–1658. https://doi.org/10.46729/ijstm.v3i6.693

Fernandez, V. (2016). Spot and futures markets linkages: Does contango differ from backwardation? *Journal of Futures Markets, 36*(4), 375–396. https://doi.org/10.1002/fut.21736

Figlewski, S. (1984). Margins and market integrity: Margin setting for stock index futures and options. *Journal of Futures Markets, 4*(3), 385–416. https://doi.org/10.1002/fut.3990040307

Fowler, C., Cai, X., Baker, J. T., Onnela, J.-P., & Valeri, L. (2024). Testing unit root non-stationarity in the presence of missing data in univariate time series of mobile health studies. *Journal of the Royal Statistical Society: Series C, 73*(3), 755–773. https://doi.org/10.1093/jrsssc/qlae010

Go, Y. H., & Lau, W. Y. (2019). Palm oil spot-futures relation: Evidence from unrefined and refined products. *Agricultural Economics (Zemědělská ekonomika), 65*(3), 133–142. https://doi.org/10.17221/31/2018-AGRICECON

Gomaa, M. (2012). An empirical investigation of the relationship between executive risk sharing and stock performance in new and old economy firms. *Accounting and Finance Research, 1*(1), 106. https://doi.org/10.5430/afr.v1n1p106

Hanitha, V., Yoyo, T., & Silaswara, D. (2022). Analysis effect of BI rates, inflation and exchange rates on the composite stock price index on the Indonesia stock exchange 2016–2021. *Akuntoteknologi, 14*(1), 1–10. https://doi.org/10.31253/aktek.v14i1.1423

Hitzemann, S. (2016). Macroeconomic fluctuations, oil supply shocks, and equilibrium oil futures prices. *SSRN*

Electronic Journal. https://doi.org/10.2139/ssrn.2513624

Holmes, M. J., & Otero, J. (2019). Re-examining the movements of crude oil spot and futures prices over time. *Energy Economics, 82*, 224–236. https://doi.org/10.1016/j.eneco.2017.08.034

Hosseini, S. H., Shakouri G, H., & Peighami, A. (2016). A conceptual framework for the oil market dynamics: A systems approach. *Energy Exploration & Exploitation, 34*(2), 171–198. https://doi.org/10.1177/0144598716631656

Hu, Y. (2016). Study on effects of CSI 300 stock index futures on Chinese stock market volatility. In *Proceedings of the 2nd International Conference on Financial Management, Education and Information Technology Applications* (pp. 344–350). Atlantis Press. https://doi.org/10.2991/IFMEITA-16.2016.65

İsik, F., Ozden, G., & Kuntalp, M. (2012). Importance of data preprocessing for neural networks modeling: The case of estimating the compaction parameters of soils. *Energy Education Science and Technology Part A: Energy Science Research, 29*(2), 871–882.

Joarder, S. (2018). The commodity futures volatility and macroeconomic fundamentals: The case of oil and oilseed commodities in India. *International Econometric Review, 10*(2), 33–50. https://doi.org/10.33818/ier.491326

Jongadsayakul, W. (2022). Determinants of the successful single stock futures market in Thailand. *Investment Management and Financial Innovations, 19*(2), 274–284. http://dx.doi.org/10.21511/imfi.19(2).2022.24

Kalra, V., & Aggarwal, R. (2017). Importance of text data preprocessing & implementation in RapidMiner. In *Proceedings of the 2017 International Conference on Information Technology and Knowledge Management*, 14, 71–75. https://doi.org/10.15439/2017KM46

Kaplan, Y. A., & Aladağ, C. (2016). The importance of the different kinds of energy sources for energy future of Turkey. In *EPJ Web of Conferences* (Vol. 128, p. 05002). EDP Sciences. https://doi.org/10.1051/epjconf/201612805002

Kara, B., Emir, Z., Seker, T., Bahadir, A., & Kaygusuz, K. (2017). Current state and future prospects of biomass energy in Turkey. *Journal of Engineering Research and Applied Science, 6*(1), 522–529.

Kaygusuz, K. (2004). The role of renewables in future energy directions of Turkey. *Energy Sources, 26*(12), 1131–1140. https://doi.org/10.1080/00908310490441449

Kilian, L., & Vega, C. (2011). Do energy prices respond to US macroeconomic news? A test of the hypothesis of predetermined energy prices. *Review of Economics and Statistics, 93*(2), 660–671. https://doi.org/10.1162/REST_a_00086

Kiliç, A. M. (2006). Turkey's main energy sources and importance of usage in energy sector. *Energy Exploration & Exploitation, 24*(1–2), 1–17. https://doi.org/10.1260/014459806779388001

Krishnan, R. S., & Mani, D. (2019). Uncertainty and compensation design in strategic interfirm contracts. *Contemporary Accounting Research, 37*(1), 542–574. https://doi.org/10.1111/1911-3846.12510

Lanne, M., Lütkepohl, H., & Saikkonen, P. (2002). Comparison of unit root tests for time series with level shifts. *Journal of Time Series Analysis, 23*(6), 667–685. https://doi.org/10.1111/1467-9892.00285

Lanne, M., Lütkepohl, H., & Saikkonen, P. (2003). Test procedures for unit roots in time series with level shifts at unknown time. *Oxford Bulletin of Economics and Statistics, 65*(1), 91–115. https://doi.org/10.1111/1468-0084.00036

Li, X., & Zeyuan, W. (2022). The application of neural network in stock and futures forecasting. In *Proceedings of the 4th International Conference on Economic Management and Model Engineering (ICEMME 2022)*, November 18–20, Nanjing, China. EAI. https://doi.org/10.4108/eai.18-11-2022.2326945

Lu, Q., Li, Y., Chai, J., & Wang, S. (2020). Crude oil price analysis and forecasting: A perspective of "new triangle". *Energy Economics, 87*, 104721. https://doi.org/10.1016/j.eneco.2020.104721

Malhotra, M. (2015). Evaluating the hedging performance of oil and oilseeds futures in India. *Paradigm, 19*(2), 184–196. https://doi.org/10.1177/0971890715609990

Miljkovic, D., & Goetz, C. (2020). The effects of futures markets on oil spot price volatility in regional US markets. *Applied Energy, 273*, 115288. https://doi.org/10.1016/j.apenergy.2020.115288

Motengwe, C., & Alagidede, P. (2016). Maturity effects in futures contracts on the SAFEX market. *Agrekon, 55*(4), 331–355. https://doi.org/10.1080/03031853.2016.1243064

Müftüler-Baç, M., & Başkan, D. (2011). The future of energy security for Europe: Turkey's role as an energy corridor. *Middle Eastern Studies, 47*(2), 361–378. https://doi.org/10.1080/00263206.2010.481176

Ningshen, N., Jindal, V., & Bedi, P. (2024). CGM: A hybrid model for forecasting future stock price. In *Symposium on Computing & Intelligent Systems (SCI)* (pp. 126–137). New Delhi, India.

Novandi, A. K., & Falah, M. F. (2023). The influence of inflation, interest rates, and exchange rates on the composite stock price index (IHSG) in Indonesia: English. *Asian Economic and Business Development,* *6*(1), 43–48. https://doi.org/10.54204/AEBD/Vol6No1August2023006

Okay, E. (2015). Creative energy alternatives: Cheap and clean future energy for Turkey. In *Handbook of Research on Developing Sustainable Value in Economics, Finance, and Marketing* (pp. 157–178). IGI Global Scientific Publishing.

Öz, S., & Alyürük, M. (2020). Energy sector overview and future prediction for Turkey. *Journal of Industrial Policy and Technology Management, 3*(1), 59–69.

Ozdamar, L., Yaşa, E., Kavas, N., & Vardar, G. (2020). Renewable energy investment prospects in Turkey's power generation sector. *International Journal of Renewable Energy Technology, 11*(1), 1–12. https://doi.org/10.1504/IJRET.2020.106513

Özdurak, C. (2021). Conditional correlations and volatility spillovers between crude oil price, Tüpraş and Enerjisa stock returns: A proposal for constructing an ultimate BIST energy index. *Journal of Finance Letters (Special Issue 2)*, 15–32. https://doi.org/10.33203/MFY.844802

Ozturk, H. K. (2004). Present status and future prospects of hydroelectric energy in Turkey. *Energy Sources, 26*(9), 829–840. https://doi.org/10.1080/00908310490451385

Pradhan, K. C. (2011). The hedging effectiveness of stock index futures: Evidence for the S&P CNX Nifty index traded in India. *South East European Journal of Economics and Business, 6*(1), 111–123. https://doi.org/10.2478/v10033-011-0010-2

Raut, S., & Shrivas, A. (2024). Stock market price prediction and forecasting using stacked LSTM. *International Journal of Scientific Research in Engineering and Management, 8*(3), 1–6. https://doi.org/10.55041/IJSREM29832

Rodrigues, N., Losekann, L., & Silveira Filho, G. (2018). Demand of automotive fuels in Brazil: Underlying energy demand trend and asymmetric price response. *Energy Economics, 74*, 644–655. https://doi.org/10.1016/j.eneco.2018.07.005

Scheitrum, D. P., Carter, C. A., & Revoredo-Giha, C. (2018). WTI and Brent futures pricing structure. *Energy Economics, 72*, 462–469. https://doi.org/10.1016/j.eneco.2018.04.039

Shirodkar, S., & Raju, G. A. (2021). Futures trading, spot price volatility and structural breaks: Evidence from energy sector. *International Journal of Energy Economics and Policy, 11*(4), 230–239. https://doi.org/10.32479/ijeep.11086

Sözen, A., & Arcaklıoğlu, E. (2007). Prospects for future projections of the basic energy sources in Turkey. *Energy Sources, Part B: Economics, Planning, and Policy, 2*(2), 183–201. https://doi.org/10.1080/15567240600813930

Sun, B. Q., Guo, H., Karimi, H. R., Ge, Y., & Xiong, S. (2015). Prediction of stock index futures prices based on fuzzy sets and multivariate fuzzy time series. *Neurocomputing, 151*(Part 3), 1528–1536. https://doi.org/10.1016/j.neucom.2014.09.018

Tevare, V., & Revankar, P. S. (2023, August). Forecasting stock prices with stack transformer. In *2023 International Conference on Circuit Power and Computing Technologies (ICCPCT)*, Kollam, India (pp. 1262–1269). IEEE. https://doi.org/10.1109/ICCPCT58313.2023.10245652

Tiwari, A. K., Trabelsi, N., Alqahtani, F., & Hammoudeh, S. (2019). Analysing systemic risk and time-frequency quantile dependence between crude oil prices and BRICS equity markets indices: A new look. *Energy Economics, 83*, 445–466. https://doi.org/10.1016/j.eneco.2019.07.014

Toklu, E., & Kaygusuz, K. (2012). Present situation and future prospect of energy utilization in Turkey. *Journal of Engineering Research and Applied Science, 1*(2), 73–86.

TradingView. (2023). BIST-TUPRS. https://www.tradingview.com/symbols/BIST-TUPRS/

Truong, L. D., & Friday, H. S. (2021). The impact of the introduction of index futures on the daily returns anomaly in the Ho Chi Minh Stock Exchange. *International Journal of Financial Studies, 9*(3), 43. https://doi.org/10.3390/IJFS9030043

Wahab, M. A. A., Mohamad, A., & Sifat, I. (2019). On contango, backwardation, and seasonality in index futures. *The Journal of Private Equity, 22*(2), 69–82. https://doi.org/10.3905/jpe.2019.1.076

Wang, J., Cheng, Q., & Dong, Y. (2022). An XGBoost-based multivariate deep learning framework for stock index futures price forecasting. *Kybernetes, 52*(10), 4158–4177. https://doi.org/10.1108/K-12-2021-1289

Wang, W., & Nie, H. (2018). Comparative study on forecasting model for stock index future price. *Modern Economy, 9*(4), 750–757. https://doi.org/10.4236/me.2018.94049

West, M. (1997). Time series decomposition. *Biometrika, 84*(2), 489–494. https://doi.org/10.1093/BIOMET/84.2.489

Xiong, X., Liang, J., Cui, Y., Zhang, W., & Zhang, Y. (2017). Analysis of the spot market's T+1 trading system effects on the stock index futures market. *Eurasia Journal of Mathematics, Science and Technology Education, 13*(12), 7679–7693. https://doi.org/10.12973/EJMSTE/77941

Xu, L. (2023). Comparison of future price prediction in context of machine learning approach. *BCP Business &*

Management, 38, 850–855. https://doi.org/10.54691/bcpbm.v38i.3786

Yildiz, T. (2010). Turkey's energy policy, regional role and future energy vision. *Insight Turkey, 12*(3), 33–38. https://www.jstor.org/stable/26334102

Yuksel, I., Arman, H., & Demirel, I. H. (2018, February). Clean energy for future energy policy in Turkey. In *2018 5th International Conference on Renewable Energy: Generation and Applications (ICREGA)*, Al Ain, United Arab Emirates (pp. 260–263). IEEE. http://dx.doi.org/10.1109/icrega.2018.8337590

Zarnowitz, V., & Ozyildirim, A. (2006). Time series decomposition and measurement of business cycles, trends and growth cycles. *Journal of Monetary Economics, 53*(7), 1717–1739. https://doi.org/10.1016/J.JMONECO.2005.03.015

Zhang, X., Wang, J., & Gao, Y. (2019). A hybrid short-term electricity price forecasting framework: Cuckoo search-based feature selection with singular spectrum analysis and SVM. *Energy Economics, 81*, 899–913. https://doi.org/10.1016/j.eneco.2019.05.026