Predictive stock market analysis for Japanese textile companies using ARIMA model

DOI: 10.35530/IT.076.04.2024158

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ABSTRACT – REZUMAT

Predictive stock market analysis for Japanese textile companies using ARIMA model

Predicting the stock prices of Japanese textile companies is crucial for several reasons. First, stock price trends provide valuable insight into the financial health and growth potential of these firms, especially in an industry subject to evolving consumer trends, technological advancements, and global competition. Investors rely on stock price predictions to make informed decisions, helping them maximise returns and manage risks effectively. The study aims to predict the stock prices of Japanese Textile Companies using the ARIMA Model by taking the top 10 textile companies listed on the Tokyo Stock Exchange (TSE) for a span of 10 years, i.e. 2014 to 2023. Upon evaluation of models, it was found that most of the corporations had either a negative impact or no impact of past lagged values on their present value, except for Global Style, which had a positive influence, maybe due to its distinct nature of textile products in comparison to other corporations. Similarly, Itochu was 91% affected by its own past lagged values, maybe due to its huge operations in textiles as well as other sectors distinct from textiles. Mostly due to lagged value of past residuals, all the corporations were negatively affected, but Global Style, Kuraray, Itochu and Yagi were positively impacted, and there was a huge impact seen in terms of Itochu.

Keywords: *textile industry in Japan, forecasting, ARIMA models, time-series, trade*

Analiza predictivă a pieței bursiere pentru companiile din industria textilă japoneză folosind modelul ARIMA

Predicția prețurilor acțiunilor companiilor din domeniul textil din Japonia este crucială din mai multe motive. În primul rând, tendințele prețurilor acțiunilor oferă informații valoroase despre sănătatea financiară și potențialul de creștere al acestor firme, în special într-o industrie supusă tendințelor de consum în continuă evoluție, progreselor tehnologice și concurenței globale. Investitorii se bazează pe predicțiile prețurilor acțiunilor pentru a lua decizii informate, ajutându-i să maximizeze randamentele și să gestioneze eficient riscurile. Studiul își propune să estimeze prețurile acțiunilor companiilor din sectorul textil japonez utilizând modelul ARIMA, luând în considerare primele 10 companii listate la Bursa de Valori din Tokyo (TSE) pentru o perioadă de 10 ani, adică perioada anilor 2014–2023. În urma evaluării modelelor, s-a constatat că majoritatea corporațiilor au avut fie un impact negativ, fie niciun impact al valorilor anterioare întârziate asupra valorii lor actuale, cu excepția Global Style, care a avut o influență pozitivă, poate datorită naturii sale distincte de produse textile în comparație cu alte corporații. În mod similar, compania Itochu a fost afectată în proporție de 91% de propriile valori anterioare întârziate, probabil datorită operațiunilor sale masive în domeniul textilelor, precum și în alte sectoare economice distincte față de sectorul textil. În principal din cauza valorii întârziate a reziduurilor anterioare, toate corporațiile au fost afectate negativ, însă companiile Global Style, Kuraray, Itochu și Yagi au fost afectate pozitiv, iar impactul asupra companiei Itochu a fost semnificativ.

Cuvinte-cheie: *industria textilă în Japonia, predicție, modele ARIMA, serii temporale, comerț*

INTRODUCTION

The history of Japanese textiles is deeply intertwined with the nation's cultural, social, and economic evolution [1, 2]. From the Nara period (710–794), when silk weaving techniques were imported from China, textiles became an essential part of Japanese craftsmanship and art [3]. Silk was highly prized, especially by the aristocracy, and the intricate patterns and vibrant colours reflected the influence of Chinese and Korean culture [4–6]. By the Heian period (794–1185), Japan developed its distinct textile art, particularly with the introduction of kasuri (ikat), shibori (tie-dye), and silk kimono production [7]. The Edo period (1603–1868) saw the flourishing of textile towns like Nishijin in Kyoto, famous for its brocade weaving [8]. The Meiji era (1868–1912) marked Japan's modernisation and the introduction of Western industrial textile machinery [9]. However, traditional techniques such as kimono dyeing, katazome (stencil dyeing), and hand-weaving have persisted, maintaining the unique and rich heritage of Japanese textiles [10, 11].

The current scenario of Japan's textile industry blends traditional craftsmanship with modern innovation [12]. While Japan's textile sector once thrived on large-scale production, global competition has shifted its focus toward high-quality, niche markets [14, 15]. Traditional techniques like shibori (tie-dye), kasuri (ikat), and Kyoto's renowned Nishijin-ori (brocade weaving) continue to thrive, preserved by artisans who emphasise craftsmanship and cultural heritage. At the same time, Japan has embraced cutting-edge textile technology, excelling in technical fabrics, sustainable fibres, and advanced manufacturing processes [16–18]. Japanese textile companies are pioneers in functional fabrics used in sportswear, medical fields, and eco-friendly materials, reflecting a strong commitment to sustainability and innovation. Collaborations between traditional artisans and modern designers have also led to a resurgence of interest in handcrafted fabrics, both domestically and globally [19]. This fusion of old and new allows Japan's textile industry to maintain its unique identity in a highly competitive global market [20].

Investing in Japanese textile companies presents a unique opportunity for investors due to the industry's rich blend of traditional craftsmanship and cutting-edge innovation [21]. Japan has a long-standing reputation for producing high-quality textiles, particularly in areas like shibori, kasuri, and Nishijin-ori, where artisanship remains a strong cultural and economic pillar [22, 23]. Alongside preserving these traditions, Japanese textile companies are at the forefront of developing advanced fabrics, such as high-performance and sustainable materials used in sportswear, healthcare, and environmental solutions. This combination of tradition and innovation positions Japanese textile companies in a unique and competitive niche within the global market.

Furthermore, predicting the stock prices of Japanese textile companies is crucial for several reasons. First, stock price trends provide valuable insight into the financial health and growth potential of these firms, especially in an industry subject to evolving consumer trends, technological advancements, and global competition [24]. Investors rely on stock price predictions to make informed decisions, helping them maximise returns and manage risks effectively. The ability to forecast stock movements also sheds light on how well these companies adapt to economic challenges, such as fluctuating raw material costs, trade policies, and environmental regulations. Additionally, Japanese textile companies are increasingly focusing on sustainability and innovation, which are critical factors for long-term growth in today's markets [25]. By predicting stock prices, investors can identify key opportunities in companies that are leading the charge in eco-friendly practices and technological advancements, ensuring their investments are aligned with future trends and market demands.

ARIMA (Auto Regressive Integrated Moving Average) is widely chosen to predict the stock prices of Japanese textile companies because of its proven effectiveness in handling time series data, particularly financial data like stock prices. ARIMA is especially useful because it can model data that exhibits trends, seasonality, and noise, common characteristics in stock market fluctuations [26]. The textile industry, like others, experiences periodic shifts influenced by economic conditions, global competition, and consumer trends, making ARIMA's ability to handle both stationary and non-stationary data highly advantageous. One of ARIMA's key strengths is its ability to forecast future values based on past patterns [27]. It relies on historical stock prices to predict future movements, making it particularly useful for industries like textiles, where market trends, raw material costs, and seasonal demand can impact stock performance. For Japanese textile companies, which balance traditional craftsmanship with modern innovation, ARIMA allows investors and analysts to capture both short-term fluctuations and long-term trends. Furthermore, ARIMA's flexibility in integrating different components (autoregression, differencing, and moving averages) makes it adaptable to a wide range of stock behaviours, improving accuracy and reliability in forecasting, which is essential for making informed investment decisions in a competitive and evolving market.

REVIEW OF LITERATURE

The stock market performance of Japanese textile companies is multifaceted, influenced by network centralisation, exchange rate fluctuations, macroeconomic conditions, and international trade policies. Understanding these factors can provide a comprehensive view of the industry's dynamics and potential stock market behaviour. The Japanese textile and apparel industry has seen significant changes in its B2B networks, particularly with the centralisation around hub companies due to the introduction of supply chain management systems and innovations in ICT and logistics technology. These centralisations have been linked to improved efficiency and potentially better stock performance due to streamlined operations [28, 29].

The short-term forecasting of stock prices impacts the investment strategies of Japanese textile companies by enabling them to make informed decisions on stock purchases and sales, anticipate market movements, and mitigate risks associated with the stock market [30].

The USD/JPY exchange rate has a notable impact on the B2B transactions within the industry. A strong yen correlates with an increase in the number of transactions, while a weak yen results in fewer transactions. This relationship suggests that fluctuations in the exchange rate can directly affect the operational dynamics and, consequently, the stock performance of textile companies [29, 31].

The performance of Japanese textile firms is also influenced by broader macroeconomic conditions. For instance, keiretsu financing and international diversification strategies have varying effects on profitability depending on the economic environment.

During times of economic scarcity, these strategic factors play a more significant role in determining financial outcomes [32]. Japan's textile industry is also affected by international trade policies and geopolitical factors. The shift from reliance on China to ASEAN countries for supplies and partnerships is a strategic move to mitigate risks and reduce costs. Japanese textile companies look for ASEAN suppliers, Textiles South East Asia, 2005 [33].

Japan has transitioned from being a major exporter to a significant importer of textiles. This shift is driven by the competitiveness of Chinese imports, which dominate the market due to lower costs and the absence of quotas. This has led to increased import values and a decline in domestic production competitiveness [34]. Specific sectors within the textile industry, such as automotive textiles, have seen growth due to increased demand from Japanese car manufacturers in the U.S. market. This sector's success reflects broader trends in the automotive industry and changing consumer preferences towards environmentally friendly products [35]. The global shift in production to low-cost countries has affected the Japanese textile industry. The industry now focuses more on managing global supply chains and retailing rather than production, which has influenced stock performance due to changing business models and competitive pressures [36].

In summary, global economic trends, including macroeconomic conditions, import-export dynamics, and sector-specific demands, play a crucial role in shaping the stock performance of Japanese textile companies.

The ARIMA model is widely used for time series forecasting in various fields such as finance, economics, and network throughput prediction. To analyse and predict stock market trends, the ARIMA model is a widely used time series forecasting method. It combines autoregressive and moving average components to capture temporal patterns in stock price data, making it suitable for short-term predictions. The ARIMA model is a robust tool for short-term stock market analysis, though its performance can be enhanced or outperformed by other models depending on the specific context and additional variables considered [37–44].

ARIMA models have shown strong accuracy for short-term and daily stock price predictions. For instance, the ARIMA model was effectively used to predict stock prices on the Bombay Stock Exchange (BSE) and National Stock Exchange (NSE) with high accuracy [45]. Similarly, it was found suitable for short-term forecasts of China Merchants Bank stock prices [46]. The process of building an ARIMA model involves ensuring data stationarity, typically through differencing, and selecting appropriate parameters (p, d, q) using criteria like AIC and BIC. For example, the ARIMA (0, 2, 1) model was chosen for Adobe stock prices based on these criteria, achieving a low Mean Absolute Percentage Error (MAPE) [42].

While ARIMA is effective, it may not always outperform other models. Neural network algorithms, for instance, have been found to better predict stock price changes compared to traditional ARIMA models [47]. Additionally, ARIMA-GARCH models, which account for volatility, can sometimes provide better forecasts than ARIMA alone [48]. ARIMA has been applied to various stock markets, including the Indonesian Stock Exchange for socially responsible investment stocks [49] and the Shanghai Stock Exchange Composite Index, incorporating additional variables like trading volume and exchange rates for more stable predictions [50].

The stock prices of textile companies are influenced by various factors, including macroeconomic conditions and commodity prices [51–54]. For instance, the volatility in crude oil prices significantly impacts the stock prices of Indian textile companies due to their dependency on petrochemical raw materials [51]. Additionally, the prices of commodities like cotton also affect the stock prices of textile companies, as shown in studies using the ARDL model [52].

For textile companies, external factors such as international trade agreements and macroeconomic policies also play a crucial role in stock price movements [54, 55]. The ARIMA model is a powerful tool for forecasting stock prices, its effectiveness can be enhanced by integrating it with other models to account for the complex factors influencing the textile industry [39, 42, 52, 56].

The seasonality of the textile industry significantly impacts the application of ARIMA models for stock price prediction. The textile industry experiences seasonal fluctuations, such as changes in cotton prices during pre-sowing and pre-harvesting periods. These fluctuations necessitate the use of ARIMA models to capture the seasonal patterns effectively [57]. Accurate seasonal forecasting helps textile companies make informed decisions about stocking or selling products to maximise profits. This is crucial in a highly volatile market where prices can fluctuate based on seasonal trends [58].

Research gap

Despite extensive research on stock market prediction, particularly with time-series models like ARIMA, there is a notable gap in focusing on specific industries within specific geographic contexts. Most studies have applied ARIMA to broad stock indices or major industries, leaving sectors like the textile industry, especially in Japan, underexplored. The Japanese textile market, which plays a critical role in the global fashion and apparel supply chain, experiences unique market dynamics influenced by factors such as seasonal demand, global trade policies, and technological advancements. However, predictive analysis tailored to this sector remains limited, hindering investors and businesses from making informed decisions based on industry-specific trends. This research seeks to address this gap by applying the ARIMA model to forecast stock prices of Japanese textile companies, providing a more nuanced and industry-targeted analysis. By doing so, it contributes to a better understanding of sector-specific stock behaviour within the context of Japan's unique economic and industrial framework.

Objectives of the study

- To develop an ARIMA-based model for forecasting stock prices of selected Japanese textile companies, aiming to enhance accuracy in predicting future stock market trends within this specific sector.
- To evaluate the performance of the ARIMA model by comparing forecasted results with actual stock price movements, determining its effectiveness in predicting short-term and long-term market fluctuations.
- To contribute to the limited literature on industry-specific stock market predictions, particularly in sectors like textiles, where predictive models are less frequently applied.

Significance of the study

Research on predictive stock market analysis for Japanese textile companies using the ARIMA model offers significant societal benefits by improving financial decision-making and economic stability. By providing accurate forecasts of stock prices specific to the textile sector, investors can make more informed decisions, reducing the risks of financial losses. This is particularly important for individual investors, pension funds, and other stakeholders whose wealth and plans are tied to the performance of such industries. Furthermore, better predictions can lead to increased confidence in the market, promoting more efficient capital allocation, which helps companies secure funding for innovation and sustainable growth. This research also benefits the broader economy, as the textile industry is a key player in Japan's industrial landscape, influencing employment and exports. Accurate market predictions contribute to the overall economic health, creating a ripple effect that strengthens not only businesses but also the livelihoods of workers and communities dependent on the textile sector.

Limitations of the study

- Data Availability and Quality: The predictive accuracy of the ARIMA model heavily depends on the availability and quality of historical stock market data. In this study, we relied on publicly available data, which may have certain limitations, such as missing values, inconsistencies, or reporting biases that could impact the model's performance. Additionally, the data used was limited to a specific period, which may not capture long-term trends or market anomalies.
- Exclusion of External Factors: The ARIMA model is purely time-series-based and does not account for external factors such as macroeconomic indicators (e.g., inflation, interest rates), global trade conditions, or company-specific events (e.g., management changes, mergers, supply chain disruptions). These factors could significantly influence the stock prices of textile companies in Japan, but they are beyond the scope of this study's analysis.
- Short-Term Predictive Focus: ARIMA models are more suited to short-term forecasting rather than long-term predictions. The predictive insights generated in this study primarily focus on near-term stock price movements, and the model may not perform well when extended to longer-term forecasting due to accumulating error and a lack of inclusion of long-term drivers of stock prices.
- Model Parameter Sensitivity: The performance of the ARIMA model is sensitive to the selection of parameters (p, d, q). While this study employed standard statistical techniques to identify the optimal parameters, alternative methods or parameter choices may yield different results. Additionally, ARIMA's reliance on past values may limit its adaptability in highly volatile or unprecedented market conditions.
- Market Volatility: Stock markets, including the Japanese textile sector, are subject to unexpected shocks and volatility (e.g., economic crises, pandemics, geopolitical events). The ARIMA model's reliance on historical data makes it less responsive to sudden changes in market conditions, and as a result, it may underperform during periods of high volatility or instability.
- Technological Limitations: This research utilised available computational resources and tools for model development and testing. However, more advanced machine learning models or hybrid approaches (e.g., integrating ARIMA with deep learning models like LSTM) might offer enhanced predictive accuracy but were not explored in this study due to the research scope and technological constraints.

RESEARCH METHODOLOGY

Research design

This research employs a quantitative approach to analyse and predict stock market trends of Japanese textile companies using the ARIMA (AutoRegressive Integrated Moving Average) model. The study is designed to explore the potential of time-series forecasting techniques, specifically ARIMA, in predicting stock prices, enabling better decision-making in the financial and investment sectors.

Data collection

The data for this research was collected from publicly available financial datasets and stock exchange platforms, focusing on the top 10 textile companies listed on the Tokyo Stock Exchange (TSE). The selection criteria for companies included their relevance in the textile industry, market capitalisation, and consistent availability of historical stock price data over 10 years (2014–2023). The source for selecting the companies was a manuscript publicly available on the textile industry by the EU-Japan Centre. The companies included were Teijin, Global Style, Itochu, Kuraray, Toyobo, Yagi, Takihyo, Toray, Sankyo Seiko, and

Toyota Tsusho. Except for Global Style, all the companies have 10 years of data.

Daily closing stock prices of these companies are obtained from financial platforms such as Investing.com, Yahoo Finance, Bloomberg, and similar sources. The dataset spans from January 1, 2014, to December 31, 2023. Each company had almost 2500 data points, and Global Textiles had 720 data points, summing to a total of 22,719 data points.

Data pre-processing

Before implementing the ARIMA model, the data undergoes several pre-processing steps:

- Handling Missing Data: Missing data points in stock prices are handled using forward fill, backwards fill, or interpolation methods to ensure the continuity of the dataset.
- Normalisation: The dataset is normalised to reduce the impact of extreme outliers, which could skew the model results.
- Stationarity Check: Since ARIMA requires a stationary time series, the Augmented Dickey-Fuller (ADF) test is conducted to check for stationarity. If the data is non-stationary, differencing is applied to achieve stationarity.

Model selection

The ARIMA model is selected for this study due to its effectiveness in time-series forecasting. ARIMA is a combination of three components:

- AR (AutoRegressive): Uses the dependency between an observation and several lagged observations.
- I (Integrated): Differencing the raw observations to make the time series stationary.
- MA (Moving Average): Models the dependency between an observation and a residual error from a moving average model applied to lagged observations.

The Box-Jenkins method is followed to identify the appropriate parameters for ARIMA, which include:

- Identification: Determining whether the time series data is stationary and identifying the order of differencing required.
- Estimation: Using the training data, the AR, I, and MA components are estimated using statistical software like Python's statsmodels package or other software like EViews, XLSTAT, Julia R, MATLAB, etc. This paper has utilised EViews 9.5.
- Diagnostic Checking: After fitting the model, residuals are checked to ensure they resemble white noise using techniques such as the Ljung-Box test.

Model evaluation

The performance of the ARIMA model is evaluated using several metrics to gauge its predictive accuracy, including Root Mean Square Error(RMSE), Plot of predicted values against actual values, Mean Absolute Percentage Error (MAPE), and residual analysis.

Software and tools

For this analysis, there are several software programs that could be used, including EViews, XLSTAT, MATLAB, Julia, Python, R, etc., but for ease and convenience, EViews 9.5 was employed for the analysis.

ANALYSIS, RESULTS AND DISCUSSION

To understand the nature of the Price data, looking at the price graphs becomes essential. From the visual estimation itself, it is evident that in figures 1 to 10, the data of the prices of the 10 textile companies taken for the study are not stationary. To make the data stationary, the data was differenced to the 1st level, and the graph adjacent to the price graphs depicts the stationary prices. The stationarity of the differenced prices was confirmed through the Augmented Dickey-Fuller (ADF) test.

After making the data stationary, it becomes essential to look at the ACF and PACF plots in the correlogram. From the values of ACF and PACF at 1st level difference, it was evident that the value of the d in (p,d,q) across the 10 companies is 1. Based on the ACF and PACF values, p and q were identified. Below is the decision table used to identify AR and MA terms and appropriate lag values.

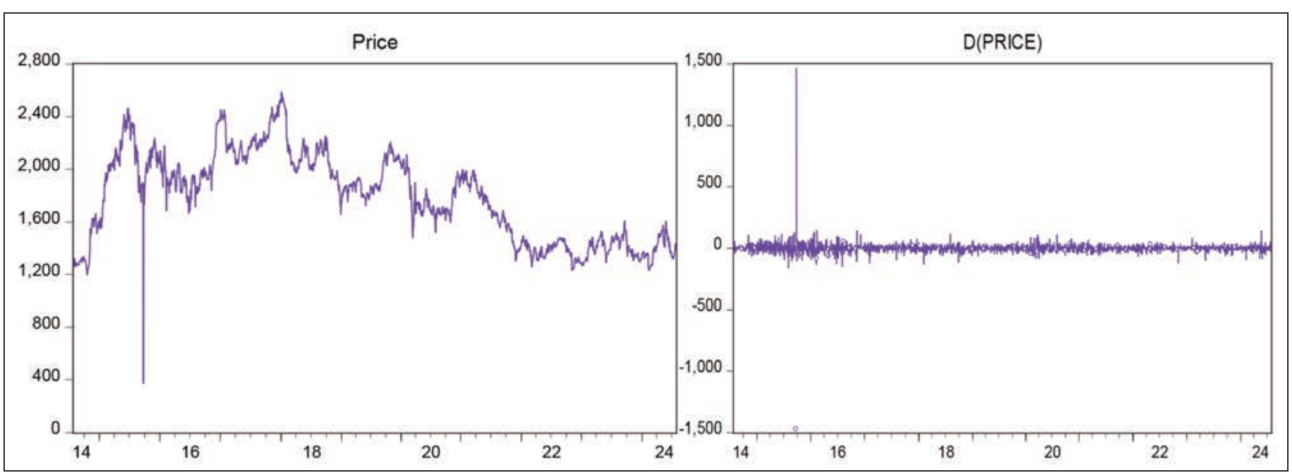


Fig. 1. Teijin price and stationary price

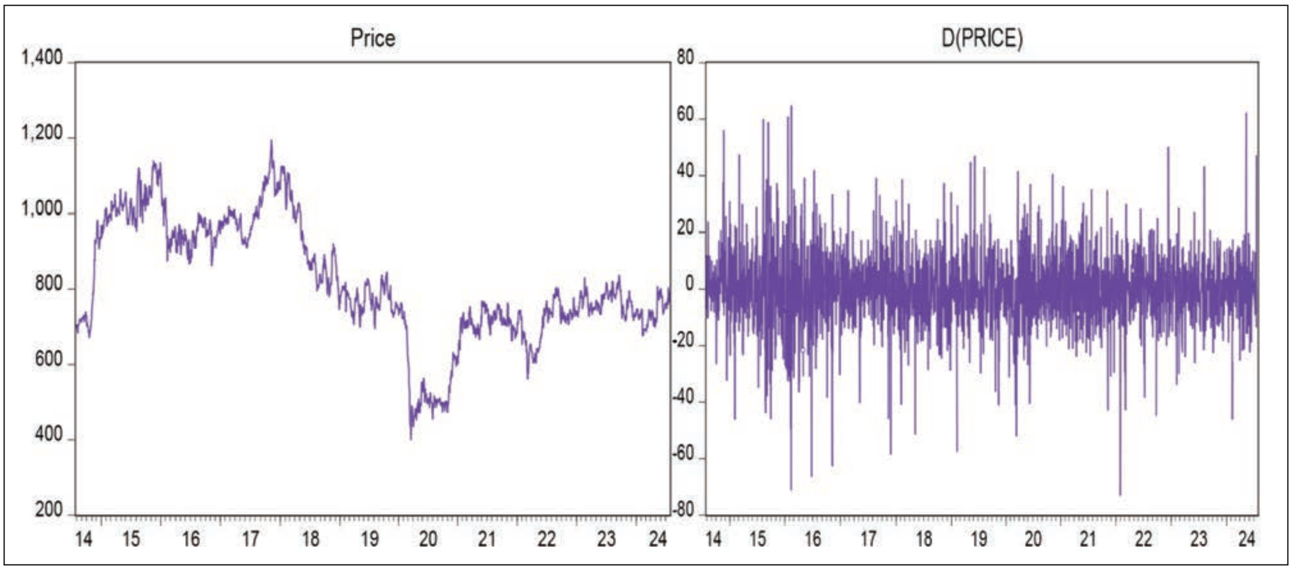


Fig. 2. Toray price and stationary price

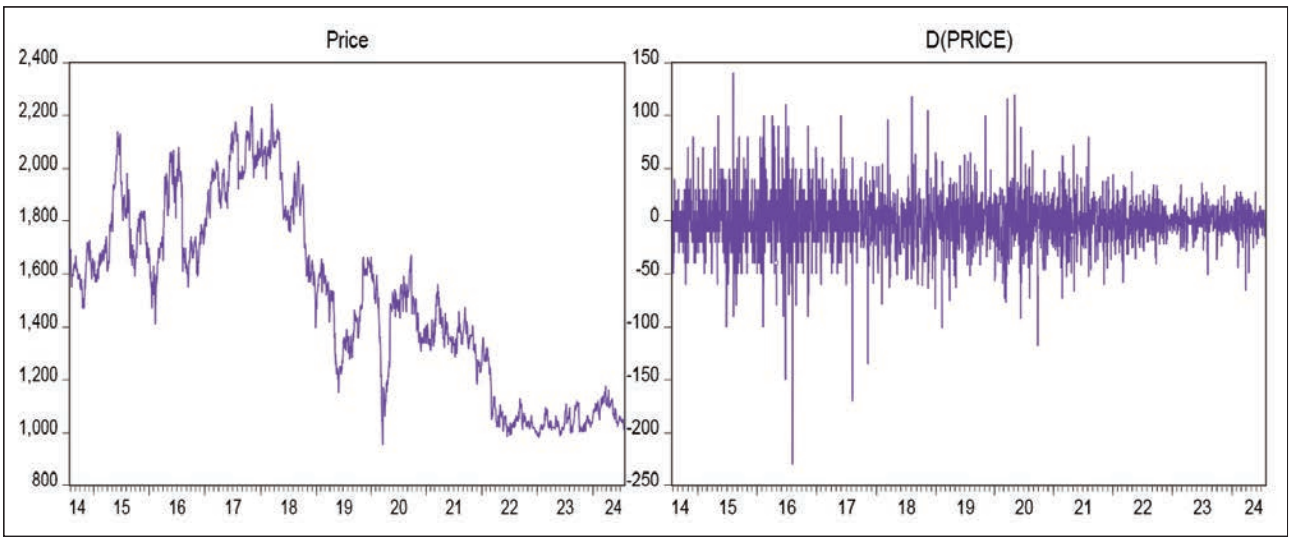


Fig. 3. Toyobo price and stationery price

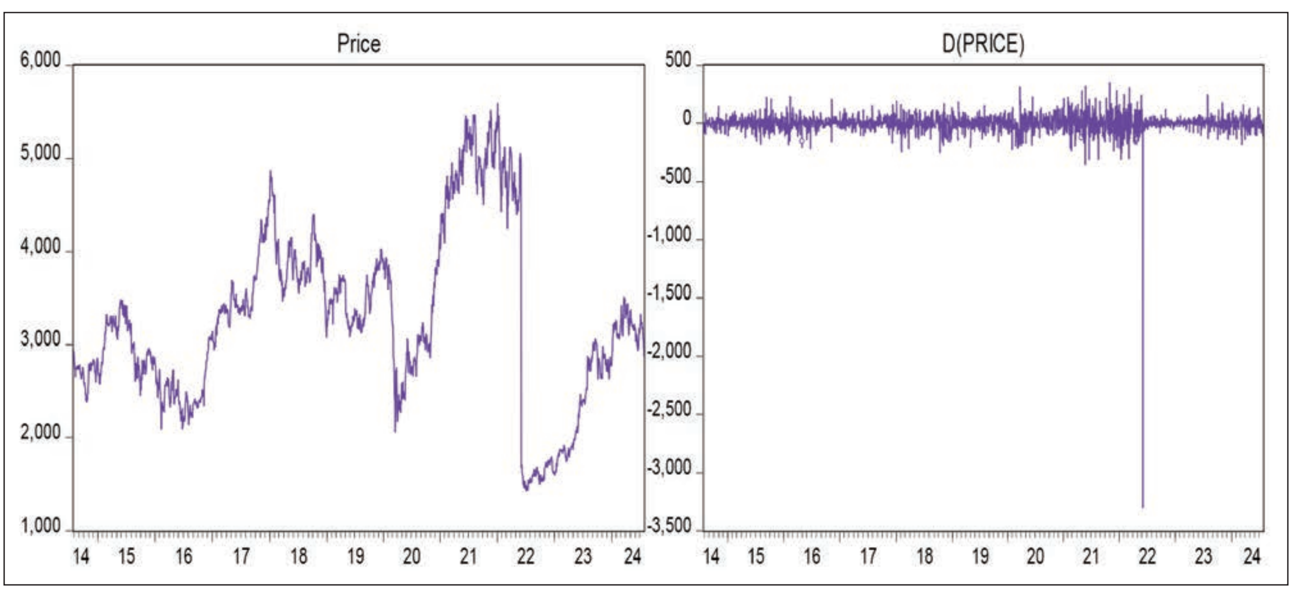


Fig. 4. Toyota Tsusho price and stationery price

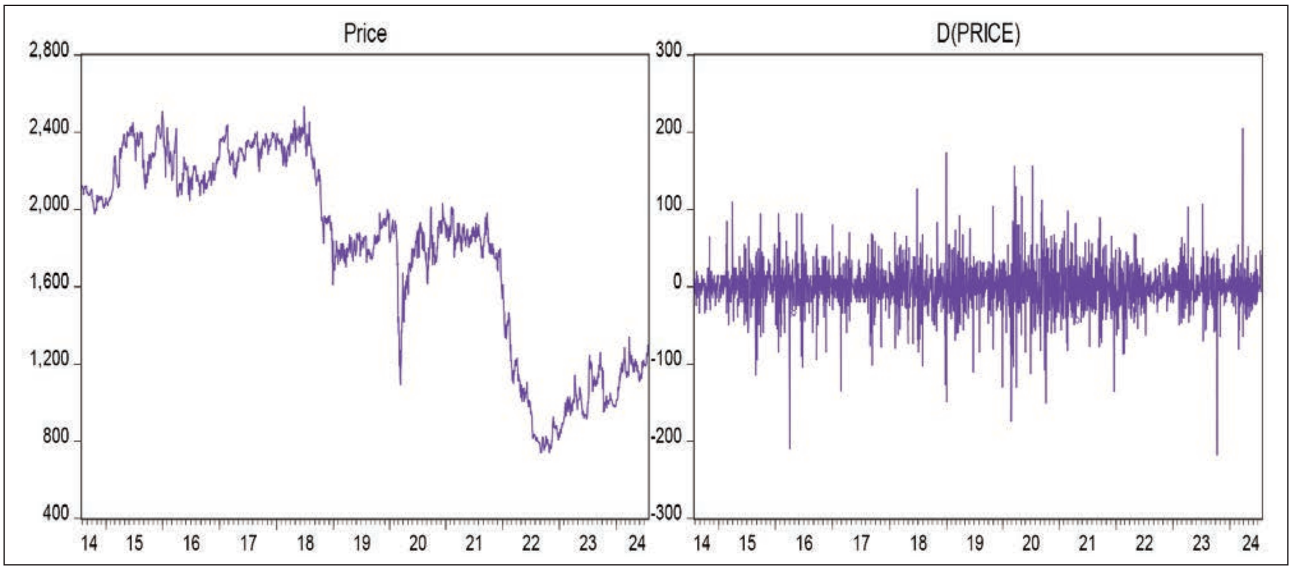


Fig. 5. The Takihyo price and the stationary price

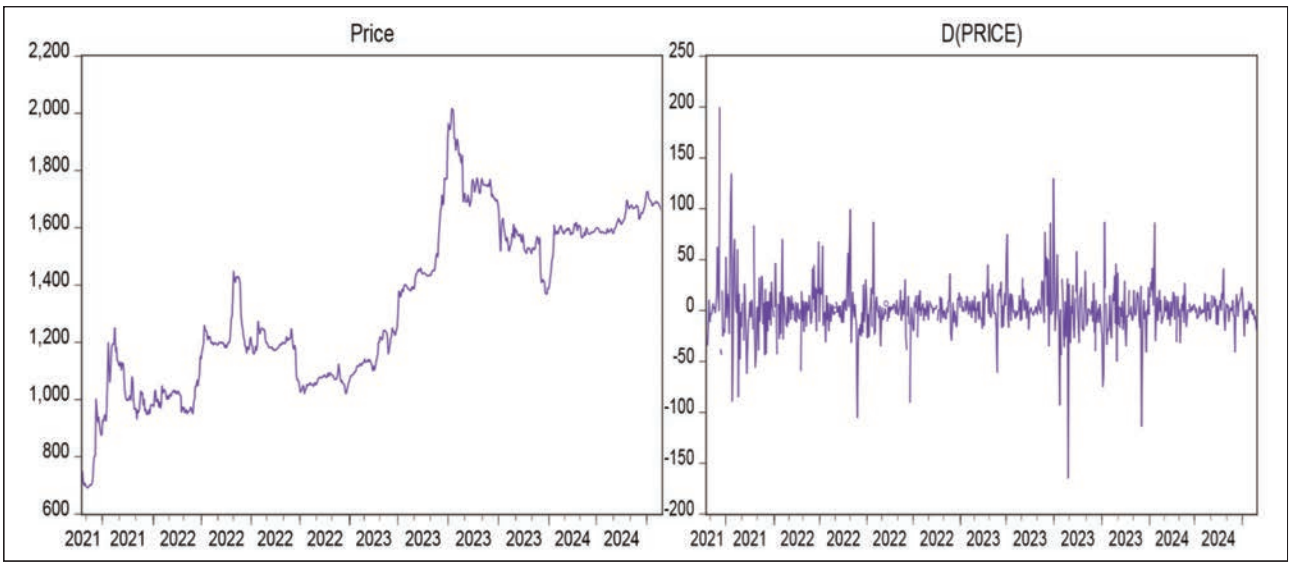


Fig. 6. Global style price and the stationary price

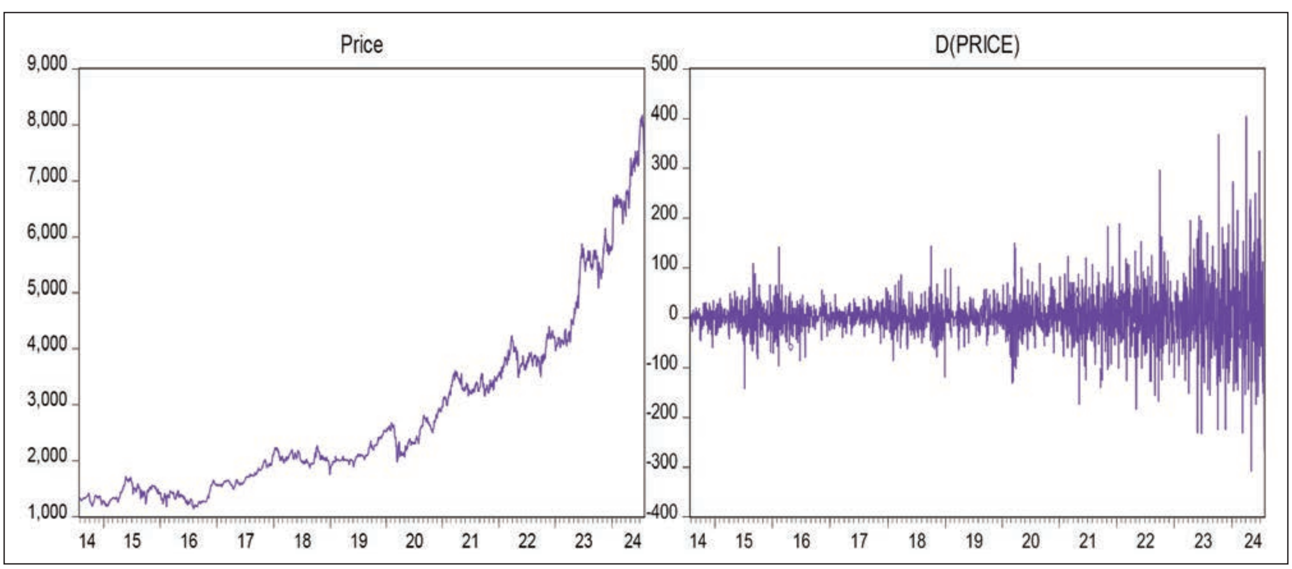


Fig. 7. Itochu price and the stationary price

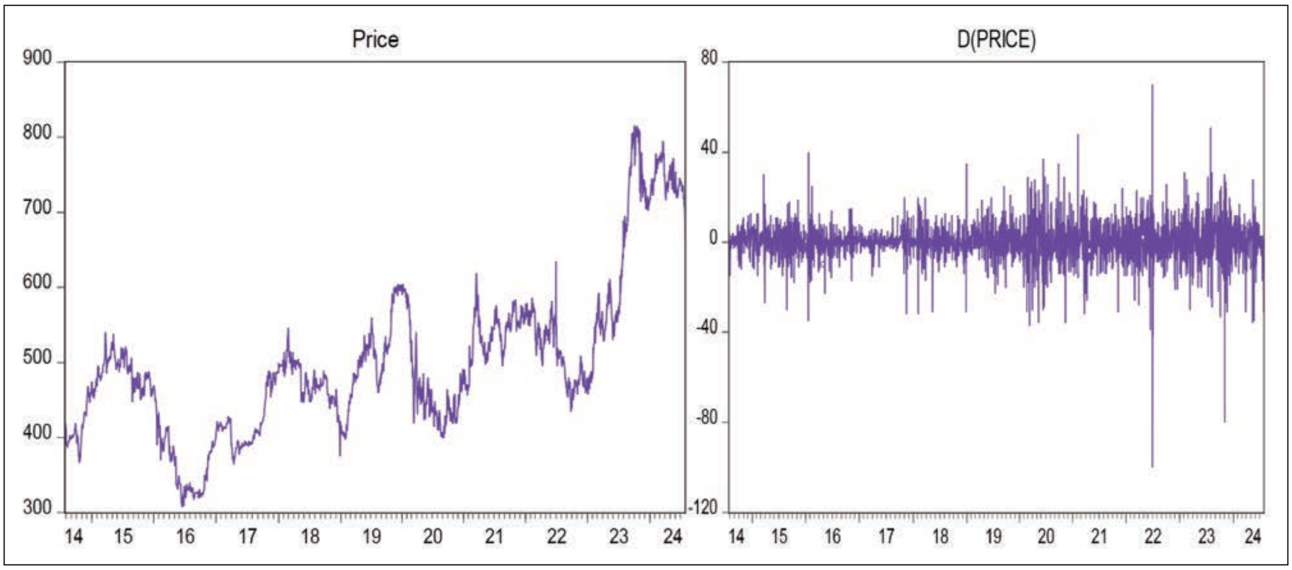


Fig. 8. Sankyo Seiko price and stationery price

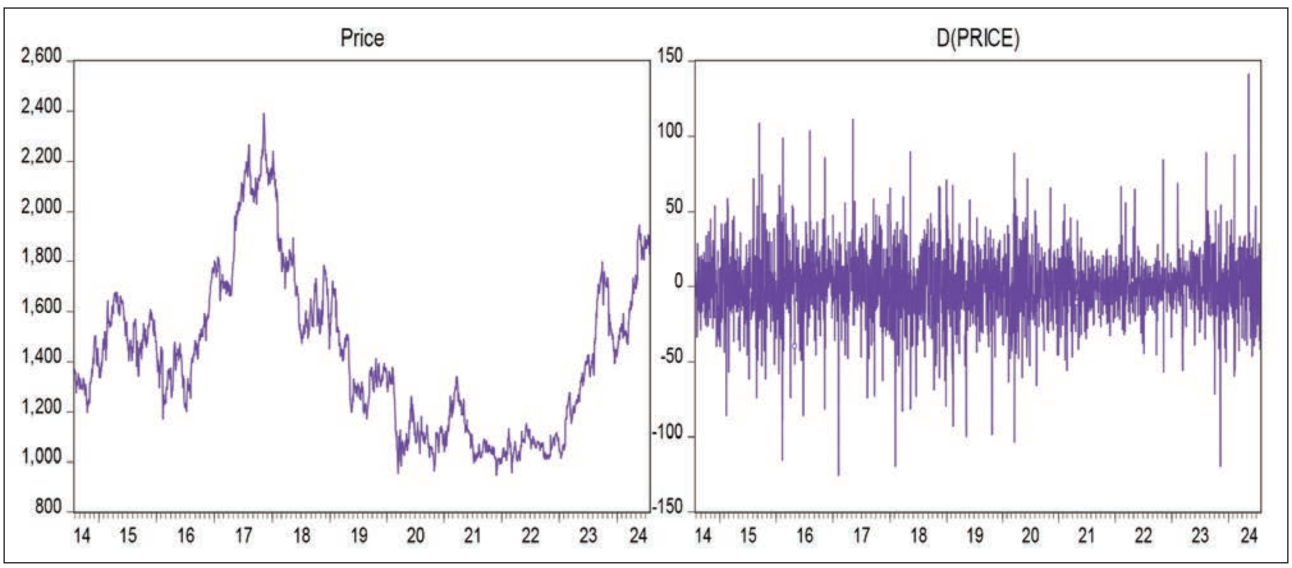


Fig. 9. Kuraray price and stationary price

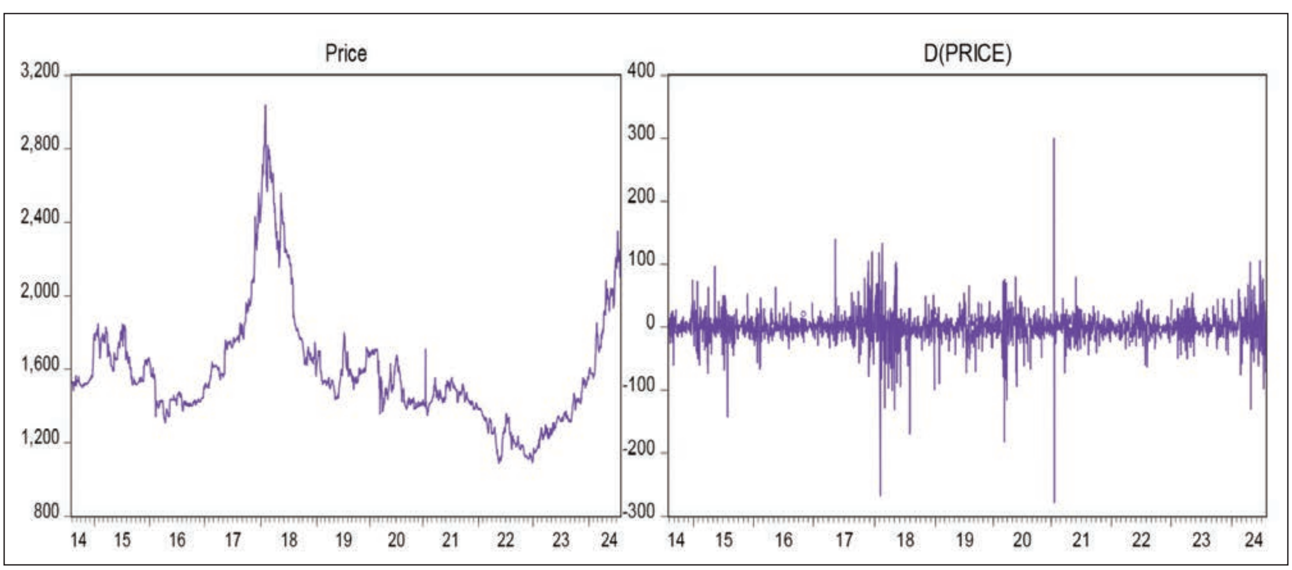


Fig. 10. Yagi price and stationary price

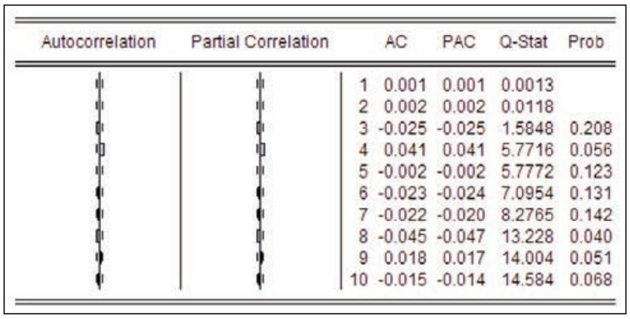
Table 1

DECISION TABLE						
Company name	**Notation**	**Akaike info criterion**	**Schwarz criterion**	**SIGMASQ**	**Adjusted R-squared**	**Significant terms**
Teijin	(0,1,1)	10.58565	10.59277	2310.572	0.123272	2
	(1,1,0)	10.61555	10.62267	2380.764	0.096638	2
	(1,1,1)	10.58443	10.59392	2305.852	0.124704	3
	(2,1,1)	**10.58337**	**10.59049**	**2305.302**	**0.125272**	**3**
	(3,1,1)	10.58594	10.59543	2309.343	0.123379	2
Global Style	(4,1,0)	9.329346	9.348594	653.9238	0.006386	2
	(4,1,4)	9.332155	9.357818	653.9234	0.004983	1
	(0,1,4)	9.329536	9.348783	654.0491	0.006196	2
	(5,1,5)	9.331708	9.357372	653.5419	0.005564	3
	(0,1,16)	9.324168	9.343416	650.3677	0.011789	2
	(16,1,0)	9.324136	9.343384	650.3503	0.011816	2
	(4,1,5)	9.324998	9.350661	649.2253	0.012132	3
	(5,1,4)	9.325139	9.350802	649.3184	0.01199	3
	(4,1,16)	**9.319075**	**9.344739**	**645.2401**	**0.018196**	**3**
Itochu	(6,1,0)	10.62936	10.63648	2413.95	0.000642	3
	(0,1,6)	10.62946	10.63658	2414.199	0.000539	3
	(0,1,7)	10.62932	10.63644	2413.853	0.000682	3
	(0,1,6)	10.62946	10.63658	2414.199	0.000539	3
	(7,1,0)	10.62929	10.63641	2413.788	0.000709	3
	(6,1,6)	**10.62503**	**10.63453**	**2401.394**	**0.005433**	**4**
	(6,1,7)	10.62863	10.63813	2410.205	0.001783	4
	(7,1,6)	10.62871	10.63821	2410.411	0.001698	4
	(7,1,7)	10.62898	10.63848	2411.02	0.001446	4
Kuraray	(4,1,0)	9.169508	9.176631	560.693	-0.000137	1
	(0,1,4)	9.169479	9.176603	560.6769	-0.000108	1
	(20,1,20)	**9.169388**	**9.178886**	**560.1582**	**0.000407**	**1**
	(4,1,20)	9.16966	9.179158	560.3167	0.000125	1
	(20,1,4)	9.169566	9.179064	560.2635	0.00022	1
Toyobo	(1,1,0)	9.395798	9.402921	703.0755	0.00018	2
	(0,1,1)	9.39584	9.402964	703.1053	0.000138	2
	(3,1,0)	9.394003	9.401126	701.8123	0.001976	2
	(0,1,3)	**9.393888**	**9.401012**	**701.7318**	**0.002091**	**2**
Yagi	(1,1,0)	9.30083	9.308044	639.3529	0.004355	2
	(0,1,1)	9.30136	9.308574	639.6922	0.003826	2
	(1,1,1)	9.299622	9.309241	638.0499	0.00597	4
	(2,1,0)	9.302442	9.309656	640.3842	0.002749	2
	(0,1,2)	9.302237	9.309451	640.2525	0.002954	2
	(1,1,2)	**9.298496**	**9.308115**	**637.3312**	**0.00709**	**3**
	(2,1,1)	9.29869	9.308309	637.4548	0.006897	3
Takihyo	(1,1,0)	9.667924	9.675047	922.961	0.007883	2
	(0,1,1)	**9.667635**	**9.674758**	**922.6942**	**0.00817**	**2**
	(1,1,1)	9.668131	9.677629	922.3965	0.008084	2
Toray	(3,1,0)	8.014305	8.021428	176.6146	0.000726	2
	(0,1,3)	8.014128	8.021251	176.5832	0.000903	2
	(3,1,3)	8.013402	8.0229	176.3101	0.00204	3
	(6,1,0)	8.01324	8.020364	176.4259	0.001793	2
	(0,1,6)	8.013173	8.020296	176.4139	0.001861	2
	(3,1,6)	**8.012315**	**8.021813**	**176.1181**	**0.003126**	**3**
	(6,1,3)	8.01238	8.021879	176.1296	0.003061	3
Sankyo Seiko	(1,1,0)	7.274954	7.282077	84.31934	0.021439	2
	(0,1,1)	7.273358	7.280482	84.1848	0.023	2
	(1,1,1)	7.272651	7.282149	84.05627	0.024092	3
	(3,1,0)	7.295584	7.302707	86.07754	0.001034	2
	(0,1,3)	7.2956	7.302723	86.07891	0.001018	2
	(3,1,3)	7.295568	7.305067	86.00556	0.00146	3
	(1,1,3)	7.273677	7.283175	84.14265	0.023089	3
	(3,1,1)	**7.27198**	**7.281478**	**83.99982**	**0.024747**	**3**
Toyota Tsusho	(7,1,0)	11.94521	11.95233	8998.995	0.001888	2
	(0,1,7)	**11.94515**	**11.95227**	**8998.468**	**0.001947**	**2**
	(7,1,7)	11.94594	11.95544	8998.188	0.001568	1

The appropriate order of AR and MA terms was chosen based on the lowest Akaike Info Criterion (AIC), Schwarz criterion, Volatility, and the highest adjusted R-squared value and number of significant terms. The values highlighted in the decision table are identified and chosen based on the discussed criterion. However, we should also look to see if the chosen model is overfitting in nature.

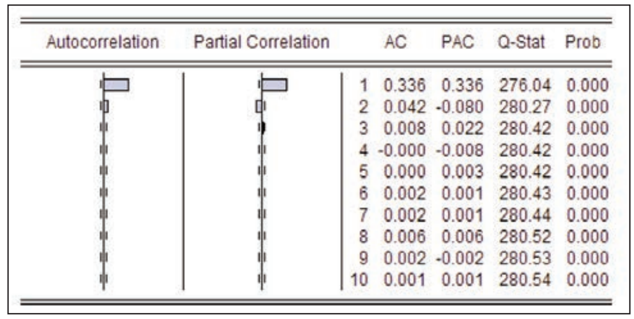
In the Box Jenkins method, the model should be parsimonious, so we will drop the higher value lags, but instead, we will be using lower lags for the analysis. For example, in Global Style, the most appropriate model seems (4,1,16), but (5,1,4) will be our choice. A similar case would be in Kuraray, based on our criteria (20,1,20) is the fittest model, but it will be better if we choose (0,1,4).

Now, after the identification and estimation of the most fit model, it becomes very essential to perform diagnostics on the models and check the residuals.



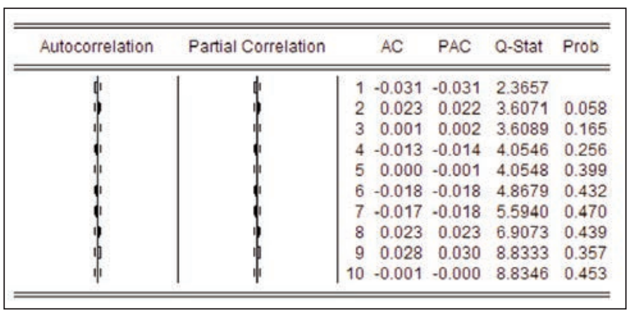
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.001	0.001	0.0013	
		2	0.002	0.002	0.0118	
		3	-0.025	-0.025	1.5848	0.208
		4	0.041	0.041	5.7716	0.056
		5	-0.002	-0.002	5.7772	0.123
		6	-0.023	-0.024	7.0954	0.131
		7	-0.022	-0.020	8.2765	0.142
		8	-0.045	-0.047	13.228	0.040
		9	0.018	0.017	14.004	0.051
		10	-0.015	-0.014	14.584	0.068

Fig. 11. Teijin correlogram of residuals



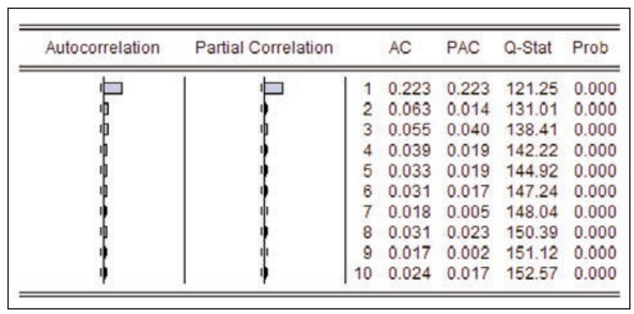
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.336	0.336	276.04	0.000
		2	0.042	-0.080	280.27	0.000
		3	0.008	0.022	280.42	0.000
		4	-0.000	-0.008	280.42	0.000
		5	0.000	0.003	280.42	0.000
		6	0.002	0.001	280.43	0.000
		7	0.002	0.001	280.44	0.000
		8	0.006	0.006	280.52	0.000
		9	0.002	-0.002	280.53	0.000
		10	0.001	0.001	280.54	0.000

Fig. 12. Teijin correlogram of residuals squared



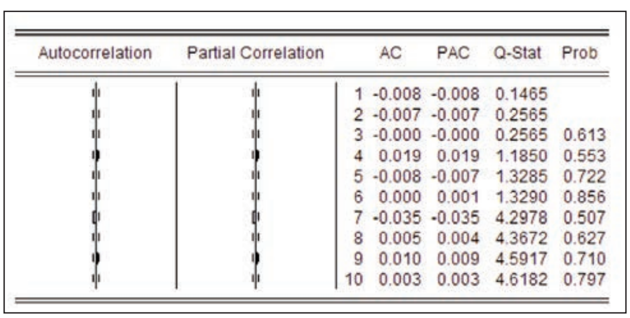
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.031	-0.031	2.3657	
		2	0.023	0.022	3.6071	0.058
		3	0.001	0.002	3.6089	0.165
		4	-0.013	-0.014	4.0546	0.256
		5	0.000	-0.001	4.0548	0.399
		6	-0.018	-0.018	4.8679	0.432
		7	-0.017	-0.018	5.5940	0.470
		8	0.023	0.023	6.9073	0.439
		9	0.028	0.030	8.8333	0.357
		10	-0.001	-0.000	8.8346	0.453

Fig. 13. Toyobo correlogram of residuals



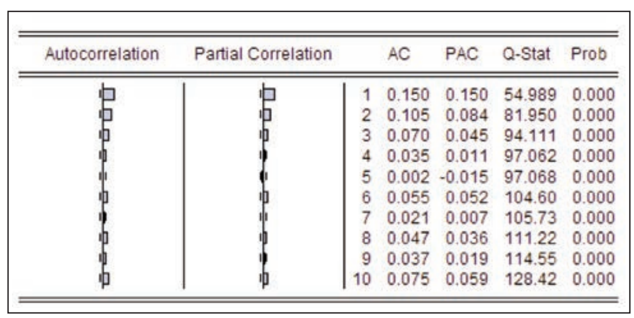
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.223	0.223	121.25	0.000
		2	0.063	0.014	131.01	0.000
		3	0.055	0.040	138.41	0.000
		4	0.039	0.019	142.22	0.000
		5	0.033	0.019	144.92	0.000
		6	0.031	0.017	147.24	0.000
		7	0.018	0.005	148.04	0.000
		8	0.031	0.023	150.39	0.000
		9	0.017	0.002	151.12	0.000
		10	0.024	0.017	152.57	0.000

Fig. 14. Toyobo correlogram of residuals squared



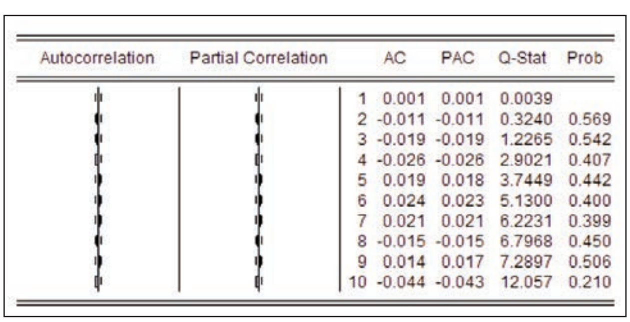
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.008	-0.008	0.1465	
		2	-0.007	-0.007	0.2565	
		3	-0.000	-0.000	0.2565	0.613
		4	0.019	0.019	1.1850	0.553
		5	-0.008	-0.007	1.3285	0.722
		6	0.000	0.001	1.3290	0.856
		7	-0.035	-0.035	4.2978	0.507
		8	0.005	0.004	4.3672	0.627
		9	0.010	0.009	4.5917	0.710
		10	0.003	0.003	4.6182	0.797

Fig. 15. Toray correlogram of residuals



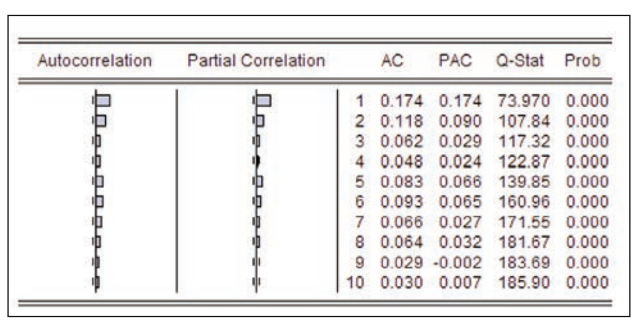
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.150	0.150	54.989	0.000
		2	0.105	0.084	81.950	0.000
		3	0.070	0.045	94.111	0.000
		4	0.035	0.011	97.062	0.000
		5	0.002	-0.015	97.068	0.000
		6	0.055	0.052	104.60	0.000
		7	0.021	0.007	105.73	0.000
		8	0.047	0.036	111.22	0.000
		9	0.037	0.019	114.55	0.000
		10	0.075	0.059	128.42	0.000

Fig. 16. Toray correlogram of residuals squared



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.001	0.001	0.0039	
		2	-0.011	-0.011	0.3240	0.569
		3	-0.019	-0.019	1.2265	0.542
		4	-0.026	-0.026	2.9021	0.407
		5	0.019	0.018	3.7449	0.442
		6	0.024	0.023	5.1300	0.400
		7	0.021	0.021	6.2231	0.399
		8	-0.015	-0.015	6.7968	0.450
		9	0.014	0.017	7.2897	0.506
		10	-0.044	-0.043	12.057	0.210

Fig. 17. The Takihyo correlogram of residuals



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.174	0.174	73.970	0.000
		2	0.118	0.090	107.84	0.000
		3	0.062	0.029	117.32	0.000
		4	0.048	0.024	122.87	0.000
		5	0.083	0.066	139.85	0.000
		6	0.093	0.065	160.96	0.000
		7	0.066	0.027	171.55	0.000
		8	0.064	0.032	181.67	0.000
		9	0.029	-0.002	183.69	0.000
		10	0.030	0.007	185.90	0.000

Fig. 18. The Takihyo correlogram of residuals squared

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.014	-0.014	0.4819	
		2	0.006	0.005	0.5560	0.456
		3	-0.010	-0.009	0.7838	0.676
		4	0.007	0.006	0.8902	0.828
		5	0.025	0.025	2.4141	0.660
		6	-0.025	-0.024	3.8921	0.565
		7	0.000	-0.001	3.8923	0.691
		8	0.010	0.011	4.1315	0.765
		9	-0.001	-0.002	4.1350	0.845
		10	-0.022	-0.022	5.2964	0.808

Fig. 19. Toyota Tshusho correlogram of residuals

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.001	-0.001	0.0007	0.978
		2	-0.001	-0.001	0.0028	0.999
		3	-0.001	-0.001	0.0040	1.000
		4	0.001	0.001	0.0061	1.000
		5	-0.000	-0.000	0.0065	1.000
		6	0.001	0.001	0.0089	1.000
		7	0.007	0.007	0.1464	1.000
		8	-0.001	-0.001	0.1474	1.000
		9	-0.001	-0.001	0.1481	1.000
		10	-0.001	-0.001	0.1500	1.000

Fig. 20. Toyota Tshusho correlogram of residuals squared

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.017	-0.017	0.7214	
		2	-0.014	-0.014	1.1791	0.278
		3	-0.009	-0.010	1.3785	0.502
		4	-0.001	-0.001	1.3792	0.710
		5	0.001	0.001	1.3822	0.847
		6	0.008	0.008	1.5273	0.910
		7	-0.021	-0.021	2.6248	0.854
		8	-0.020	-0.020	3.5870	0.826
		9	0.005	0.003	3.6386	0.888
		10	0.012	0.011	3.9680	0.914

Fig. 21. Kuraray correlogram of residuals

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.152	0.152	56.620	0.000
		2	0.119	0.098	91.367	0.000
		3	0.056	0.026	99.118	0.000
		4	0.038	0.016	102.74	0.000
		5	0.036	0.021	105.96	0.000
		6	0.020	0.005	106.92	0.000
		7	0.036	0.026	110.05	0.000
		8	0.043	0.031	114.55	0.000
		9	-0.005	-0.024	114.62	0.000
		10	0.001	-0.006	114.62	0.000

Fig. 22. Kuraray correlogram of residuals squared

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.000	-0.000	3.E-05	
		2	-0.001	-0.001	0.0052	
		3	-0.007	-0.007	0.1372	0.711
		4	-0.026	-0.026	1.8204	0.402
		5	-0.007	-0.007	1.9407	0.585
		6	-0.009	-0.009	2.1199	0.714
		7	-0.044	-0.044	6.6922	0.245
		8	-0.021	-0.022	7.7138	0.260
		9	0.005	0.005	7.7821	0.352
		10	-0.014	-0.016	8.2901	0.406

Fig. 23. Yagi correlogram of residuals

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.321	0.321	248.56	0.000
		2	0.052	-0.057	255.09	0.000
		3	0.052	0.059	261.71	0.000
		4	0.048	0.017	267.22	0.000
		5	0.085	0.072	284.61	0.000
		6	0.021	-0.034	285.68	0.000
		7	0.050	0.060	291.60	0.000
		8	0.086	0.051	309.48	0.000
		9	0.032	-0.015	311.98	0.000
		10	0.052	0.046	318.45	0.000

Fig. 24. Yagi correlogram of residuals squaredd

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.026	0.026	0.5017	
		2	-0.028	-0.029	1.0822	
		3	0.032	0.034	1.8284	0.176
		4	0.002	-0.001	1.8317	0.400
		5	-0.001	0.001	1.8319	0.608
		6	0.005	0.004	1.8478	0.764
		7	0.003	0.002	1.8528	0.869
		8	0.018	0.018	2.0793	0.912
		9	-0.064	-0.066	5.0616	0.652
		10	0.004	0.009	5.0744	0.750

Fig. 25. Global style correlogram of residuals

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.142	0.142	14.440	0.000
		2	0.067	0.048	17.634	0.000
		3	0.056	0.041	19.877	0.000
		4	0.033	0.017	20.636	0.000
		5	0.009	-0.003	20.695	0.001
		6	-0.006	-0.012	20.722	0.002
		7	0.009	0.009	20.784	0.004
		8	0.076	0.076	24.951	0.002
		9	0.068	0.050	28.314	0.001
		10	0.030	0.007	28.975	0.001

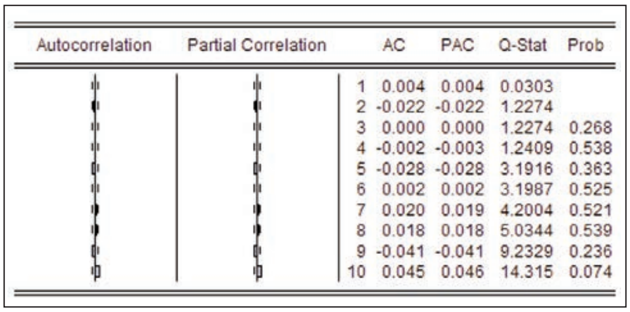
Fig. 26. Global style correlogram of residuals squared

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.006	-0.006	0.1028	
		2	-0.013	-0.013	0.4993	
		3	-0.008	-0.008	0.6512	0.420
		4	-0.006	-0.006	0.7400	0.691
		5	0.019	0.018	1.5790	0.664
		6	0.003	0.003	1.5995	0.809
		7	-0.044	-0.043	6.3055	0.278
		8	-0.004	-0.004	6.3375	0.386
		9	0.007	0.006	6.4431	0.489
		10	0.020	0.019	7.4177	0.492

Fig. 27. Itochu correlogram of residuals

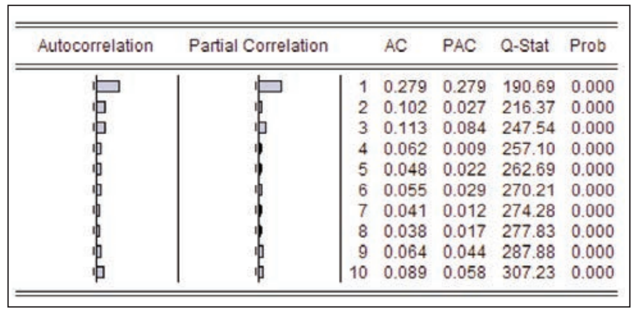
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.154	0.154	58.290	0.000
		2	0.165	0.144	124.53	0.000
		3	0.194	0.156	216.24	0.000
		4	0.156	0.096	275.52	0.000
		5	0.101	0.028	300.31	0.000
		6	0.115	0.045	332.89	0.000
		7	0.192	0.133	423.74	0.000
		8	0.074	-0.006	437.02	0.000
		9	0.118	0.046	471.33	0.000
		10	0.108	0.026	499.81	0.000

Fig. 28. Itochu correlogram of residuals squared



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.004	0.004	0.0303	
		2	-0.022	-0.022	1.2274	
		3	0.000	0.000	1.2274	0.268
		4	-0.002	-0.003	1.2409	0.538
		5	-0.028	-0.028	3.1916	0.363
		6	0.002	0.002	3.1987	0.525
		7	0.020	0.019	4.2004	0.521
		8	0.018	0.018	5.0344	0.539
		9	-0.041	-0.041	9.2329	0.236
		10	0.045	0.046	14.315	0.074

Fig. 29. Sankyo Seiko correlogram of residuals



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.279	0.279	190.69	0.000
		2	0.102	0.027	216.37	0.000
		3	0.113	0.084	247.54	0.000
		4	0.062	0.009	257.10	0.000
		5	0.048	0.022	262.69	0.000
		6	0.055	0.029	270.21	0.000
		7	0.041	0.012	274.28	0.000
		8	0.038	0.017	277.83	0.000
		9	0.064	0.044	287.88	0.000
		10	0.089	0.058	307.23	0.000

Fig. 30. Sankyo Seiko correlogram of residuals squared

Above are the Correlograms depicting the residuals and their squares, to make the model parsimonious, in two of the cases, models of lower order have been chosen as discussed previously. What is very interesting to note is that we have witnessed an almost perfectly flat residuals chart for all 10 companies taken for the study. This confirms that the models chosen based upon AIC, SC, Sigma Squared, and Adjusted R-squared are a perfect fit.

However, we can observe from the residuals squared correlograms that in most of the cases there are spikes in mostly 1st value of ACF and PACF both except in the case of Kuraray (0,1,4). What can be attributed to this unique phenomenon is related to the impact of extraneous and confounding regressors. For ease of understanding, let's consider it as White noise.

Since the squared residuals do not seem to be serially correlated, we will go ahead with the chosen models. Figures 31–50 present the forecast evaluations of the chosen models.

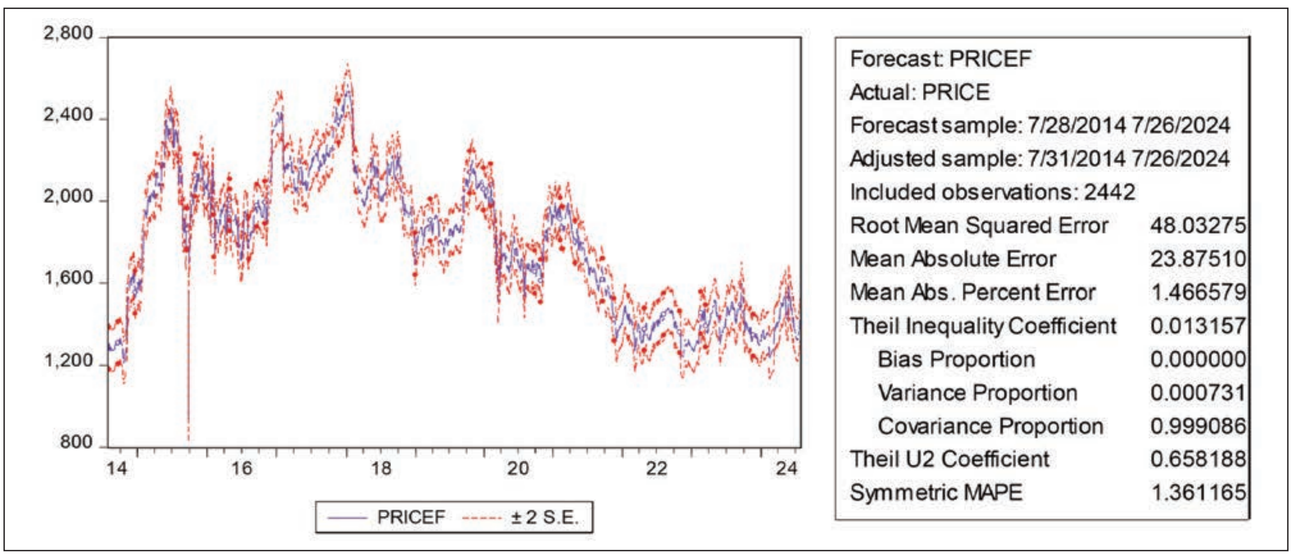
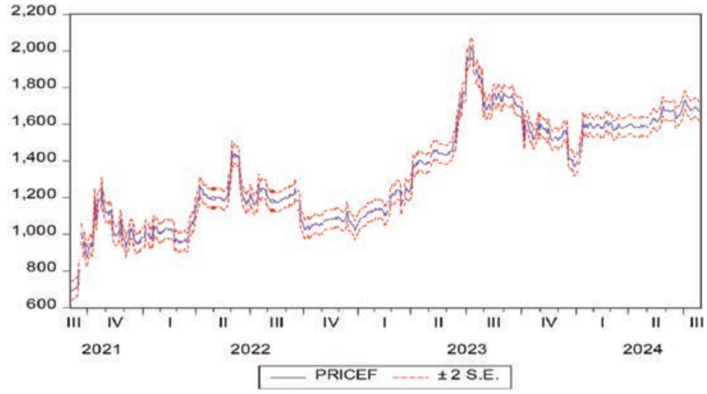


Fig. 31. Teijin forecast graph

Fig. 32. Teijin actual and forecast comparison graph



Forecast: PRICEF	
Actual: PRICE	
Forecast sample: 8/25/2021 7/26/2024	
Adjusted sample: 9/02/2021 7/26/2024	
Included observations: 707	
Root Mean Squared Error	25.52222
Mean Absolute Error	15.53193
Mean Abs. Percent Error	1.217933
Theil Inequality Coefficient	0.009372
Bias Proportion	0.000014
Variance Proportion	0.001304
Covariance Proportion	0.998680
Theil U2 Coefficient	0.991954
Symmetric MAPE	1.221310

Fig. 33. Global style forecast graph

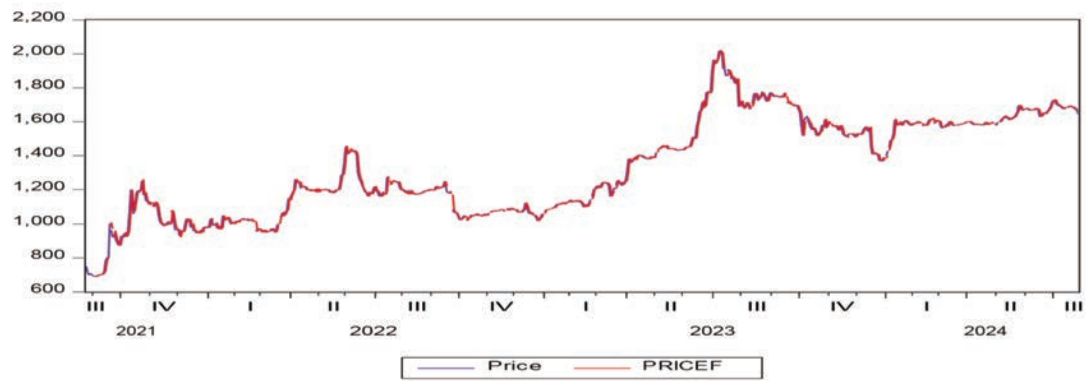
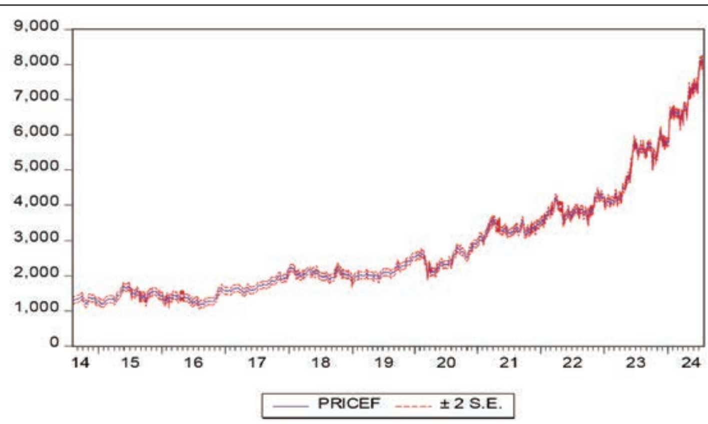


Fig. 34. Global style actual and forecast comparison graph



Forecast: PRICEF	
Actual: PRICE	
Forecast sample: 7/28/2014 7/26/2024	
Adjusted sample: 8/06/2014 7/26/2024	
Included observations: 2437	
Root Mean Squared Error	49.06050
Mean Absolute Error	31.24266
Mean Abs. Percent Error	1.120011
Theil Inequality Coefficient	0.007627
Bias Proportion	0.000000
Variance Proportion	0.002864
Covariance Proportion	0.997166
Theil U2 Coefficient	1.002179
Symmetric MAPE	1.119131

Fig. 35. Itochu forecast graph

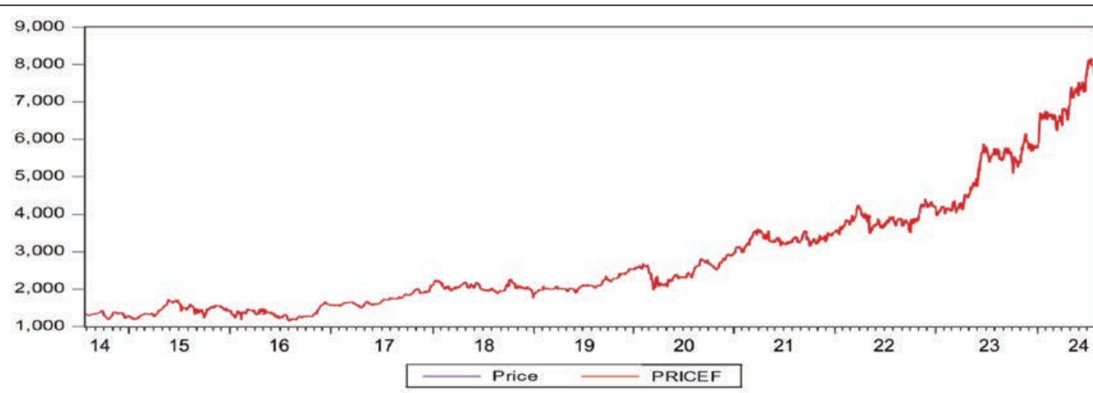
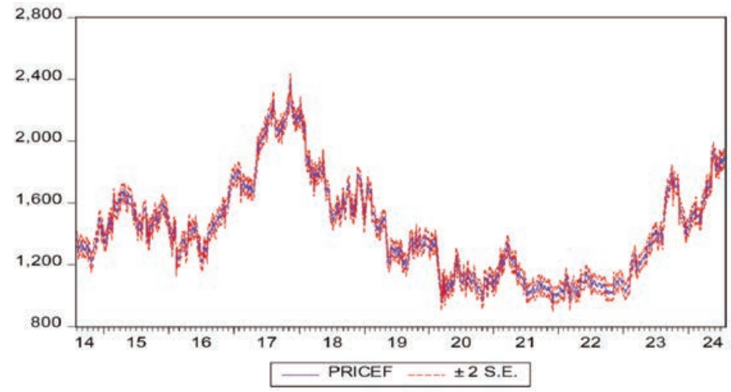


Fig. 36. Itochu actual and forecast comparison graph



Forecast: PRICEF	
Actual: PRICE	
Forecast sample: 7/28/2014 7/26/2024	
Adjusted sample: 7/29/2014 7/26/2024	
Included observations: 2443	
Root Mean Squared Error	23.67862
Mean Absolute Error	17.19231
Mean Abs. Percent Error	1.230066
Theil Inequality Coefficient	0.008113
Bias Proportion	0.000000
Variance Proportion	0.000011
Covariance Proportion	0.999488
Theil U2 Coefficient	0.999540
Symmetric MAPE	1.229445

Fig. 37. Kuraray forecast graph

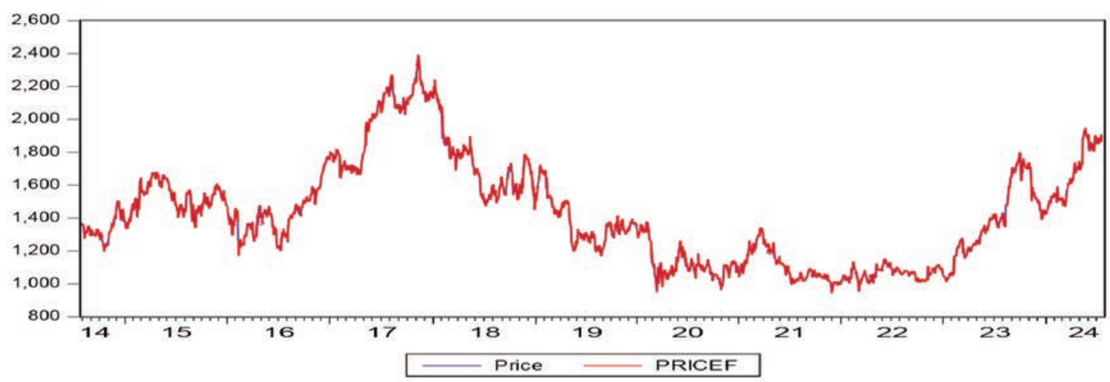
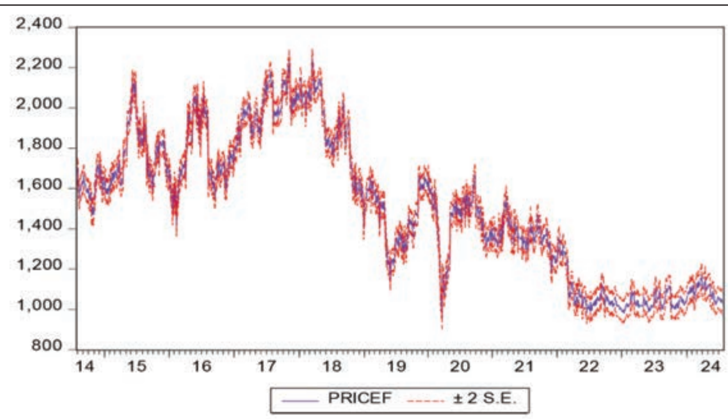


Fig. 38. Kuraray actual and forecast comparison graph



Forecast: PRICEF	
Actual: PRICE	
Forecast sample: 7/28/2014 7/26/2024	
Adjusted sample: 7/29/2014 7/26/2024	
Included observations: 2443	
Root Mean Squared Error	26.49022
Mean Absolute Error	18.49478
Mean Abs. Percent Error	1.221791
Theil Inequality Coefficient	0.008543
Bias Proportion	0.000000
Variance Proportion	0.000046
Covariance Proportion	1.000102
Theil U2 Coefficient	0.997890
Symmetric MAPE	1.221325

Fig. 39. Toyobo forecast graph

Fig. 40. Toyobo actual and forecast comparison graph

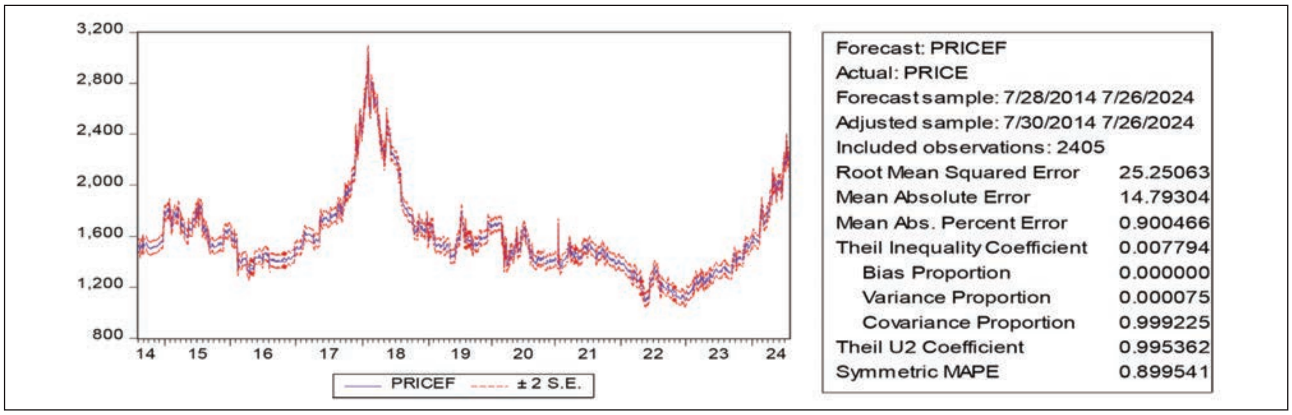


Fig. 41. Yagi forecast graph

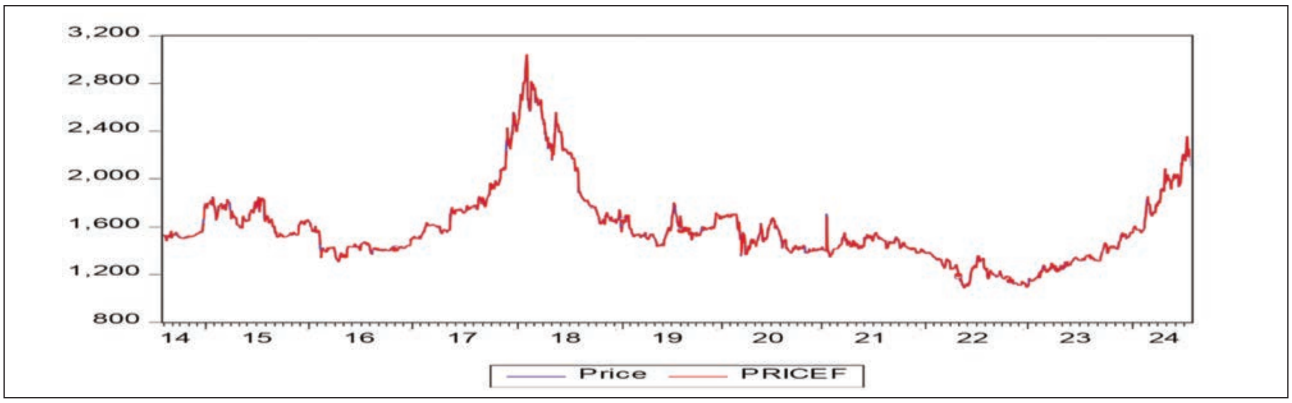


Fig. 42. Yagi actual and forecast comparison graph

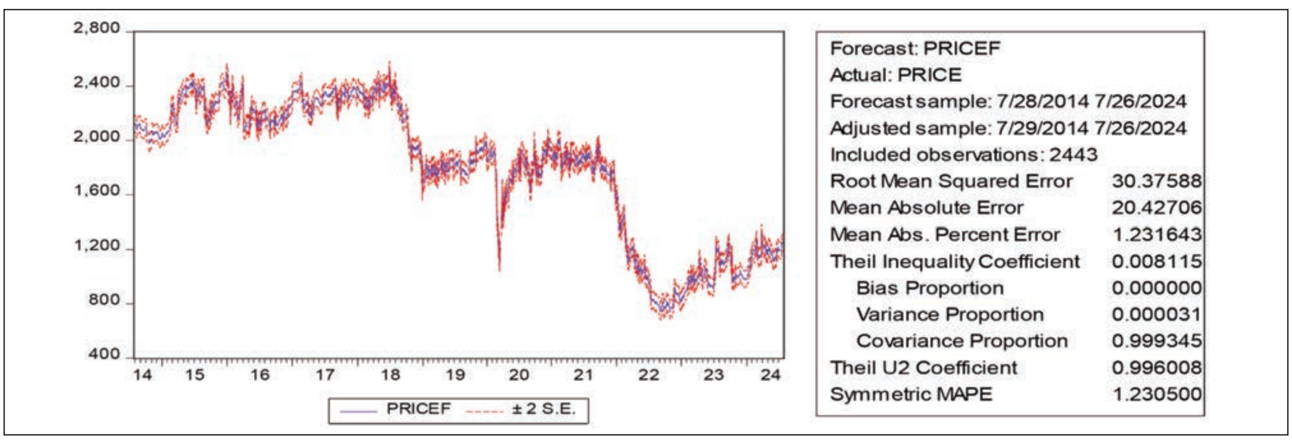


Fig. 43. Takihyo forecast graph

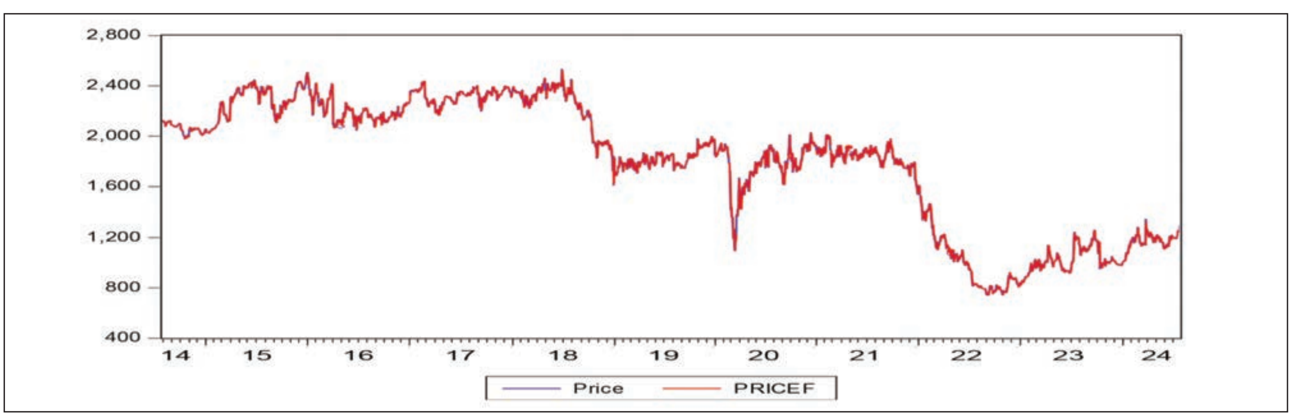


Fig. 44. Takihyo actual and forecast graph comparison

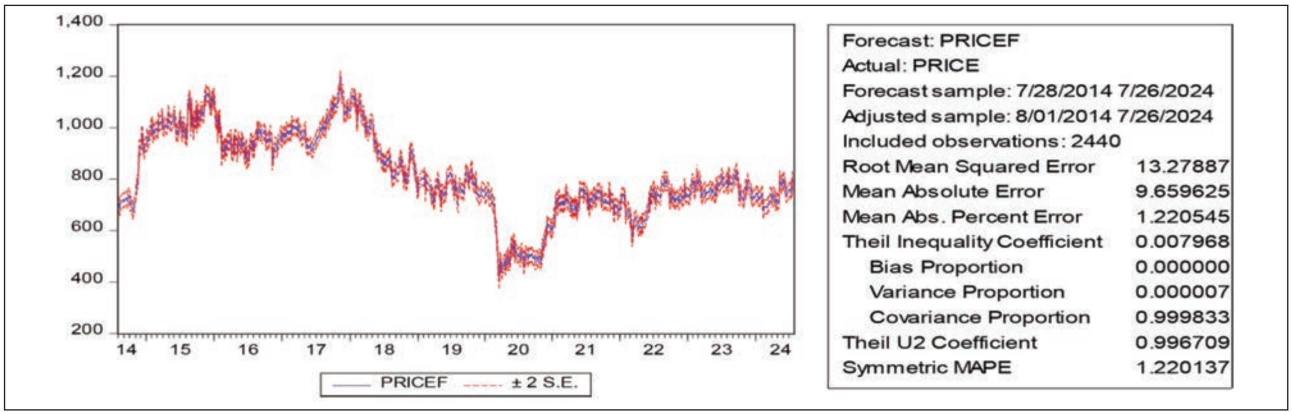


Fig. 45. Toray forecast graph

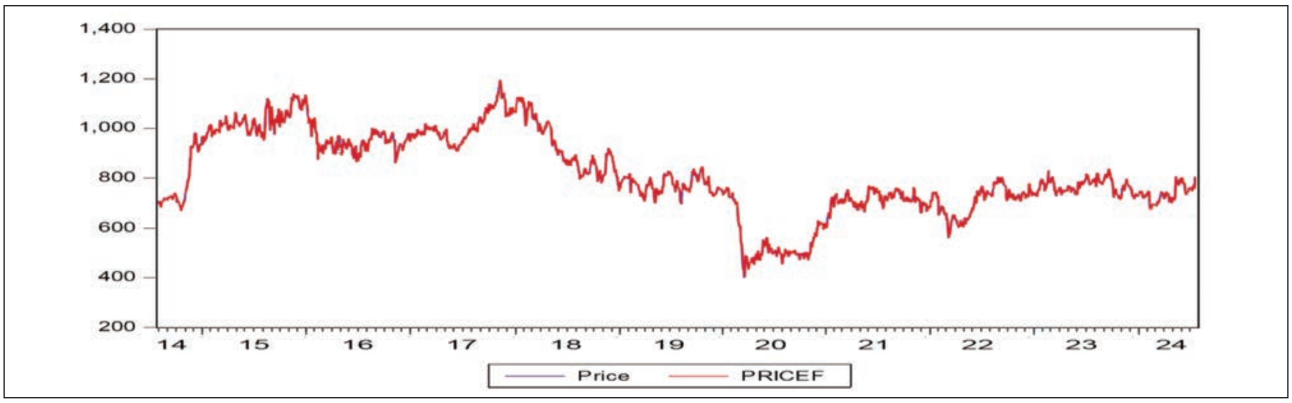


Fig. 46. Toray actual and forecast comparison graph

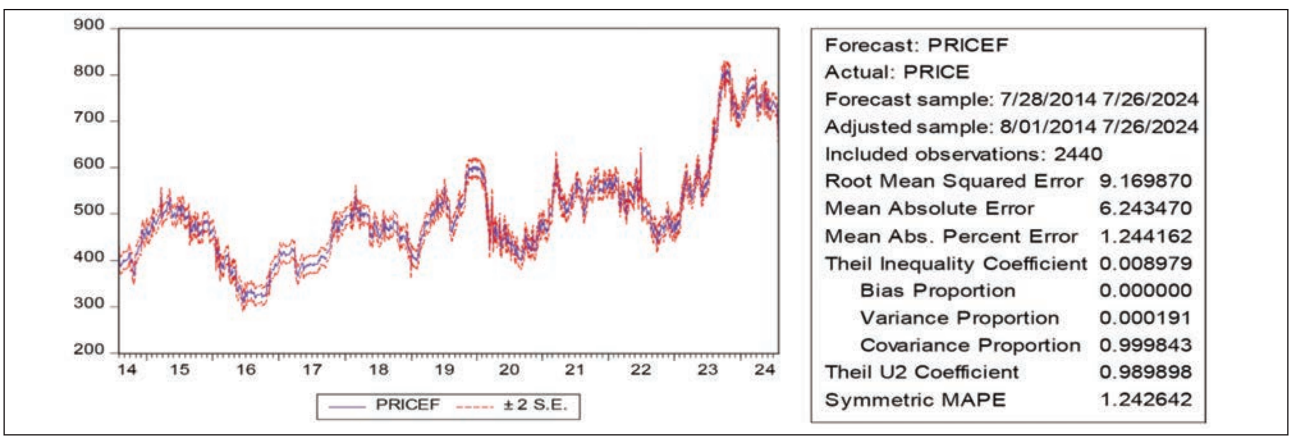


Fig. 47. Sankyo Seiko forecast graphh

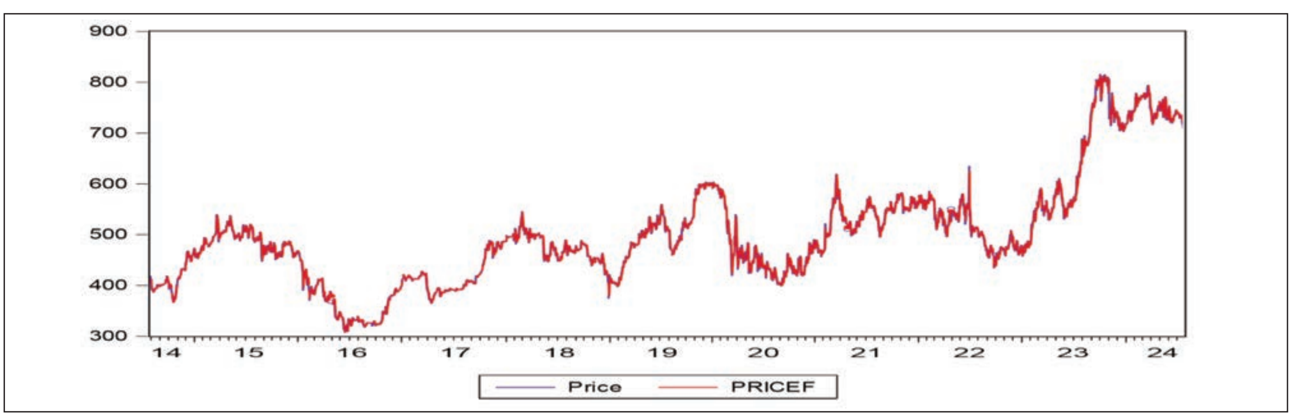


Fig. 48. Sankyo Seiko actual and forecast comparison graph

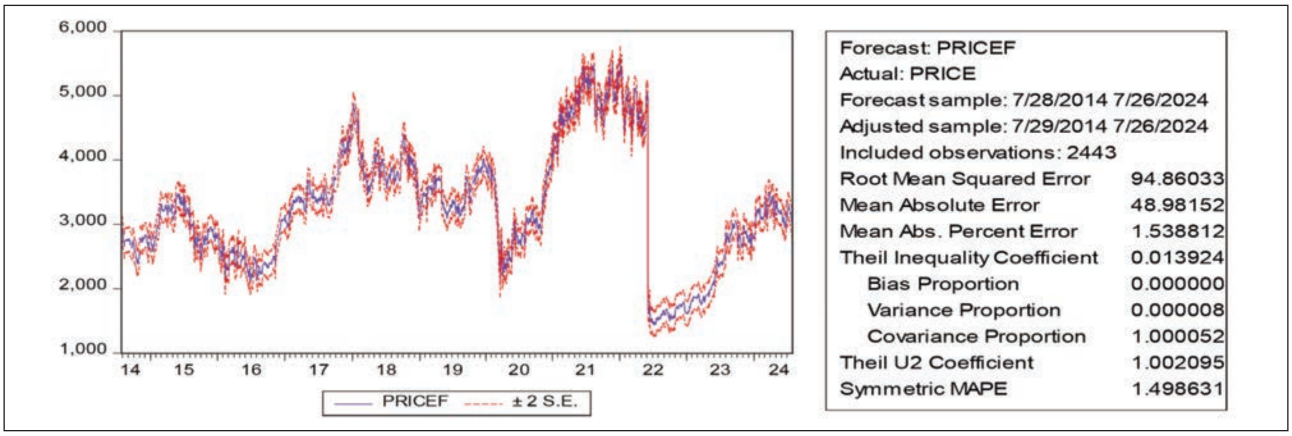


Fig. 49. Toyota Tsusho forecast graph

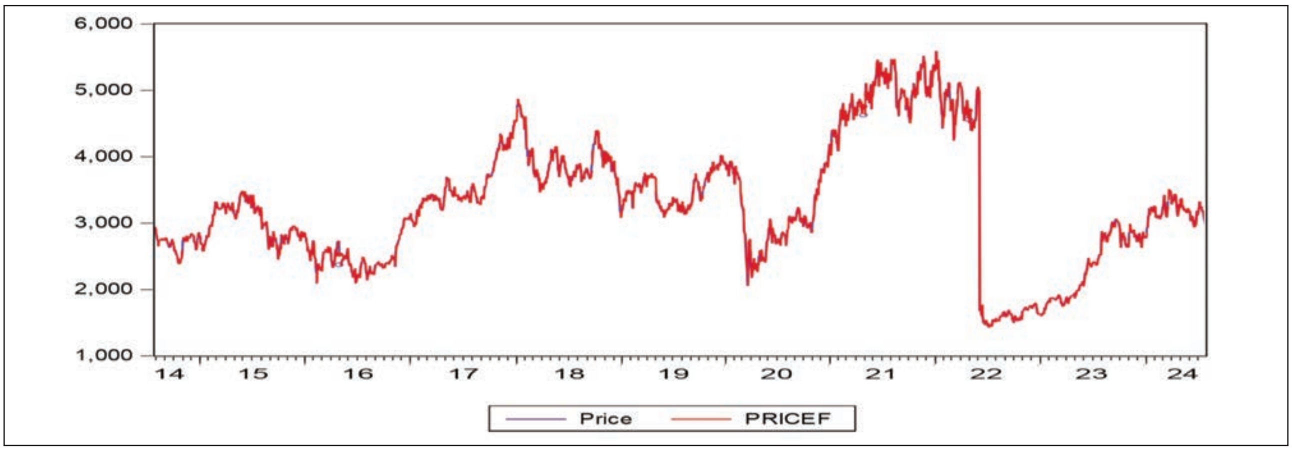


Fig. 50. Toyota Tsusho Actual and Forecast Comparison Graph

From the Symmetric MAPE value, it is clear that the forecasted values are likely precise, and the value is always around 1.5 or below. Mean error values are also very low, and it is mostly around 1 and 1.4. In the case of Yagi, we have achieved excellent forecasting statistics. It is also to be noted that the statistics prove some room for imperfections, which signifies that our chosen models are not overfitting in nature.

From comparison graphs, it is also evident that the values between the forecasted and actual values are quite similar, and the difference is quite low. The accuracy can also be estimated from the Covariance Proportion value of the forecast statistics, which is in all cases approximately equivalent to 1.

Now let us look at the nature of the model and the Prices of the 10 companies chosen for the study through a table.

Before moving further to the values discussed in table 2, we should first understand a few things in advance. The notation denotes the order of ARIMA

Table 2

MODEL PREDICTIONS OF AUTOCORRELATIONS

Company name	Notation	Intercept	AR (p)	MA(q)
Teijin	(2,1,1)	0.053521	–0.0511	–0.37764
Global Style	(5,1,4)	1.22291	0.084719	0.096148
Itochu	(6,1,6)	2.513588	–0.9099	0.873841
Kuraray	(0,1,4)	0.196592	-	0.027223
Toyobo	(0,1,3)	–0.27654	-	–0.05487
Yagi	(1,1,2)	0.259149	–0.06773	0.057988
Takihyo	(0,1,1)	–0.34529	-	–0.09649
Toray	(3,1,6)	0.027799	–0.04093	–0.05358
Sankyo Seiko	(3,1,1)	0.101501	–0.04698	–0.16094
Toyota Tsusho	(0,1,7)	–0.02031	-	–0.05296

forecasting in the form (p,d,q). The intercept denotes the constant term, signifying the average value of the price of the first difference when all the other values are constant.

The AR(p) denotes the autoregressive term of order p, meaning the current value of the first differenced price is influenced by its past p values. The MA(q) denotes the moving average of order q, meaning the current value of the differenced price is influenced by the residual of q periods ago. The coefficients of AR and MA denote the direction and strength of the influence of AR and MA on future values.

This should be noted that a positive coefficient of AR and MA leads to a positive value in the present, and a negative value suggests a negative relationship.

Now coming to the values of the table, firstly we should acknowledge that except for Itochu, none of the companies have a Significant intercept P-value at a 95% confidence level. In most cases, either the present values are not impacted by the AR term, that is, the autoregressive values of the past or are negatively impacted, except in the case of Global Style. It is also surprising to note that the present values are impacted less than 10% in all the cases, except Itochu, having a negative impact of almost 91%.

When taking into consideration MA terms, that is the impact due to past residuals or error terms, it has a certainly higher impact on present value than AR terms. Mostly, it is also negatively impacting the present values, but also positive in some cases, like Global Style, Kuraray, Itochu and Yagi. Again, Itochu is highly impacted by the MA terms, with an impact of almost 87%.

At this moment, it is also very important to note that none of the terms in Kuraray were found statistically significant, but still, the model accurately predicts the values. Additionally, it should be noted that the textile industry is impacted by its past values and residuals for up to a week.

CONCLUSION, RECOMMENDATIONS AND SUGGESTIONS

Japan has had a rich legacy of textiles for more than 1000 years and has been maintained even though it was not formally part of the Silk Route trade, along with all the historical crests and troughs Japan faced, including events revolving around before and after the Meiji Revolution. Like other industries, the textile industry also thrived in Japan, and in 2022, it was the 20th largest textile exporter in the world with an export of $8.11 billion. One thing that needs to be noted here is that Japan is a world leader and the largest producer of technical textiles.

Not much study about the Japanese textile sector as a whole has been conducted regarding the stock prices of Japan's major textile companies. 10 companies were studied, chosen based on the document on textiles published by the EU-Japan centre based on market capitalisation, with almost 10 years of historical data from 2014 to 2024 studied through appropriate ARIMA models identified through the Akaike info Criterion, Schwarz Criterion, Sigma squared value and R-squared value. The companies chosen included Teijin, Global Style, Itochu, Kuraray, Toyobo, Yagi, Takihyo, Toray, Sankyo Seiko, and Toyota Tsusho. Except for Global Style, all the companies have 10 years of data. The (p, d, q) values of the analysis included (2,1,1), (4,1,16), (6,1,6), (20,1,20), (0,1,3), (1,1,2), (0,1,1), (3,1,6), (3,1,1), (0,1,7) respectively in the order as the corporations are previously mentioned. To make the model parsimonious, higher values were dropped, and values of lower order were preferred. After identification of the appropriate models, it was diagnosed for the presence of any squared residuals was diagnosed. In all the cases, no presence was established. However, in squared analysis, except for Kuraray, a spike in the first value of ACF and PACF was observed, attributed to extraneous and confounding nature variables (considering white noise for simplicity), and it should be noted that squared residuals were not serially correlated. Upon evaluation of models, it was found that most of the corporations had either a negative impact or no impact of past lagged values on their present value, except for Global Style, which had a positive influence, maybe due to its distinct nature of textile products in comparison to other corporations. Similarly, Itochu was 91% affected by its own past lagged values, maybe due to its huge operations in textiles as well as other sectors distinct from textiles. Mostly due to lagged value of past residuals, all the corporations were negatively affected, but Global Style, Kuraray, Itochu and Yagi were positively impacted, and there was a huge impact seen in terms of Itochu.

On average, all the Japanese textiles taken into consideration are impacted by their past values and residuals by almost a week. It can be noted that most of the Japanese textile corporations react to the market dynamics and macroeconomic variables similarly but the reason for the difference in reaction is due to the structure of the corporations where most of the corporations have a deep-rooted textile legacy with similar scale of operations in other sectors as well, this makes stock prices vulnerable to muti fluctuations due to varied reasons. ARIMA seemed to be a fine model in order to analyse and predict stock prices, but it has been established by many studies that machine learning models, in most cases, have better accuracy in predictions. One of the most common Machine Learning models is LSTM. This model is a derivative of RNN. Due to a lack of training and constraints on various fronts, employing machine learning models didn't seem feasible. However, there are several advanced models like Support Vector Model (SVM), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Artificial Neural Network (ANN), Random Forest decision tree, XGBoost, etc., that could have been used and may be more efficient than ARIMA. This paper was a novel step in understanding the movement of textile companies in a freely traded financial market, which is reflective of the sentiments of the corporation. Future researchers are recommended to consider the gaps and limitations of this study and then work on the hidden aspects that this paper was unable to identify and address. It is suggested that the use of machine learning seems imperative, but all the models have their accuracy, efficiency and limitations under certain circumstances, along with outperforming capabilities in some situations.

Hence, researchers would be required to evaluate the proper scenario and then employ the preferred model. But one major limitation of this research is its inability to account for external factors that can significantly influence the stock prices of Japanese textile companies. The model primarily focuses on historical price data, overlooking variables such as fluctuations in raw material costs, exchange rates, changes in trade policies, and evolving consumer preferences for sustainable products. These external factors can lead to sudden, unpredictable market movements, reducing the accuracy of purely time series-based predictions. Future studies may address this limitation by integrating external macroeconomic indicators and sentiment analysis to enhance predictive accuracy and better capture the complexities of the market. Similarly, in the present era of machine learning, while the ARIMA model is suitable for time series analysis due to its simplicity and effectiveness in capturing linear trends, it has limitations in predicting complex, non-linear stock price movements. The model relies heavily on the assumption of stationarity and cannot effectively handle sudden market changes or intricate patterns influenced by external factors. As a result, it may fall short in forecasting highly volatile or irregular stock prices of Japanese textile companies. Future research could explore advanced machine learning models, such as Long Short-Term Memory (LSTM) networks, which are better equipped to learn non-linear dependencies and capture long-term trends, potentially offering greater robustness and accuracy in predictive analysis.

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