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Prediction of Dow Jones Index, US Inflation, and Interest Rate with Kernel Estimator and Vector Error Correction Model

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ABSTRACT

The Dow Jones Industrial Average (DJIA) is the oldest running U.S. stock market index, established by Dow Jones & Company under Charles Dow. Comprising thirty major publicly traded companies, the DJIA is a key indicator of macroeconomic health, reflecting investor confidence and economic stability. This study applies a quantitative research approach to forecast DJIA stock prices, inflation, and U.S. interest rates using time series analysis. Two forecasting methods are compared: Vector Error Correction Model (VECM) and Kernel regression. VECM, a parametric approach, estimates both short- and long-term relationships among economic variables, while Kernel regression, a nonparametric technique, effectively captures complex, nonlinear relationships without strict model assumptions. The results indicate that the Gaussian Kernel method provides the most accurate predictions, achieving a Mean Absolute Percentage Error (MAPE) of 5.72%. The analysis also shows that despite annual fluctuations, the DJIA has exhibited a steady growth trend from 2009 to 2024, with both its starting and ending prices increasing over time. This research is significant for investors, policymakers, and financial analysts, offering insights into market trends and economic indicators. By providing a reliable forecasting model, it aids in better decision-making regarding stock market investments and economic policies.

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A. INTRODUCTION

The stock market plays a strategic role in the economy, both as a source of funding for companies and as an investment instrument for the public. Shares, which represent proof of partial ownership of a company, grant their holders rights to a portion of the company's capital (Farooq et al., 2022). Through the stock market, companies can raise capital to support their operations and growth, while investors have the opportunity to participate in the company's growth and gain profits from the increase in stock value (Acheson et al., 2017). The US is known for having an efficient and transparent stock market, supported by strict regulations from the Securities and Exchange Commission (SEC). The stock market in the US shows a high level of liquidity, allowing stocks to be traded in large volumes and with relatively low transaction costs (Abudy, 2020). In addition, major stock indices such as the S&P 500 and the Dow Jones Industrial Average have become important indicators for measuring the economic health of the country. Investor confidence in the US stock market has been driven by a history of stable economic growth, corporate innovation, and monetary policies that support the capital market.

The Dow Jones Industrial Average (DJIA) was introduced in 1896 by Dow Jones & Company, through Charles Dow, as a measure of industrial performance in the stock market. The DJIA consists of the thirty largest publicly traded companies in the United States and is considered one of the main indicators of economic conditions (Lin et al., 2021). The performance of stock indices like the DJIA is often influenced by various macroeconomic factors, such as inflation and interest rates. For example, in March 2020, when the Covid-19 pandemic peaked, the DJIA experienced a sharp decline of 6,400 points in just four trading days, equivalent to a 26% drop. However, several sectors, such as healthcare, food, natural gas, and software, actually recorded higher gains during that period (Akhtaruzzaman et al., 2021). In addition to being an influential index in the US, the DJIA also has relationships with stock indices of other countries. Lesmana, (2022) through his research using the multiple linear regression method, found that the DJIA and Nikkei225 indices have a positive relationship with the IDX (Indonesia Stock Exchange).

Inflation and interest rates play an important role in influencing stock market movements. High inflation rates tend to increase companies' operational costs, which can reduce profit margins and the value of company stocks. The study by Sathyanarayana & Gargesa (2018) found that there is a negative relationship between inflation and returns in the countries of Austria, Belgium, Canada, China, Chile, and France. Interest rates, set by the central bank, reflect the cost of borrowing in the economy and have a significant impact on the stock market. An increase in interest rates generally raises the cost of debt for companies, which can reduce profitability and put pressure on stock prices.

Higher interest rates also attract investors to switch to low-risk instruments, such as bonds, which offer fixed returns and are more attractive compared to stocks. Conversely, a decrease in interest rates encourages higher lending activity, lowers the cost of capital, and increases the growth opportunities for companies, which can drive up stock prices. Research by Pinem et al., (2023) with a case study on the Jakarta Composite Index (JCI) shows that changes in interest rates significantly affect stock returns, reflecting the market's sensitivity to monetary policy.

To understand the dynamic relationships based on time series between the stock market, inflation, and interest rates, multivariate time series analysis is a relevant approach. One commonly used method is the Vector Error Correction Model (VECM), which is a VAR model for non-stationary data with integration that can estimate short-term and long-term relationships between variables. Multivariate time series analysis offers robust tools to explore these interdependencies. One commonly used method is the Vector Error Correction Model (VECM), which is a VAR model for non-stationary data with integration that can estimate short-term and long-term relationships between variables. VECM extends the Vector Autoregression (VAR) framework to accommodate non-stationary data that are cointegrated, allowing for the estimation of both short-term dynamics and long-term equilibrium relationships among variables. This approach is particularly useful in capturing how deviations from long-term equilibrium influence short-term adjustments, providing a comprehensive understanding of economic indicators' interplay (Shehu et al., 2024).

In addition to parametric models like VECM, nonparametric approaches such as kernel regression have gained attention for their flexibility in modelling complex, non-linear patterns without imposing strict assumptions about the functional form of relationships. Kernel regression assigns weights to data points based on their proximity to the point of estimation, effectively capturing intricate data structures and potentially yielding lower prediction errors. Unlike parametric approaches, this method does not require explicit assumptions about the relationship between variables, making it more adaptive to complex patterns in the data Nonparametric approaches such as kernel regression are also considered effective due to their flexibility in capturing data patterns and producing lower prediction error rates. Unlike parametric approaches, this method does not require explicit assumptions about the form of the relationship between variables, making it more adaptive to complex patterns in the data (Arena et al., 2024). This adaptability makes it suitable for analyzing the nuanced interactions between the stock market, inflation, and interest rates, where relationships may not adhere to linear assumptions. In multivariate time series analysis, kernel regression can be used to predict the value of the target variable by considering the contribution of other non-linear variablesIn multivariate time series analysis, kernel regression can be used to predict the value of the target variable by considering the contribution of other non-linear variables.

Given the importance of understanding stock market movements in response to macroeconomic variables, this study aims to analyze the relationships between the DJIA, inflation, and interest rates using both the VECM and kernel regression approaches. The primary objective is to compare the effectiveness of these methods in capturing dynamic dependencies and making accurate predictions. This study contributes to the literature by providing empirical insights into the predictive power of traditional and nonparametric models in financial time series analysis. The results are expected to offer valuable implications for investors, policymakers, and financial analysts in formulating data-driven investment and economic policies.

B. METHODS

1. Data and Data Sources

The data used in this study is secondary data obtained from https://www.investing.com/. The variables used are the Dow Jones Stock Index, inflation rate, and United States interest rates with a time period of May 2009 to April 2024. The dataset consists of 180 observations.

2. Research Methodology

This study employs two time series forecasting methods: the Gaussian Kernel Estimator and the Vector Error Correction Model (VECM). The analysis was conducted using EViews for VECM estimation and RStudio for the Kernel Gaussian approach. The research procedure is structured systematically as follows:

a. General Stage
   1) Collects data on the Dow Jones Stock Index, inflation rate, and interest rates.
   2) Divide testing data and training data in a ratio of 90:10.
   3) Perform descriptive analysis of the research variables.
   4) Visualize the time series data through plots.

b. Analyze predictions using the *Vector Error Correction Model* (VECM) method on *training* data, with the following steps:
   1) Conduct Bartlett's Test to examine correlations between variables.
   2) Test for stationarity using the Augmented Dickey-Fuller (ADF) Test.
   3) Determine the optimal lag length using multiple information criteria (AIC, SC, HQ, FPE).
   4) Perform cointegration tests to assess long-term relationships among variables.
   5) Estimate the VECM model and evaluate variable significance based on R^2 values.
   6) Conduct the Granger causality test to determine causal relationships.
   7) Analyze Impulse Response Functions (IRF) to assess the impact of shocks on variables.
   8) Predict testing data and calculate Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE).

c. Analyze predictions using the Gaussian Kernel estimator method on *training* data, with the following steps:
   1) Identify the optimal bandwidth using Generalized Cross-Validation (GCV).
   2) Construct the kernel model based on the selected bandwidth.
   3) Choose the best kernel function based on the minimum GCV value.
   4) Make predictions using the Gaussian Kernel model and evaluate accuracy using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE).

d. Compares the two time series methods that will be used to predict based on the MAPE and RMSE value.
e. Calculate the return and dividend yield of the DJIA Stock Index.

C. RESULT AND DISCUSSION

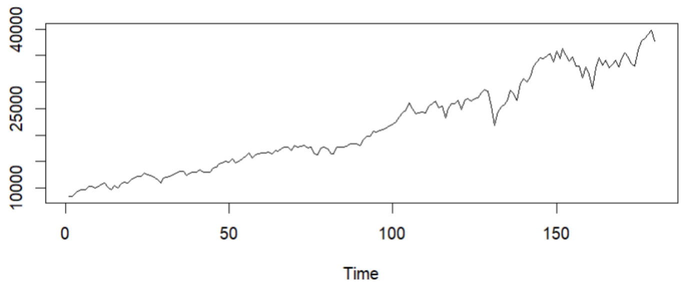
1. Data Characteristics

The initial step in the analysis involves performing a descriptive statistical evaluation, including the minimum and maximum values of the Dow Jones stock index data, inflation rates, and U.S. interest rates, as summarized briefly in Table 1 below.

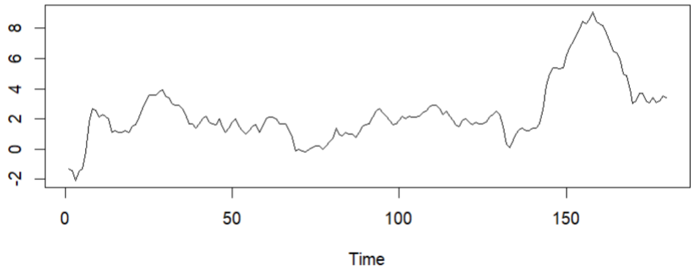
Table 1. Data Characteristics

Variable	Maximum		Minimum	
	Value	Time	Value	Time
Dow Jones Index	39.807,37	04/2024	8.447,00	06/2009
Inflation Rate	9,10	06/2022	-2,10	07/2009
Interest Rate	5,33	08/2023	0,05	04/2020

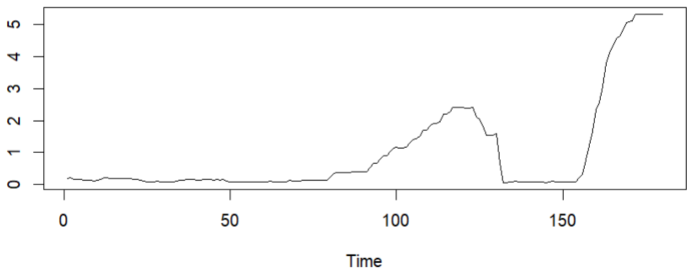
Based on data used in the period May 2009 to April 2024, the Dow Jones stock index has an average value of 21,579.51 with a standard deviation value of 8,854.345. The inflation rate of the United States has averaged 2.445 with a standard deviation of 2.09. The Federal Bank of the United States interest rate has an average value of 1.012 and a standard deviation of 1.515. The three variables experienced fluctuations visualized by the time series plot in Figure 1 as follows.



(a)



(b)



(c)

Figure 1. Time Series Plot for (a) Dow Jones Index (b) Inflation (c) Interest Rate

2. Bartlett's Test of Sphericity

The Bartlett test determine whether the correlation matrix is an identity matrix and to assess the adequacy of the sample. This test is used to confirm the presence of correlations among variables, ensuring the appropriateness of multivariate time-series modelling (Simiyu, 2015).

Table 2. Bartlett's Test of Sphercity

Approx. Chi-Square	Degree of Freedom	Sig.
177,656	3	0,000

Based on Table 2, the significance value is 0.000, which is less than alpha 0.05. This indicates the presence of a correlation among the Dow Jones Stock Index, inflation rate, and U.S. interest rates, allowing the analysis to proceed using the Vector Autoregressive (VAR) method.

3. Stationary Test

Vector Autoregressive (VAR) method is used when data is stationary. Therefore, a unit root test is conducted to assess the stationarity of the data, as non-stationary data can lead to spurious regression results (Gyedu et al., 2021).

Table 3. Stationarity Test

Variable	Critical Value	Level		1st Difference	
		ADF	p-value	ADF	p-value
Dow Jones Index	5%	-0,393385	0,9065	-11,84481	0,0000
Inflation Rate	5%	-2,662312	0,0827	-8,069199	0,0000
Interest Rate	5%	-1,170592	0,6868	-3,632118	0,0060

Based on Table 3, it is evident that the research data is not stationary at the level (indicated by a p-value greater than the significance 0.05). Consequently, differencing is required. After the first differencing is applied, the p-value falls below the significance level, indicating that the data has become stationary. This allows the analysis to proceed to the model identification process.

4. Selection of Optimal Lag

The identification of the Vector Autoregressive (VAR) model focuses on determining the optimal lag length. This selection can be guided by several criteria such as Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), and Hannan-Quinn Information Criterion (HQ) (Nwuju et al., 2024).

Table 4. Optimal Lag Criterion

Lag	LogL	FPE	AIC	SC	HQ
1	**-1172,061**	**1058,206**	**15,47793**	**15,7161**	**15,57448**
2	-1164,913	1084,300	15,50213	15,92807	15,67109
3	-1159,836	1141,769	15,55341	16,14761	15,79478
4	-1146,881	1084,973	15,50171	16,27417	15,81550
5	-1144,884	1190,263	15,59326	16,54398	15,97946
6	-1130,567	1112,078	15,52375	16,65274	15,98236
7	-1124,030	1150,936	15,55594	16,86319	16,08697
8	-1112,208	1112,417	15,51905	17,00456	16,12249

According to Table 4., the optimal lag is determined by the lowest value for each criterion (Huang & Jiang, 2023). Based on Table 4, lag 1 produces the lowest value across all criteria, making it the optimal choice for the next stage of analysis. Following this, a stability test will be conducted on the selected optimal lag.

5. Model Stability Test

The stability of a VAR model is rigorously determined through the examination of the modulus of its characteristic roots (Elalaoui et al., 2021). The model is classified as stable if and only if all root moduli are strictly less than one, signifying their confinement within the boundaries of the unit circle (Dinh, 2020).

Table 5. Stability Test

Root	Modulus
0,632862	0,632862
0,376503	0,376503
-0,140146	0,140146

According to Table 5, the modulus values of all roots are strictly less than one, confirming that the VAR model at lag 1 meets the stability test requirements.

6. Cointegration Test

The cointegration test investigate the existence of long-term equilibrium relationships, stability, and the degree of co-movement among variables (He et al., 2023). This diagnostic is pivotal in determining the appropriate analytical framework. The presence of cointegration warrants the adoption of the VECM approach to capture the inherent dependencies, while its absence justifies proceeding with the VAR methodology to model short-term dynamics (Sallam, 2021).

Table 6. Cointegration Test

Method	Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0,05 Critical Value	Prob
Trace	None *	0,412384	147,4684	29,79707	0,0001
	At most 1 *	0,261162	62,93100	15,49471	0,0000
	At most 2 *	0,088912	14,80547	3,841466	0,0001
Maximum Eigenvalue	None *	0,412384	84,53742	21,13162	0,0000
	At most 1 *	0,261162	48,12553	14,26460	0,0000
	At most 2 *	0,088912	14,80547	3,841466	0,0001

Based on the results of the cointegration test using the trace and maximum eigenvalue methods, a probability value of less than the significance level of 0.05 was obtained, indicating cointegration among the Dow Jones Stock Index, inflation rates, and United States interest rates. Therefore, the data analysis will proceed with the VECM method.

7. VECM Estimation

The data used meets the nature of cointegration so that analysis can be carried out with the VECM method. The significance of the variable can be seen in Table 7, where the variable is said to be significant if the test statistical value is more than the t-statistic of 1.977 with a significance level of 0.05. The estimated results of VECM (1, 1) are given in Table 7 as follows.

Table 7. VECM Model Estimation

Variable	Estimation		
	D(DowJones,2)	**D(Inflation,2)**	**D(Interest,2)**
C	-1,236005	0,000136	6,65 x 10^{-6}
	-0,14456	-5,90 x 10^{-5}	-1,70 x 10^{-5}
	[-8,55007]	[2,30045]	[0,38770]
D(DowJones,2)	0,103726	1,65 x 10^{-6}	2,12 x 10^{-5}
	-0,09357	-3,80 x 10^{-5}	-1,10 x 10^{-5}
	[1,10856]	[0,04290]	[1,91245]
D(Inflation,2)	-146,502	-0,23558	-0,01527
	-184,303	-0,07555	-0,02187
	[-0,79490]	[-3,11813]	[-0,69808]
D(Interest,2)	-1429,77	0,312356	-0,6469
	-712,687	-0,29215	-0,08459
	[-2,00617]	[1,06918]	[-3,12919]
R^2	**57,79%**	**15,57%**	**13,69%**

Based on Table 7, interest rates affect the value of the Dow Jones stock index with a value of -1429.77. This means that every increase in interest rates by 1% will affect the decline in the value of the Dow Jones stock index by 1429.77. The model's good measures for Dow Jones Stock Index data, inflation rates, and U.S. interest rates were 57.79%, 15.57%, and 13.69%, respectively, which explained the magnitude of variables in the study affecting the values in the study and other values explained by variables outside the study. These results indicate that VECM is relatively effective in explaining Dow Jones Index movements, but less effective in capturing variations in inflation and interest rates.

8. Granger Causality Test

The Granger Causality Test is utilized to analyze short-term causal relationships between variables (Shojaie & Fox, 2022). Evidence of short-term causality is established when the p-value falls below the predefined significance threshold of 0.05.

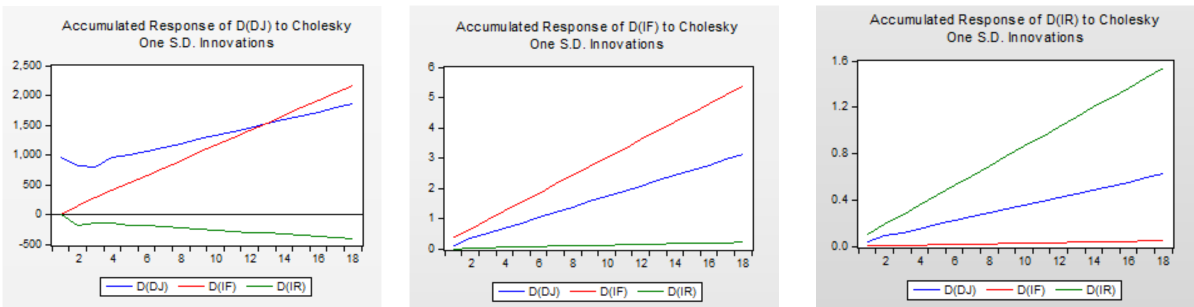
Table 8. Granger Causality Test

Null Hypothesis	F-Statistics	Prob.	Results
Inflation Does Not Affect Dow Jones Stock Index	2,01505	0,1539	Accept H_0
Dow Jones Stock Index Does Not Affect Inflation	2,32368	0,1292	Accept H_0
Interest Rates Do Not Affect the Dow Jones Stock Index	0,37362	0,5418	Accept H_0
Dow Jones Stock Index Does Not Affect Interest Rates	4,76494	0,0304	Reject H_0
Interest Rates Do Not Affect Inflation	7,54369	0,0066	Reject H_0
Inflation Does Not Affect Interest Rates	50,9204	0,0000	Reject H_0

Based on Table 8, The Granger causality test results reveal that the Dow Jones Index influences interest rates, while interest rates and inflation exhibit significant bidirectional causality. This suggests that stock market fluctuations can impact monetary policy decisions by the Federal Reserve.

9. Impulse Response Function

The Impulse Response Function (IRF) is a critical analytical tool used to examine the dynamic impact of a shock or disturbance in one variable on the behaviour of another variable over time (Fuchs et al., 2022). The Impulse Response Function test on the three research variables is given in Figure 2.



(a) (b) (c)

Figure 2. Impulse Response Function for (a) Dow Jones Index (b) Inflation (c) Interest Rate

Based on Figure 2, several things can be known as follows.

a. In Figure 2(a), it can be seen that the Dow Jones Stock Index responds positively to shocks or changes in the value of inflation and the value of the Dow Jones Stock Index itself while the Dow Jones Index responds negatively to changes in interest rates.
b. In Figure 2(b), the inflation rate responds positively to shocks from the value of the Dow Jones Stock Index and the value of inflation itself. The inflation rate tends to slope at the equilibrium point when there is a shock in the interest rate.
c. In Figure 2(c), interest rates respond positively to shocks in the value of the Dow Jones Stock Index and shocks in interest rates themselves. Interest rates tend to slope around the equilibrium point with respect to changes in the value of the inflation rate.

10. Estimation with Gaussian Kernel Method

For comparison, the method will be estimated with the Gaussian Kernel method. The basis for selecting the optimum bandwidth in the Gaussian Kernel method is based on the average GCV value of all the minimum variables (Dani et al., 2021) The selection of the optimum bandwidth value is given in Table 9 as follows.

Table 9. Bandwidth Selection

Bandwidth	GCV			Mean
	Dow Jones Index	Inflation	Interest	
0,1	48802027	4,143050	0,001368	12200507,8
0,2	48575272	4,144998	0,004865	12143819,1
0,3	48193531	4,127447	0,009254	12048383,9
0,4	**47982485**	**4,140359**	**0,015266**	**11995622,4**
0,5	48109932	4,153513	0,024104	12027484,2

Based on Table 9, the optimal bandwidth that can be used in predicting the value of Dow Jones Stock Index data, inflation rate, and United States interest rates simultaneously with the minimum GCV value is 0.4.

11. Selection of Best Prediction Method

After conducting analysis, a comparison will be made to choose the best method in predicting Dow Jones Stock Index data, inflation rates, and United States interest rates for the next few periods. A comparison of time series methods based on MAPE and RMSE values is given in Table 10.

Table 10. MAPE and RMSE Comparison

Variable	VECM		Kernel Gaussian	
	MAPE	RMSE	MAPE	RMSE
Dow Jones Index	18,85%	7442.89	4,42%	1904.03
Inflation Rate	20,54%	0.9832	9,88%	0.5133
Interest Rate	29,28%	2.0719	2,85%	0.1487
Mean	22,89%	2481.983	5,72%	634.896

These findings confirm that the Gaussian Kernel model significantly outperforms VECM in predicting economic variables, with substantially lower prediction errors. Additionally, the RMSE values further validate the superiority of the Gaussian Kernel method, with a significantly lower RMSE (634.896) compared to VECM (2481.983), indicating better predictive accuracy and reduced overall error. The superiority of the Gaussian Kernel Estimator lies in its flexibility to capture non-linear relationships between variables without requiring strict distributional assumptions (Shi et al., 2022). The lower RMSE values across all variables confirm that the Gaussian Kernel model reduces prediction errors more effectively than VECM. A comparison visualization of prediction testing data with both methods and actual data is given in Figure 3.

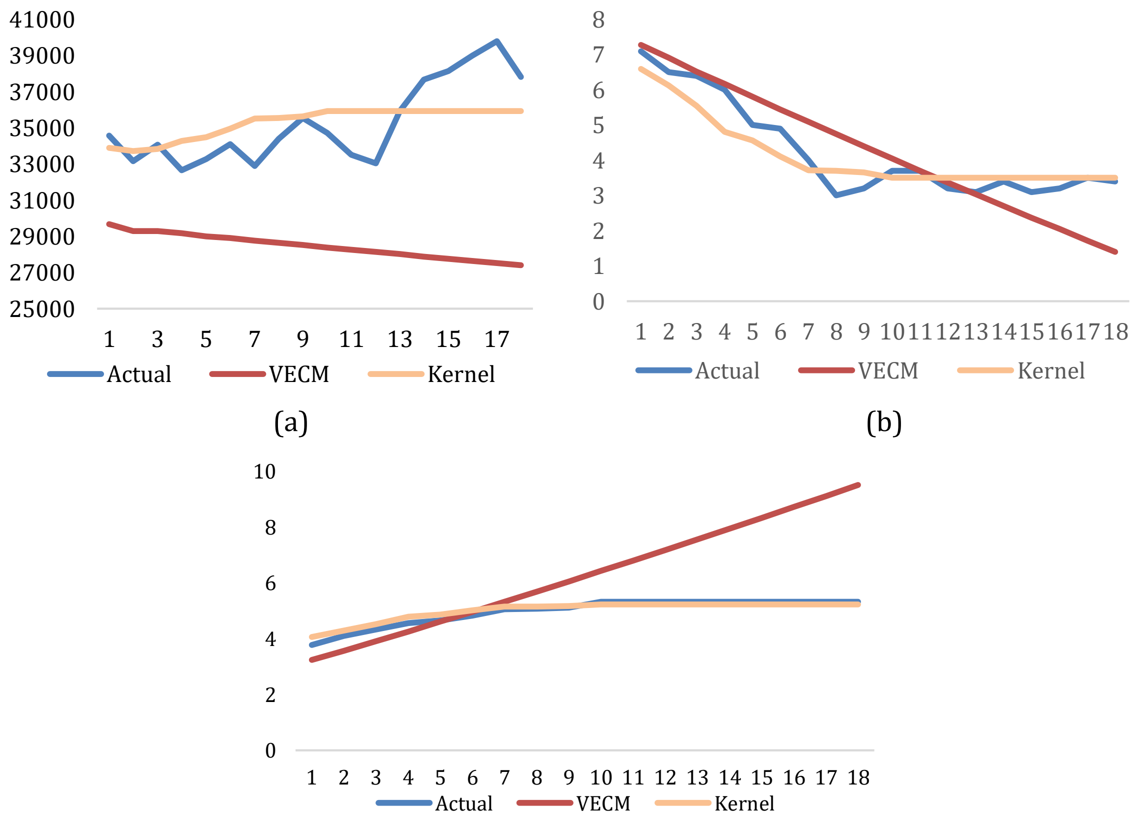


Figure 3. Prediction Plot for (a) Dow Jones Index (b) Inflation (c) Interest Rate

Previous studies using VECM such as Kismawadi (2024) have demonstrated its capability in identifying long-term relationships among macroeconomic indicators. However, this study introduces the Gaussian Kernel Estimator as an alternative, offering a better predictive accuracy by capturing non-linear dependencies that traditional parametric models fail to address. The findings of this research align with prior studies from Mishra & Mishra (2021) emphasizing the influence of interest rates and inflation on stock indices.

12. Calculation of Return and Dividend Yield

An approximation will be made of the calculation of return and dividend yield from the Dow Jones Industrial Average (DJIA) Stock Index. The importance of calculating dividend return lies in a comprehensive understanding of investment performance and returns earned by shareholders. The calculation results are given in Table 11.

Table 11. Calculation of Return and Dividend Yield

Year	Starting Price (USD)	Final Price (USD)	Dividend	Annual Return (%)	Dividend Yield (%)	Total Return (%)
2009	9.034,69	10.548,50	1,424	14,35	0,013	14,36
2010	10.583,95	11.569,70	1,523	8,52	0,013	8,53
2011	11.670,75	12.217,55	1,739	4,48	0,014	4,49
2012	12.397,379	12.938,11	1,961	4,18	0,015	4,19
2013	13.412,54	16.504,28	2,109	18,73	0,013	18,75
2014	16.441,34	17.983,07	2,426	8,57	0,013	8,59
2015	17.832,99	17.603,86	2,798	-1,30	0,016	-1,29
2016	17.148,93	19.762,59	3,128	13,23	0,016	13,24
2017	19.881,75	24.719,22	3,153	19,57	0,013	19,58
2018	24.824,00	23.062,40	3,849	-7,64	0,017	-7,62
2019	23.346,24	28.462,14	4,321	17,97	0,015	17,99
2020	28.868,80	30.409,56	3,908	5,07	0,013	5,08
2021	30.223,89	36.398,07	4,267	16,96	0,012	16,97
2022	36.585,05	33.147,25	5,153	-10,37	0,016	-10,36
2023	33.136,37	37.689,53	5,379	12,08	0,014	12,09

Based on Table 11, it can be seen that this index showed a steady growth trend during that time period. Despite annual fluctuations in the price of the index, both the starting price and the ending price tend to increase from year to year, reflecting consistent economic growth. The annual return of the index varies from year to year, with some years experiencing high returns and other years experiencing moderate decline or growth. Nevertheless, the overall total return tends to be positive, indicating that investments in the Dow Jones index gave good returns during the observed period. Dividend yield also shows stability, indicating that dividends paid to shareholders remain consistent in providing returns. However, some years may experience significant fluctuations that can be influenced by external factors such as global economic conditions, government policies, or geopolitical events. For example, price declines in 2022 could be influenced by factors such as monetary policy, trade tensions, or the COVID-19 pandemic. Thus, the data shows that despite the fluctuations, investments in the Dow Jones index as a whole resulted in strong performance over the observed period.

D. CONCLUSION AND SUGGESTIONS

This study finds that the Dow Jones Index, inflation, and interest rates exhibit a cointegration relationship, justifying the use of VECM for long-term analysis. However, the Gaussian Kernel Estimator demonstrates superior predictive performance, with an average MAPE of 5.72%, compared to 22.89% for VECM. From a statistical standpoint, the Gaussian Kernel Estimator effectively captures non-linear patterns in economic data without requiring rigid assumptions. In practical applications, this method offers greater flexibility and significantly improved accuracy over regression-based models such as VECM. To further enhance prediction accuracy, future research should consider incorporating additional variables, including economic growth (GDP) which influences corporate earnings and investor confidence, directly affecting stock market indices and exchange rates that impact trade balances and capital flows, which, in turn, affect inflation and interest rate policies, making it a critical factor in financial forecasting.

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